Evaluating Total Productivity of Cement Manufacturing Options with Mass Customisation Technologies

A thesis submitted by

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ABSTRACT

Flexible and fast-paced mass customisation cement businesses require advanced production facilities and a skilled global workforce in a COVID-19 epidemic worldwide manufacturing environment. It is a problem to measure frequently changing production lines' productivity. This thesis introduced the classic Cobb-Douglas production methods and empirical stochastic frontier analysis tools with various sub-tools, including simulation, the voice of the house of the deployment in mass customisation, and modern production methods, etc., using trial-and-error approaches, seeking optimal return of scale for optimum resource use—minimising investment while maximising profit. Two scenarios illustrate the proposed methods. Scenario 1 closely examines the classic Cobb–Douglas production functions and develops the linear equations for the stochastic frontier analysis with technical efficiency with simulation optimisation processes, and the survey results using trial-and-error methods to study two types of geopolymer-based (metakaolin and fly ash) cement paralleling production and productivity, resulting in demand and customers' needs in alignment with a tactic for just-in-time delivery, maximising profit. Scenario 2 closely examines the classic Cobb–Douglas production functions and develops the linear equations for stochastic frontier analysis with technical efficiency using trial-and-error methods with simulation optimisation processes and survey results to study ordinary Portland, blended Portland, and high early strength cement because of in demand and customers' needs in alignment with a tactic for just-in-time delivery, maximising profit and minimising resources use. The main findings are the classic Cobb–Douglas production function is suitable for either labour- or machine-intensive traditional cement manufacturing. The empirical stochastic frontier function is a functional equation which requires multiple skills to collect and analyse different sources to determine a suitable regression equation to examine the state-of-the-art cement optimisation in return for scale. As a result, the classic Cobb-Douglas production function is not one of the typical cases of the empirical stochastic frontier analysis based on the two scenarios' outcomes. It is an alternative. So, it is a variation in Lin et al. (2014). Thus, the empirical stochastic frontier analysis equation focuses on speedy manufacturing technology productivity measures.

CERTIFICATION OF THESIS

I, Chi Shing **CHAN,** declare that the Thesis entitled *Evaluating Total Productivity of Cement Manufacturing Options with Mass Customisation Technologies* is not more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. The thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

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ABBREVIATIONS

A	productivity factor
A_i	amplitude of the wave
A_s	SiO_2 silica dioxide
a_i	available
AM	alumina modulus
App	the word application which is software program that's designed to perform a specific function directly for user or, in some cases, for another application program
ASTM	American society for testing and materials
AS	Australian standard
b_i	available
BVAR-DSGE	Bayesian vector autoregressive dynamic stochastic general equilibrium-dynamic stochastic general equilibrium modelling
CCAA	cement concrete & aggregates Australia
CO_2	carbon dioxide
CDPF	Cobb–Douglas production function
COVID-19	coronavirus disease of 2019
d	travel distance
5W1H	five (where, what, which, who, when) and one (how)
ECRS	manufacturing and eliminating wastes with (e)liminate, (c)ombine, (r)earrange, (s)implify
$exp\{v_i\}$	exponential function in terms v_i
F	Fe_2O_3-Iron (III) oxide
f (x, ß)	function for the empirical stochastic frontier analysis, it includes x and ß vector of parameters.
FA	fly ash
FATank	fly ash tank
FI	fineness index: general purpose Portland cement (GP)is in the range 350-400m^2/kg while for high early strength (HE) cement is about 450m^2/kg (CCAA, 2020)
GP	general Portland cement and bulk density of bagged general Portland (GP) cement is approximately 1000-1300kg/m^3
GB	builder cement or blend cement and its density is approximately 100-1250kg/m^3
GBBFS	ground granulated blast furnace slag
FluidSplit	split fluid in different pipelines
Fluidexit	fluid exit to another process
HE	high early strength cement and same structure of general Portland and blend Portland cement. But the main different is extra fine grinding
hr/day/ps	hours/day/person
Hr/yr/pr	hours/year/person(s)
HMI	human machine interface
Ir Prof	Ingenieur Professor
IT	information technology
k	wavenumber

K	amount of capital including production facilities and raw materials yearly
KOH	potassium hydroxide
KOHtank	potassium hydroxide tank
L	direct and indirect labours yearly
LAN	local area network
LF	likelihood function
LH	it is a general Portland (GP) cement blended with supplementary cementitious called ground granulated blast furnace slag
LOF	level of fineness (% passing a 45-micron sieve)
LOI	loss of ignition (unburned coal remaining in the fly ash)
LSF	lime saturation factor
Ln or exp	natural logarithm (ln) or exponential logarithm (exp)
Log	logarithm
NaOH	sodium hydroxide
NaOHtank	sodium hydroxide tank
MC	mass customisation
MK	metakaolin
MHU	material handling unit
MEP	mechanical, electrical, and plumbing
MiC	modular in construction
mixTank	mix tank
ML	maximum likelihood
NZ	New Zealand
α_i	the output elasticity capital constant variable
β_i	the output elasticity of labour constant variable
OPC	ordinary Portland cement like general Portland cement (GP)
PD	panel data
Pers	persons
PLC	programmable logic controllers
ProcessTank1	number 1 process tank
ProcesTank2	number 2 process tank
Q	productivity for the classic Cobb–Douglas Production Function Measures
Q_i	variable of productivities
S	calcium oxide
S_i	distance travel; i=1,…,n
S_c, S_0	pool dimension
scada	supervisory control and acquisition system
S_b	vessel dimension
SCMs	supplementary cementitious material(s)
SFA	empirical stochastic frontier analysis
SM	silica modulus
SR	sulphate resisting cement complies with AS 3972 limits the peak temperature rises below 23°C when tested in accordance with AS 2350.7-Langavant test
ST	standard times

t	time
TE	ratio between maximum feasible and production facilities output based on stochastic frontier analysis with assistance of mass customisation technologies
TE=1	obtains the maximum feasible output of the production facilities
$TE_i < 1$	provides the shortfall of the production facilities
Tank1	number 1 tank
Tank2	number 2 tank
Tank3	number 3 tank
u_i	production facilities utilization rates for $i = 1, \ldots, n$ using stochastic frontier analysis method with assistance of mass customisation technologies
$v_i = 1$	number of frequently downfall of production facilities using empirical stochastic frontier analysis method with assistance of mass customisation technologies
v	linear velocity
Valve1	number 1 valve
Valve2	number 2 valve
Valve3	number 3 valve
Valve4	number 4 valve
Valve5	number 5 valve
Valve6	number 6 valve
Valve7	number 7 valve
VOC	voice of customers
Wi/Fi	wireless fidelity
X_i	available
Y_i	available
	process
	inspection
	flow foreword
	stop
ω	wave's angular frequency
φ	phase of the sine wave given in radian
3D printer	three-dimensional printer

CHAPTER 1: INTRODUCTION

1.1 Research background

For the past few decades, Australian-owned factories have used build-to-stock mass production methods to fabricate ordinary Portland cement (Chan, 2018) that fits most construction projects, resulting in sub-contracted small lot cement businesses looking for overseas solutions to improve shortening delivery time. However, this decision leads to reduced company profit. Thus, the micro-medium cement companies need to rethink using advanced production methods fabricating customised cement in domestic factories, resulting in rebounding business performance after the COVID-19 pandemic and one of the factors of gross domestic product (GDP) growth in manufacturing sectors for the fast-moving variety of small lot tailored-made cement businesses. Australian Bureau of Statistics (2022) addressed building market size is estimated at USD 10.27 billion in 2024 and is expected to reach USD 13.06 billion by 2029, causing customised cement in demand market. Such leading figures in the Australian industry have recognised the productivity and efficiency gains (CIF, 2021) that advanced manufacturing techniques can offer to cement entrepreneurs. As a result, it caused a tight labour market, rising input costs, and increased demand due to government incentives. The construction and building industries have experienced significant price inflation in most states. It is one of the momentums of maximising resource use.

Due to a better understanding of the distribution manufacturing method (Chan et al., 2011b), whether made-in worldwide factories of the customised cement performances and clients' expectations, the capability planning in enterprise resources planning (ERP) and material requirements planning (MRP) software can assist by leveraging overall production events (William, 2011), including contracted small lot orders to outboard cement companies for better quality assurances, asset management and seamless manufacturing operations (Samara, 2015; Bay and Ross, 1968; Wacker, 1975). They cannot directly solve the productivity measure problem until there is a tailor-made module, but this is costly. Facing this challenge of driving down cost, micro/medium Australian-owned cement companies use a spreadsheet because it can perform the same functions as ERP/MRP software, which can provide a trial-and-error method to conduct the classic Cobb–Douglas production function and empirical stochastic frontier analysis methods to probe further productivity measures. But a customised spreadsheet is one of the economical and efficient ways to achieve this goal.

1.2 Aim

This research aims to develop a productivity measurement framework for the cement industry with less investment and resource use to maximise profit. It can provide a solution for entrepreneurs who prefer a mass customisation approach, allowing them to optimise their customisation of various types of various types of cement, such as Portland-based, geopolymer-based cement with homogenous and heterogenous structures and so on, in paralleling manufacturing using state-of-the-art cement production technologies that meet different civil and construction contractors' cement applications on time and at the agreed cost. It also provides an alternative to improving market share worldwide by using competitor advantages for sustainable cement business (Company X, 2021).

1.3 Research objective

The research objective is to develop a proposed productivity measures framework for optimising the small lot production of customised variety Portland-based and geopolymer-based cement and improving customer satisfaction by using state-of-the-art manufacturing methods. The proposed framework consists of the following:

1) The main tools, such as the classic Cobb–Douglas production function, the empirical stochastic frontier analysis and so on, measure productivity optimisation using the trial-and-error method for optimal operation.
2) Sub-tools, including simulation and the voice of the house in the deployment of mass customisation, are used to collect optimum process data to develop customised empirical stochastic frontier analysis equations. This is a primary procedure of the main tools used to intensively examine manufacturing options, including capital investment and processes study, using a trial-and-error method to seek optimisation.

Further, the proposed framework can measure advanced machine-intensive productivity and lean manufacturing without affecting regular cement production and can minimise production facilities investment. Comparing the two tools reveals both advantages and limitations.

Additionally, the outcome of the proposed framework can provide information to suit cement entrepreneurs who wish to reorganise their manufacturing strategies. The research poses the following questions:

1)What kinds of manufacturing methods are suitable for mass customisation technologies?
2) Which factors affect technical efficiency and productivity?
3) What sorts of data and parameters can further examine the productivity models?
4) What kind of data sources can be used to develop main and sub-tools for the productivity optimisation measure?

1.4 Research significance

The research provides optimal productivity measures using the proposed framework, which consists of two productivity tools, several sub-tools, parameters, and data. Their roles are as follows:

a) Validating two productivity tools, several sub-tools and identified valued parameters:

a1). The two main productivity tools are as follows:

- The classic Cobb–Douglas production function, which focuses capital and labour
- The empirical stochastic frontier analysis, which is for machine-intensive performance measures

a2). Several sub-tools provide expert opinions for the optimisation process choice:

- Simulation (e.g., agent-based models), as one of the source providers
- The voice of the house of the deployment in the mass customisation matrix is a quantitative measure of customer voices and manufacturer capability for modularity preference that is enhances using popular methods from articles
- Traditional cement production and state-of-the-art production technologies

a3). Valued parameters and data for two tools and sub-tools for further study equations:

- Formulating parameters for capital, labour force, elasticity, productivity factor, technical efficiency and production facilities data into the equation.

b) Investigating, identifying, and developing:

b1). Investigating and identifying data to develop a linear regression of the empirical stochastic frontier analysis equation instead of format function status (e.g., $f(x_i,\beta)$)

b2). Developing, based on data from multiple sources using XLMiner™ (Chan, 2018), the regression equation for empirical frontier analysis measures. This also provides valuable data for the classic Cobb–Douglas production function using trial-and-error methods concerning new manufacturing technologies and production methods.

c) Comparing the two tools' advantages and disadvantages for seeking alternatives, such as a normal scale of return, and the tools' application to customised varieties of geopolymer-based and Portland-based cement manufacturing as a result of using a similar process for optimising paralleling production

1.5 Research chapter outline

Chapter 1	This chapter illustrates the research background, objectives, aims and significance and outlines each chapter.
Chapter 2	This chapter features a literature review focused on cement production technology, mass customisation, simulation, cement production facilities layout and survey, total productivity for optimisation measures, small lot production and research gaps. The research questions were developed based on the findings and evaluation of alternative frameworks.
Chapter 3	This chapter discusses the development of an advanced proposed framework for productivity measures of cement manufacturing based on evaluation of various researchers' approaches outcomes. It includes five-level hierarchy chart that includes the collection of primary and secondary data, methods of productivity measures, methods of development regression equations, and mass customisation technologies associated with simulation modelling suitable for this research.
Chapter 4	This chapter includes data collection, traditional, simulation and productivity measure methods of optimisation for small lot cement manufacturing to develop scenario-based further analysis. Primary and secondary data were collected from different sources. Primary data were gathered from simulation models and surveys. Secondary data were obtained from the literature review, targeted companies' financial reports, cement and concrete associations, the Australian Bureau of Statistics (ABS), and other sources. These data assist in developing agile and flexible cement manufacturing studies to satisfy various worldwide clients' just-in-time delivery.

Chapter 5	This chapter details Scenario 1: the study of geopolymer-based manufacturing that it aligns with the findings with the outcome of Chapter 4. The Cobb–Douglas production function and empirical stochastic frontier analysis associated with simulation and voices of the house of deployment in mass customisation to measure productivity for various parameters seek to optimise the technology-intensive manufacturing environment of an Australian-owned cement factory.
Chapter 6	This chapter details Scenario 2: the study of Portland-based manufacturing that it aligns with the outcome of Chapter 4. The classic Cobb–Douglas production function and the empirical stochastic frontier analysis associated with simulation and voices of the house of deployment in mass customisation to measure productivity for various parameters seek to optimise the technology-intensive manufacturing environment of an Australian-owned cement factory
Chapter 7	This chapter examines the results and further validates the proposed methodology, evaluating cement productivity options and mass customisation technologies.
Chapter 8	This chapter discusses the overall research, detailing outcomes, objectives and research questions, limitations, and future research.

CHAPTER 2: LITERATURE REVIEW

Over the past decade, the Australian-owned cement industry has produced 9.1 million tonnes of cement annually, including fly ash (FA)-based geopolymer cement; 5,000 people are directly and indirectly involved in this business. In 2019, the industry turnover was around A$2.4 billion (Cement Industry Federation [CIF], 2019). Compared with other countries, in terms of business performance and technologies concerning production facilities and methods, customer expectations, and market share (Global Cement, 2020), this is a low turnover. Consequently, this study's research questions, and methodology have been developed based on these international business challenges and further findings in optimal productivity improvement. Developing a tool to address the below factors will shorten this gap between the Australian and international cement industry:

1) Traditional cement production methods, including current and advanced plant layout with state-of-the-art cement facilities for agile mass customised cement manufacturing
2) Methods of mass customisation for the cement industry
3) Data collection method, including a survey, simulation and related articles
4) Productivity measures (Classic Cobb–Douglas production function and empirical stochastic frontier analysis)

2.1 Cement production technology

Joseph Aspin, a UK builder, developed Portland cement and patented it in 1824. The product is called Portland cement because it resembled Portland stone. The first extensive use of Portland cement was in the construction of the London sewerage system from 1859 to 1867, which led to the cement's increased popularity and, ultimately, its widespread use in the construction industry for more than one hundred years. This led to several versions and manufacturing methods because of various applications and financial and environmental considerations (Gani, 1997; Cohrs, 2012, Gani,1997; Chan, 2018; Bye,2010 and Davidovits,2013) summarised the composition of Portland-based and geopolymer-based cement characteristics and production methods, as shown in Table 2.1 and according to the American Standard of Testing Material and the Australian cement standard. Their work offers an opportunity to identify the homogenous and heterogeneous materials of Portland-based and geopolymer-based cement that gives Anderson's (2005) approach to study attribute independence (raw material), process independence and process similarity for optimal processes of customised cement varieties for parallel production and meeting customer needs using modelling methods.

Table 2.1 Composition of Portland Cement, Geopolymer-based Cement, Characteristics and Application (Gani, 1997; Chan, 2018, p. 11; Bye, 2010; Davidovich, 2013; Aragaw, 2018; Hewlet and Liska, 2019)

Composition of Portland Cement (BS EN 197-1 2000)

Cement	Grey (%)	Black (%)	White (%)	Grey (%)	Black (%)	White (%)
SiO_2	19–23	21.7	23.8	LSF 90–98	98.4	97.2
Al_2O_3	3–7	5.3	5.00	LCF -	96.2	93.8
Fe_2O_3	1.5–4.5	2.6	0.20	S/R 2–4	2.7	4.6
CaO	63–67	67.7	79.80	A/F 1–4	2.0	25.0
MgO	0.5–.5	1.3	0.08	C_3S% -	65.4	58.4
K_2O	0.1–1.2	0.5	0.03	C_2S% -	12.9	23.5
Na_2O	0.07–0.4	0.2	0.03	C_3A% -	9.6	12.9
SO_3	2.5–3.51	0.7	0.06	C_4AF% -	7.9	0.6

Application and Characteristics (ASTM)

Portland-based Cement	Type	Characteristics	Uses
Portland cement	I	Non-especially hydraulic cement	Most structures and pavements
High Portland cement	II	Generates less heat from its hydration and is more resilient to sulfate attack than type I	Structures with large cross-sections
High-early-strength Portland cement	III	Allows earlier removal of forms and shorter periods of curing	High strengths within few days
Low heat Portland cement	IV	Generates less heat during hydration than type II; gains strength more slowly than type I	Mass concrete constructions
Sulfate - resisting Portland cement	V	High-sulfate resistance cement that gains strength more slowly than type I	Used when concrete is exposed to severe sulfate attack
Air- entraining Portland cement	1A, IIA, IIIA	Air-entraining agents, underground with the cement clinker, purposely causes air in minutes, closely spaced bubbles to occur in concrete	Entrained air makes the concrete more resistant to the effects of repeated freezing and thawing, used on pavements
Portland - blast furnace slag cement	1A, IS-A, MH, MS	Made by grinding granulated high-quality slag with Portland cement clinker; type IS cement gains strength more slowly in initial stages, but ultimately has about the same 28 days' strength as type 1 cement	Air entrainment type is IS-A, moderate heat-of-hydration type is MH and moderate sulfate resistance type is MS
Portland - Pozzolan cement	IP, IP-A	A blended cement made by intergrading Portland cement and pozzolanic materials	Used under certain conditions for concrete not exposed to air

Geopolymer-based Cement (Davidovits, 2013)

Slag-based geopolymer cement		MK-750 with blast furnace slag and silicate or GBBFS-based geopolymer cement	Construction materials
Rock-based geopolymer cement		MK-750 with selected volcanic tuffs yield geopolymer cement and less CO_2 emission than the simple slag-based geopolymer cement	Construction materials
Fly ash-based geopolymer cement		*Type 1*: requires heat hardening at 60-80C and is not manufactured separately. Si/Al= 1 to 2 *Type 2*: room temperatures cement hardening. Si/Al=2	Building and construction materials
Ferro-sialate based geopolymer cement		Similar of those rock-based geopolymer cement but involve geopolymer elements with high iron oxide contents	Construction materials

Further, silica modulus (SM), alumina modulus (AM) and lime saturation factor (LSF) % at 100°C test methods are used for identifying general Portland (GP), blend general Portland (GB) and high early strength (HE) cement, including sulphate resisting, shrinkage limited cement and whether they are homogeneity structures, resulting in organising paralleling either in simulation or pilot-run fabrication that improves productivity and meets aggregate production plans. As a result, their characteristics are as follows:

- High early strength (HE) cement (see AS standard AS3972, AS1478, AS3582.2 to AS3582.3, AS3972) is usually compositionally like GP but milled to a higher level of fineness (CCAA, 2020).
- Blend general Portland (GB) (AS3972) cement can be produced using the below methods:
    - ➢ a post-blending operation mixed the supplementary cementitious material (SCM), which is milled with fly ash, slag and silica fume that was previously in the appropriate proportions for manufacturing general Portland cement based on AS3582.3-2002 standard. This is typical for fly ash blends.
    - ➢ clinker and the supplementary cementitious materials (SCMs) are internally ground with gypsum and any mineral addition to form the blended cement (typical for slag blends).

- Special-purpose cement, except high early strength (HE) cement, is typically blended cement made by either post-blending or internally grinding. This method depends on the supplementary cementitious material (SCM) type used.
- The cement with supplementary cementitious material (SCM) is the same as that used in commercial type shrinkage limited (SL) or type sulphate resisting (SR) cement products, but it cannot be classified as SL or SR until cement suppliers can proceed with the appropriate tests on special-purpose cement to prove their performance and issue a test certificate accordingly.
- Most supplementary cementitious materials (SCMs) used in concrete production are supplied as separated products, with batching methods involving a mix with GB or GP cement, water, admixtures, and aggregate materials. As a result, there is market demand, and this is the most popular cement in the construction and building industries.

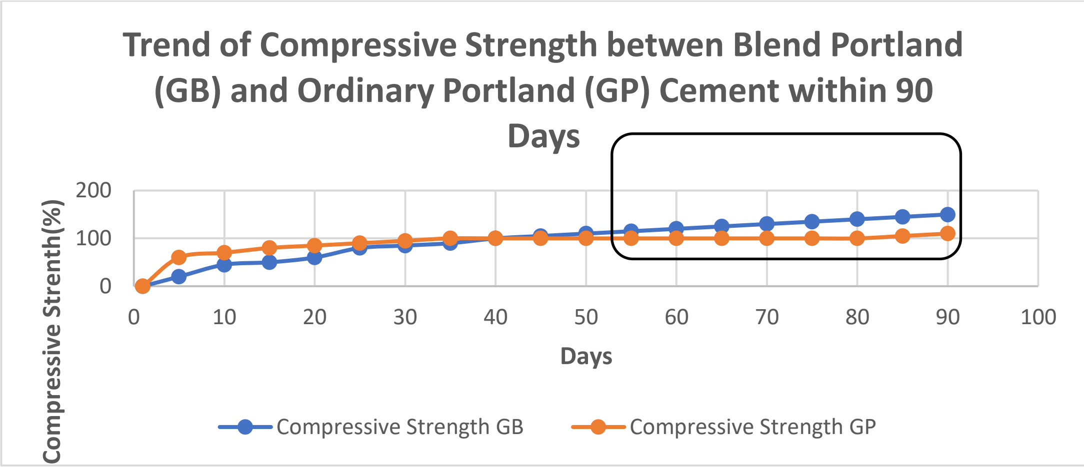


Figure 2.1 Comparative Mortar Compression Strength Performances—GP and GB Cement (CCAA, 2020)

The black boxes in Figures 2.1 and 2.2 illustrate the trend of compressive strength development in the daily based method for general Portland (GP) and blend general Portland (GB) cement types and the characteristics of peak temperature rise, including lower heat (LH) cement based on Australian Standard AS3972. As a result, early rates of strength gain for blend general Portland (GB) are lower than for general Portland (GP) because its extra-fine properties and blend general Portland (GB) cement has a lower carbon footprint its temperature does not fit for other types (Chan, 2018). The finding types of GP, GB and LH cement are homogeneous structures. Therefore, consideration of similar processes in paralleling production (Anderson, 2004) uses the simulation (see Section 2.3) for optimal manufacturing in response to market demand and customers expectation regarding mass customisation production (see Section 2.2).

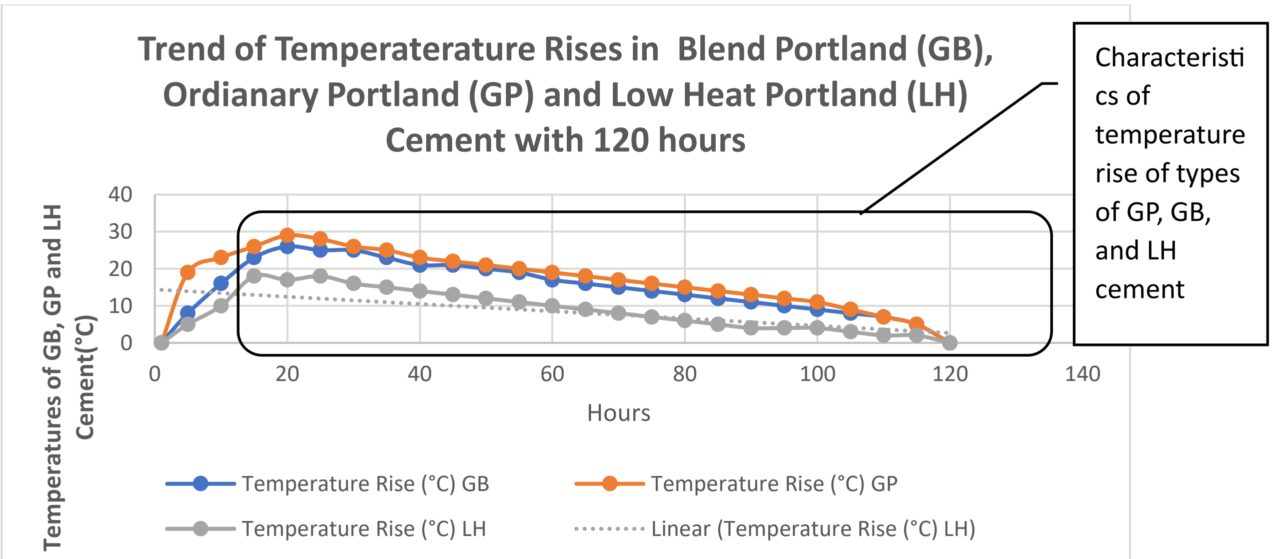


Figure 2.2 Typical Peak Temperature Rise = GP, GB and LH Cements (CCAA, 2020)

Further, low heat (LH) cement is also general Portland (GP) cement blended with supplementary material called ground granulated blast furnace slag (GGBFS). It is common to use this in mass concrete structures where the temperature rises, and the maximum temperature achieved is controllable by reducing the risk of thermal cracking. GP, GB and LH cement show the typical peak temperature rise, as shown in the dark bold box in Figure 2.2, due to cement hydration. Engineers can verify cement composition, fineness and contents, aggregate contents and the coefficient of thermal expansion, and select geometry, pavement and ambient temperatures, thus meeting client expectations. LH types generate lower heat than Portland cement, characteristic is a 28-day shrinkage level of ≤ 750 micro-strain. Types of sulphate-resisting cement are typically blended cements containing fly ash (≥25%) or slag (≥65%). With 16-week expansion values of <300 micro-strain, these blends can provide suitable shrinkage resistance (SR) cement performances.

The varieties of Portland-based cement properties provide data to develop different types of attributes and manufacturing methods to simulate optimal production processes as follows:

- The attributes of independence are general purpose Portland (GP), blend general purpose Portland (GB) and high early strength (HE) cement.
- Process independent attribute is grinding, material handling, kiln process, and more.
- High early strength (HE) attributes need extra-fine grinding to meet the requirements, identifying as a similar process of general Portland (GP) and blend general purpose Portland (GB) cement.

Combined various temperatures of general Portland (GP), blend Portland (GB) and high early strength (HE) working strength characters with alumina modulus (AM), silica modulus (SM) and lime saturation factor (LSF) % test results, development fundamental modelling method for validating the optimisation processes for parallel production (see Section 2.3, simulation model can be found in Chapters 5 and 6. Further, the expected outcomes also provide data (criteria) to the voice of the house of deployment in the mass customisation matrix for modularity preference (see Section 2.2 for further discussion).

2.2 Voice of the house development mass customisation

Pine (1993) and Davis (1987) first defined the meaning of mass customisation. Rocha et al. (2015) and Bolores et al. (2008) addressed the production of individually customised goods using flexible and highly responsively advanced manufacturing systems at mass-produced goods cost. Masayoshi (2004) has noted that the mass customisation strategy, which provides companies with the most effective method, generates mass production which can satisfy personalised requirements. Aartsengel and Kurtoglu (2015), Viana et al. (2027), Kassala (2016) and Zhang et al. (1990) used the same approaches of developing the voice of the house of deployment in quality (e.g., mass customisation) by collecting and analysing customer needs, resulting in integrating two voices. The first voice is customer needs. The second voice is manufacturing capability (modularity methods) to satisfy the company's business interest (Figure 2.3). The two voices are as follows:

- Customer needs based on product specifications
- Manufacturer capability, including various modularity

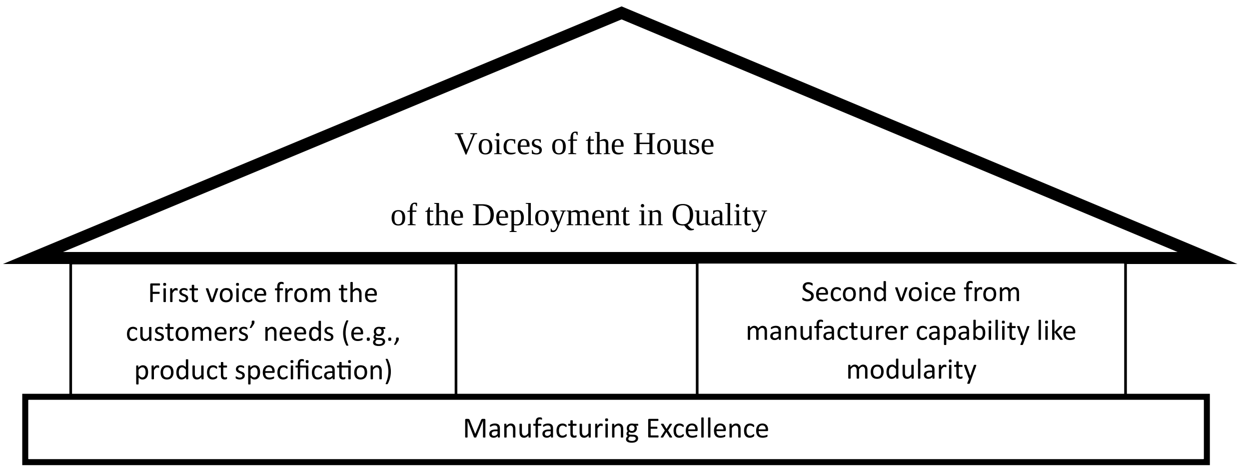


Figure 2.3 Voice of the House of Deployment in Quality (Zhang et al., 1990; Gonzalez et al., 2011; Kassela, 2016; Bolar et al., 2017)

This research adapts and extends Kassel's (2016), Zhang et al. (1990) and Bolar et al. (2017) methods as one of the sub-tools associated with productivity tools for better modularity preference and customer relationships (see Chapter 3, Section 3.3 for further discussion).

Further, Mintzberg et al. (2014) and Ducker (1995) addressed information technology as a way of satisfying individual customer expectations at once. It is an advantage of an electronic business that it can quickly match a customer's inseam of customised cement, classifying it as cut-to-fit modular, resulting in one of the preferred candidates for the voice of the house of deployment in the mass customisation matrix development. The Hong Kong Government (2022) used modular integrated construction (MiC) to accelerate building capability and satisfy housing market demand. The MiC involves producing standardised structural components in a factory, assembling them on-site according to architects' design opinions and classifying them as section modular. KPMG (2016) also claimed that it could increase construction productivity by 7% in Britain. Tang et al. (2018a; 2018b) used wavelet technologies to monitor mill structural health, ensuring that all components meet an expected performance, resulting in organising conditional maintenance. It classifies as a component-swapping modular. Brandt (2011) also deployed noise and vibration technologies in industrial areas, using bus modularity of generating wavelets to measure each structural performance. This method is suitable for fault distance recognition. Matson (2018) addressed wave with vibration technologies that can accelerate chemical reactions among sodium hydroxide and fly ash in a special-design pool due to two raw materials intensive mix, resulting in maximising geopolymer-cement mixing standard, classification as a mix-&-add-in modular. Table 2.2 summarises six types of modularity as identifying the mix-&-add-in modular is suitable for the cement industry, which involves many mixing processes for optimum production facilities.

Table 2.2 Various Types of Modularity (Cheng and Han, 2014; Vinodh et al., 2010; Piroozfar and Frank, 2016; Dzeng and Wu, 2013; Mintzberg, 2014; Viana et al., 2017; Brant, 2011; Tang et al., 2018a and 2018b; Hong Kong Government, 2022)

	Variety Modularity Process	Outlines and Application
1	Component-sharing (Piroozfar and Frank,2016)	Take the same components used in multiple products, such as in part fabrication
2	Component-swapping (Tang et a., 2018a and 2018b)	Add different components to produce a wide variety, such as in a restaurant
3	Cut-to-fit (Mintzerg, 2014)	Take basic components to meet individual contractor needs
4	Mix-&-add-in (Matson, 2018)	Use wave and vibration technologies with vertical integration manufacturing methods in mixing and grinding raw materials instead of ball and vertical roller mills processes for productivity improvement.
5	Bus (Brant, 2011)	Put standard structure and different items can be added, such as in the housing industry
6	Sectional (Hong Kong Government, 2016)	Assemble section-by-section based modularity, such as in the housing industry

Section 2.1 discusses the general cement specifications, which classify the voice of customers (Cudney et al., 2015). Table 2.2 illustrates six modularity processes classified as the voice of manufacturers (Kassela et al., 2016). The common interest of the two approaches is customer and manufacturer focus. Integrated with them, the house of deployment is a customer and manufacturer matrix that shows how customer requirements are directly related to manufacturers' fabrication methods (e.g., modular), suiting the Australian-owned cement industry. Due to the demand for customising a variety of small lot cement businesses in the domestic market, Trappey et al. (2017) used the voice of the house of deployment metric, involving measures for customers' needs, and achieved promising results. Chan et al. (2005b; 2010d) and Zhang et al. (1990) addressed the voice of house of deployments in a mass customisation matrix that can measure the two voices' modularity preference performances. Adapting and extending their approaches as below:

- Voice of the customers' needs is cement characteristics, properties, and application, as shown in Figure 2.3
- Voice of the manufacturer's capability is based various modularity arrangements, as shown in Table 2.2.

2.3 Simulation

Grigoryev (2018) addressed modelling a realist manufacturing process using virtual reality technologies for making visual management happen, seeking optimal process data. Paolucci and Sacile (2014) and Long et al. (2015) noted that simulation aligned with the design and analysis of the influence of the different design alternatives on the performance of systems. Here, the simulation modelling method expects to provide optimal production process data and validate its function process for the empirical stochastic frontier analysis equation development instead of the format function. Additionally, the classic Cobb–Douglas production function and the traditional stochastic frontier analysis methods are based on simulation model outcomes in trial-and-error in various parameters to discover a general direction or strategic intent (Flouris and Oswal, 2019; Bellemare, 2015) for mass customisation production methods in the cement business using modelling methods.

Further, the below elements are specific sub-tools for simulation model development that aim to generate an optimisation process and data collection (Anderson, 2004; Viana et al., 2017):

A. Attribute independence
B. Process independence
C. Process similarity.

A. Attribute independence*:*

This considers raw materials such as sand, clay, limestone/lime, slag, gypsum, fly ash and metakaolin to fabricate a variety of Portland-based and geopolymer-based cement (e.g., Table 2.1).

B. Process independence:

This involves various production facilities and raw materials flow to produce Portland-based or geopolymer-based cement via assigned production processes such as rough grinding, mix, kiln, fine grinding to packing and more (see Appendices 2 to 6).

C. Process similarity:

This involves identifying similar manufacturing processes in parallel fabricating for similar structures using add-in or removing processes in a virtual production environment.

Further, AnyLogic™ includes several sub-tools such as discrete, system dynamics and agent-based modelling methods. However, the agent-based simulation is suitable for an agile small-lot variation of cement production (Appendix 7) due to enabling data sharing with other modelling methods and Microsoft Office like Excel™ for further analysis. It is also easy to tackle all assigned task performances. Grigoryev (2018) and Das (2019) addressed the below functions:

- It works with individual active components with autonomy and self-direction.
- It can generate machine parameters such as production facilities' capability.
- It provides ideal process flow performances and can share data with a spreadsheet, tracking individual and overall efficiency and inefficiency performance analysis. This provides data for further study of the two productivity equations.
- It can cross-link with other models of observation data from different setting processes flow once at a time, as shown in Figure 2.4.

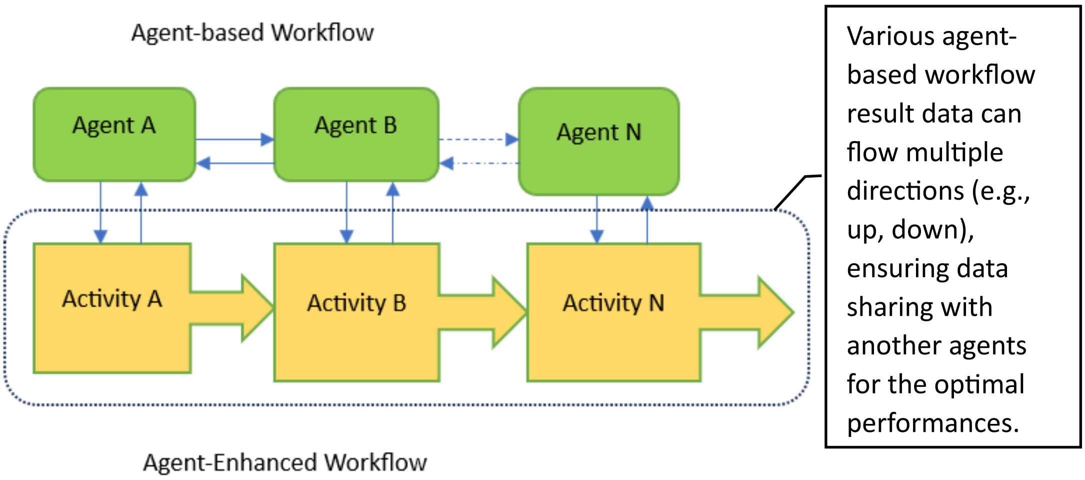


Figure 2.4 Two-Options in Design Workflow in Agent-Based Simulation Model (Paolucci and Sacile, 2014)

Additionally, the package AnyLogic™ can be used. It can provide customise-made programming via JavaScript™ to monitor the specific process concerning optimisation at minimum cost. It systematically analyses cause-and-effect to solve business bottlenecks. The expected outcomes are as follows:

- Current assets: cash, inventory, finished goods, work in progress, etc.
- Fixed assets: production facilities/equipment, building, etc.
- Liability (debt): direct and indirect workforce salaries, raw materials cost, etc.
- Equity (stockholders/owners): asset minus liability equals equity.

AnyLogic™ has many advantages, but Song et al. (2016) used another brand simulation model, Witness™, to study and analyse the factors of logistics distribution systems to improve efficiency. However, they did not intensively examine alternative material flow to maximise capability for multi-cements to satisfy client needs nationwide. Tako and Robinson (2010) also used Witness™ to evaluate process optimisation according to simulation taxonomy. Witness™ does not present overall production order statuses, particularly in a small lot customised product. This package is not user-friendly and is costly; therefore, it was not used.

The discussion of the simulation model method above relies on simulation software, seeking optimum processes data. Xiao and Shao (2018) based on one of the industrial engineering methods called "5W1H" approach. The short form of the "5W" represents (W)hat, (W)hy, (W)here, (W)hen, (W)ho and "H" stand for (H)ow, is associated with ECRS (e.g., manufacturing and eliminating wastes): (E)liminate, (C)ombine, (R)earrange, (S)implify to develop a simulation model to optimise production line balance, classifying as the system-and-push method (Lebasque et al., 2007; Jacobs, 2005; Shoo and Yahav, 2017) and only in mass production of assigned products like ordinary Portland cement. However, mass customisation cement production seldom uses the 5W1H with ECRS methods because the customised cement plant manufacturing process frequently changes production lines. In order to collect online optimal processes and their outcome data, the simulation model can perform this goal efficiently. Further, this thesis considers the overall productivity, resulting in a probe of further modern production methods, seeking any opportunity for optimisation (see Chapters 5 and 6, scenarios 1 and 2 for further discussion).

Hajifathalian et al. (2012) addressed the pull-and-push manufacturing method associated with the simulation Stroboscope™. However, this package is not user-friendly and is costly. Aurora Construction Materials (Onggo, 2014) launched two-to-one modelling methods combining systems dynamics and discrete simulation models. Data sharing using this simulation is one of the issues.

AnyLogic™ associated with XLMiner™ has the most advantages for this research. It is because the simulation model AnyLogic™ can be able to export data optimal production data to XLMiner ™, which can analyse and derive data into stochastic frontier analysis equations for productivity measures of machine performances.

Their outcomes can be used to further study the two main tools' equations (see Chapter 4 for further discussion).

2.4 Layout for cement production facilities and survey

2.4.1 Layout for cement production facilities

Chan (2018) developed an advanced environmentally friendly Portland-based and geopolymer-based cement plant, as shown in Figure 2.5.

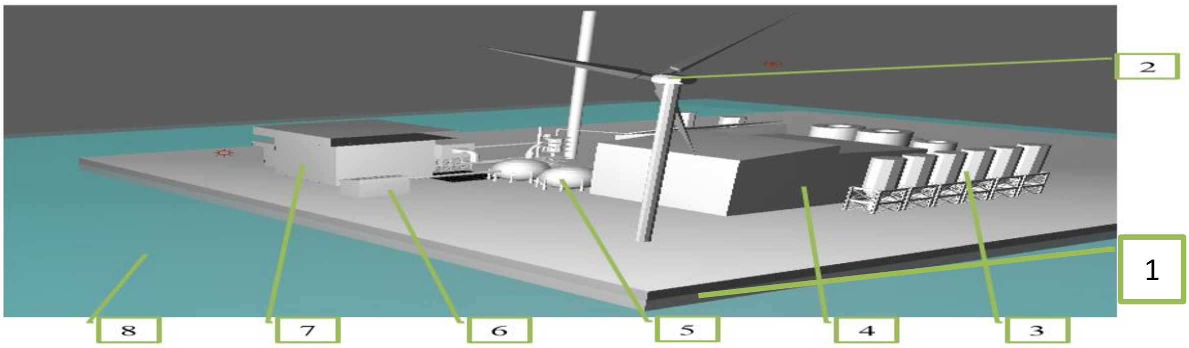


Figure 2.5 Classic Mini Cement Plant Layout (Chan, 2018, p. 241)

Legend			
1	Waste heat from boiler	5	Chlorine solution silos
2	Wind power	6	Chlorine plant
3	Raw material silos	7	Coal-fired power station
4	Fly ash based geopolymer cement factory	8	Sea

Its layout solves three areas:

1) Optimise production: optimise ordinary Portland cement and blend Portland, ordinary Portland cement with SCM like high early strength cement and FA-based cement manufacturing using linear programming methods.
2) Minimise carbon dioxide emission: use lime instead of limestone and liquified petroleum fuel or electric power, thus minimising carbon footprint.
3) Using fewer natural resources: minimise natural resources consumption in cement production.

This thesis has adapted Chan's (2018) approach and extended items 1) and 2) using new production technologies and two tools instead of traditional cement production for optimisation (see Appendices A6 and A7, Appendix A10, and Appendices A12 to A14).

Because of involving the new production technologies discussed in Section 2.4.1, more data are needed for further study of the classic Cobb–Douglas production function and the empirical stochastic frontier analysis methods. Thus, the first step of the survey design focused on collecting original data for small lot cement production within Australian-owned factories, including Portland-based cement and geopolymer-based whole-year forecasting orders, modern production facilities capability (e.g., Figure 2.4), machine breakdown rates and manufacturing methods and so on. Afterwards, spreadsheet was used for further analysis of the technical efficiency of each single production facility for equation development.

2.4.2 Survey

The survey (see Appendix 11) used the questionnaire method for data collection. Figure 2.6 illustrates the data mining tools aligned with Excel™ to re-organise data to an equation instead of the function format of the empirical stochastic frontier analysis. In addition, the outcomes also provide data for the advanced study of two elasticities, α and β, for the capital and labour setting of the classic Cobb–Douglas production function equation (see Chapters 5 and 6, scenarios 1 and 2 for further discussion).

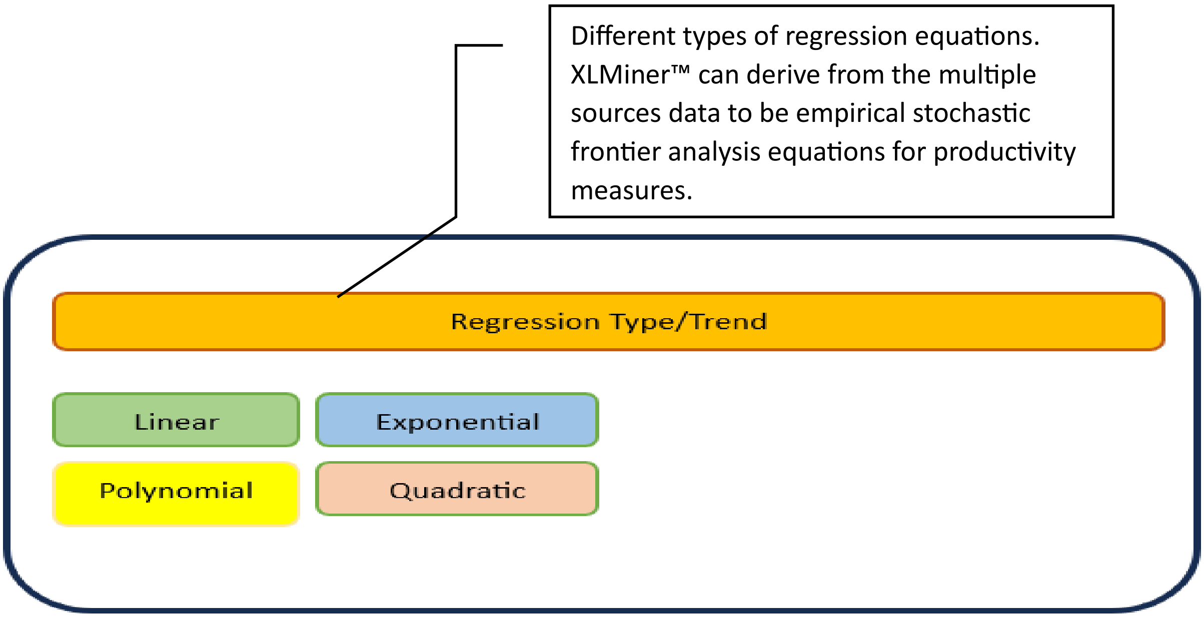


Figure 2.6 Variety of Regression Charts from Analytic Solver™ and XLMiner ™ in Excel™

2.5 Total productivity for optimisation measure

From 1927 to 1947, Paul H Douglas and CW Cobb used their development of the classic Cobb–Douglas production function equation to measure the American manufacturing industry's productivity based on the mathematical representation of the relationship among capital (L), capital (K) and output (Y). This was expressed in mathematical format with three combinations of α and β, $Y = f\ (L, K) \rightarrow Y = AL^{\alpha}K^{\beta}$ obtained as follows:

$$f(L, K) = AL^{\alpha}K^{\beta} \begin{cases} \alpha + \beta \leq 1 \\ \alpha + \beta = 1 \\ \alpha + \beta \geq 1 \end{cases}$$

Additionally, Cobb–Douglas uses flexible ranges in elasticity to keep constant labour and capital for productivity measures in the car industry. As a result, the productivity optimisation when the exponents of labour are 0.75; later, the National Bureau of Economic Research confirmed this as 0.741. Further, Cobb and Douglas' methods in the exponents of capital and labour elasticities can vary in use across various industries and sectors. Therefore, in adapting and extending the classic Cobb and Douglas outcome, this research uses the trial-and-error method in a technology-intensive cement manufacturing environment, seeking optimisation by changing two elasticity parameters of the capital from 0.3 and increasing by 0.01 with a corresponding labour decrease of 0.01. As a result, three combinations of elasticities resulted in three types of returns to scale: below, normal, and above. This outcome provides expert opinion for determining the size of factories, workforce, capability and the nature of investment for a small cement company.

Further, numerous researchers, including Naghiloo et al. (2011) and Dzeng and Wu (2013), probed further and found that the Cobb-Douglas equation is a linear homogeneous production in which there is proportionate change in all factors of production and the output also increases in the same proportion. This method is suitable for mass production and constant returns to scale business situations.

Customised cement production relies on machine-intensive needs extra capital and requires highly skilled workers, resulting in the influence of return-to-scale performances (Xue and Zhang, 2018; Wacker, 1975; Weber and Lippiatt, 1983; Williams, 2011). Therefore, the working capital test ratio is a sub-tool associated with the classic Cobb–Douglas production function before heavy investment, maximising profit and resource uses (see Chapter 4, section 4.2.5.3 for further discussion).

Nadi (2019) and Wacker (1975) also used different approaches by keeping productivity factors, labour, and capital constants, allowing them to change the combination to elasticities for productivity measures in the bank industry. The disadvantages of this method did not consider the reliability of production facilities. The classic Cobb–Douglas Production Function Measures for productivity measures relied on the working conditions of production facilities and skilful workers. If one of the production facilities (capital) breaks down, the output becomes zero (Biddle, 2012; Bhatt, 2014). This is because cement manufacturing is one of the continuous process plants (Bhattachary, 2012). One of them is out. As a result, productivity drops to zero. This is another disadvantage of the classic Cobb–Douglas Production Function Measures.

In 2021, the federal government stimulus plan focused on civil work (CIF, 2019), creating a small lot customised cement production boom. This is a vital step for customising small lot manufacturing businesses. In order to balance voices from both the market and manufacturing sides, new technologies are used in cement fabrication because of machine-intensive technology. The classic Cobb–Douglas production analysis method does not collect the necessary data for productivity measures because of two elements concerning capital and labour parameters, regardless of machine efficiency and capability. Coelli et al. (2005) also introduced the empirical stochastic frontier analysis method to measure productivity. This is because one element can measure the efficiency, TEi, of the production facilities, but it is in format function. To solve this issue, the software Frontier™ and STATA™ collect all essential data to develop the equation. This software is not suitable for small cement companies and is costly.

Zhang et al. (2014) developed dynamic stochastic frontier analysis to study financial systems and collected longitudinal data to develop the equation. However, this method is time-consuming.

Satya and Sriram (2018) pointed out that the stochastic frontier analysis method has a variety of stochastic frontier analysis efficiency models. The most important ones are those that consider exogenous determinants of inefficiency effects in addition to estimating the firm's efficiency. This inefficiency effects model is divided into two groups. The first group of models follows a two-step procedure. In the first step, the production frontier is estimated, and the technical inefficiency scores obtained for each firm are regressed against a set of variables. As a result, the second step, based on the first step outcome, is to be examined using the hypothesised firm's inefficiency. This method is classified as a static stochastic frontier analysis method but is not suitable for the cement industry.

Lai and Kumbhakar (2018) collected panel data using the empirical stochastic frontier analysis equation associated with the statistical method to study productivity in financial sectors. However, this method only focused on dynamic technical inefficiency.

Hodge et al. (2008) also developed the Bayesian vector autoregressive dynamic stochastic general equilibrium method modelling for forecasting small businesses in the Australian economy and productivity measures. However, this model requires a significant quantity of historical time-series financial data (taxes) to build competitiveness with the benchmark econometric model. It is an econometrics statistical model. As a result, one completed forecasting model is for productivity measures. Further, this method used the American and Japanese automobile car data for productivity measures. It does not directly relate to the cement industry.

Hasan et al. (2012) developed the Cobb–Douglas stochastic to measure domestic Malaysian-owned banks' productivity and efficiency. The disadvantage of this method is that it needs to collect multi-dimensional data, including the probability of observing data using the ordinary least square equations method. This method is time-consuming for data collection, and it is easy to make calculation mistakes.

2.6 Small lot production

Vanzela et al. (2017) noted that a small number of product fabrication varieties frequently change production status. The characteristics of the customised cement business mean that production methods periodically require reorganising production methods, and machine parameters for manufacturing need justifying to meet clients' needs. Therefore, the empirical stochastic frontier analysis can be a set of customised equations to meet different mass customisation manufacturing environments. However, Dasu (1988) also addressed the time taken for equation development. The classic Cobb–Douglas production function is a rigid equation, resulting in mass production for productivity measures because of less flexibility in assigned processes and machines. Mizutani et al. (2016) broke down large-scale mass production into calculations of single processes to assemble products to measure productivity. This method is time-consuming to arrange before beginning the calculation. Song et al. (2017) used the stochastic multi-item method to capacitate a lot-sizing problem using a fix-and-optimised approach to solve customised steel production. This method requires time to set the machine for next operation. Additionally, Zhang et al. (2015) from China Railway Baoji (Nanjing) developed a multi-variety and small lot limited productivity scheduling method to calculate a precise equipment daily plan. This method can evaluate equipment productivity, but it is patented. Vanzela et al. (2017) linked all production facilities using a local area network or wireless fidelity (Wi/Fi); the scheduling and plan goes directly to a workstation for customised cement production priorities, but only well-trained workers do so, resulting in technology diversity all around a plant for productivity improvement.

The Summer Olympics is an upcoming international multi-sport event scheduled to take place between 23 July to 8 August 2032 in Brisbane, Queensland, Australia. The Brisbane Masterplan includes 32 venues within South-East Queensland for the 28 Olympic sports, including a rebuilt 50,000-capacity Gabba as a main stadium to host the ceremonies, 17,000-capability inner-city Brisbane Arena to host swimming with a temporary pool constructed within the new arena, the Brisbane Indoor Sports Centre to host basketball, proposed a new 10,000-capability Chandler Indoor Sports Centre would replace the existing Arens to host gymnastics and the cross-river rail projects, etc., are scheduled for the coming years, solving issues with millions of tourists visiting at the games from happening (Australian Bureau of Statistic, 2022) that causing market demand in a variety customised fast-moving cement.

So, the reasons why the construction project selected lower carbon footprint cement because of avoiding less carbon emission, the cement companies take an opportunity to re-organise production method to get more businesses (see Appendix A7, Appendices A12 to A14). Japan's overall construction business is not in demand (Mizutani et al., 2016). Mass production cannot satisfy the market, and shifting to flexible manufacturing methods leads to extra costs. Australian-made cement is preferred by the contractors because of its quality and competitive price, resulting in a new paralleling mass customisation technologies operation. To better understand clients' dynamic delivery plans, ERP with a data warehouse module is one of the types of advanced integrated software for production scheduling and capability planning for mass customisation production. It can link to the customers' computer system for data sharing. Williams (2011) used dynamic order allocation make-to-order manufacturing networks to solve the customised product. However, this method relies on expensive enterprise resources planning (ERP) software capability. As a result, it is not suitable for small-micro-scaled cement firms. For cost reduction in software issues, Ma et al. (2018) also developed a mixed-integer linear programming model using a dynamic programming-based heuristic to solve a lot-sizing problem for frequently reorganising production priorities. The problem is how to capture dynamic data at the same time from customer and manufacturer performances.

Further, Vanzela et al. (2017) developed an integrated lot-sizing tool to reduce stock with saw cycle constraints in the furniture industry and to reduce raw material waste, production, and inventory costs. However, this method is not directly related to productivity optimisation. Additionally, Toyota's success in using both mass production and mass customised fabrication advantages runs parallel varieties of car production in Japan-based factories, delivering a just-in-time (JIT) car worldwide market to keep the production rate as smooth as possible, minimising small inventory and shortage costs (Lebacque et al., 2007). This thesis adapted Toyota's experience in periodically launching the voices of the house of deployment of quality to collect customers' and product voices in the brand name car and extended in the cement industry using the voice of the house of deployment in the mass customisation matrix methods (Chan et al., 2010d; 2005b and Zhang et al., 1990) for modularity preference to fabricate products for customer needs. Thus, this method consists of the voices. The first voice is customer needs (product criteria). The second is manufacturers with modularity. The two voices measure customer needs and manufacturer capability using grade-scaled surveys that ensure optimal modularity. Further discussion is in Chapters 3 and 4.

2.7 Research gap

This literature review has identified several research gaps:

1) Mass customisation methods are seldom used to solve small lot production orders delivering just-in-time (JIT) to meet cement production schedules for a variety of cement users worldwide. This is because different manufacturing industries have different businesses. Therefore, select modularity is very difficult as a result of understanding customer needs, manufacturer capability and plant layout.
2) Few in the customised cement industry use the classic Cobb–Douglas production function to measure productivity. The Cobb–Douglas early outcome provides a clue as to why. Their approach in the cement industry is adapted and extended. Another measuring tool—the empirical stochastic frontier analysis method, which needs multiple sources to form an equation—is used. To gather data together, XLMiner™ plays an active role due to its ability to work collaboratively with Excel and its suitability for the small cement industry. Here, Chan's (2018) approach is adapted and extended for the cement industry.
3) The empirical stochastic frontier analysis is seldom used to measure cement productivity and factors that affect their performance, such as the non-efficiency of the machine measure.
4) Two productivity methods are seldom used to examine mechanism advantages and disadvantages.

2.8 Research questions

The research questions are based on the literature review findings and develop a proposed framework to optimise cement manufacturing and improve its income revenue, satisfying contractors' cement use expectations with respect to the research objective. However, this proposed framework faces a challenge, as detailed below; consequently, the research questions are as follows:

A) *Research questions related to mass customisation and classic Cobb–Douglas production function and stochastic frontier analysis:*

A1) How does mass customisation technology (mix-&-add-in modularity) work collaboratively with simulation models to provide information for optimising the production manufacturing process?

A2) How does the function $f(x_i, \beta)$ from the stochastic frontier analysis equation derive from the first and second sets of data sources, such as simulation, survey, cement, Cement Concrete and Aggregate Australia (CCAA) and so on? How do changed parameters in the classic Cobb–Douglas production function affect productivity measures?

B) *Productivity measures for small lot production orders for just-in-time (JIT) delivery:*

B1) What are the application areas and limitations of the classic Cobb–Douglas production function and stochastic frontier analysis in the cement industry? What sorts of input data can be used to develop these two models and what output data can be expected for small lot productivity measures?

CHAPTER 3: METHODOLOGY

This chapter develops the proposed framework, which consists of two main tools and three sub-tools for productivity measures. The main tool is for optimum productivity. The sub-tools comprise simulation for the optimisation process, survey, and the voice of the house of deployment in mass customisation for modularity preference, resulting in expert opinions for modelling and equations development.

3.1 Introduction

The section uses relevant articles and comparison methods to identify the main tools to measure productivity with the assistance of sub-tools, including productivity measures, mass customisation (modularity), simulation, productivity with efficiency measures, small lot production, classic Cobb–Douglas production function and empirical stochastic frontier analysis methods. The roadmap is as follows:

1) Examine current methods for regular-based and agile customised cement productions, ensuring time to market without extra investment
2) Investigate methods of developing the format function into a regression equation to measure productivity for the mass production of flexible small lot customised cement
3) Change the parameters for further study of the two main tools and related sub-tools using known parameters such as labour, capital, elasticity, machine capability and machine performance concerning efficiency and non-efficiency suitable for the Australian-owned manufacturing environment.

Tables 3.1 to 3.4 use the above items 1) to 3) as guidelines to summarise what various researchers have achieved, resulting in a selection of popular and scientific methods for the proposed framework development:

a) Table 3.1: measures a variety of mass customisation technologies based on modularity
b) Table 3.2: measures productivity associated with simulation and its outcome panel data
c) Table 3.3: measures different methods with a variety of modularity
d) Table 3.4: measures different modularity methods of small lot productivity measures.

3.1.1 Measure variety of mass customisation technologies based on modularity

Six modular approaches are identified in multiple sources, including the below:

1) Components sharing
2) Components swapping
3) Cut-to-fit
4) Mix-&-add-in (e.g., cement and chemical industries)
5) Bus
6) Sectional (e.g., modular integration construction).

Items 1 to 6 have their advantages and disadvantages because of the differing nature of industries worldwide, and their essential applications are as follows:

1) Components-sharing modularity is used as a standard part (e.g., process) for sharing with other products, such as those from the food and brewery industries, research, and development sectors, and so on.
2) Components-swapping modularity is used in common parts such as electrical adaptors for the electronics and electrical industries, the plastics industry, and so on.
3) Cut-to-fit modularity is a big item divided into small pieces as necessary such as meat in the Food industry, Clothing industry, and so on.
4) Mix-&-add-in modularity is used in chemical process plants because of mixing processes such as those involved in the cement and concrete industry, the medical industry and so on.
5) Sectional modularity (modularity integration construction) is commonly used for large-scale housing projects that are divided into sections and assembled at the work site, as in the construction industry.

Compared with various modularity methods for different industries, the result extended to the voice of house of the deployment in the mass customisation matrix for modularity preference in the cement industry using two voices measures. The first voice is from customers; the second is from manufacturers (e.g., modularity) to satisfy the manufactures' capability.

Table 3.1 Measure Variety of Mass Customisation Technologies Based on Modularity

Authors	Titles	Variety of Mass Customisation Technologies based on Modularity					
		Component sharing	Component-swapping	Cut-to-fit	Mix-&-add-in	Bus	Sectional
Rocha et al. (2015)	Adapted product modularity in house building to support mass customisation	√	√	√			√
Anderson D.M. (2004)	Build-to-order and mass customisation—the ultimate supply chain management and lean manufacturing strategy for low-cost, on demand products without forecasts or inventory	√	√			√	√
Cunha et al. (2010)	Selection of modulus for mass customisation	√	√	√	√	√	√
Andújar-Montoya et al. (2015)	A construction management framework for mass customisation in traditional construction	√	√				√
Dolores et al. (2008)	Construction management framework for mass customisation in traditional construction		√				√
Drachal (2015)	Labour-capital relations in the construction sector in Poland	√					
Duguay et al. (1997)	From mass production to flexible/agile production	√					√
Gosling (2011)	Flexibility strategies for engineer-to-order construction supply chains	√	√	√			√
Liu et al. (2010)	Modularity analysis and commonality design: a framework for the top-down platform and family design	√	√	√	√	√	√
Long et al. (2015)	The comparison analysis of total factor productivity and eco-efficiency in China's cement manufacturers	√					√

Table 3.1 Measure Variety of Mass Customisation Technologies Based on Modularity (Continued)

Masayoshi (2004)	A choice model for mass customisation of lower cost and higher performances Housing in sustainable development	√	√	√	√	√	√
Rocha et al. (2015)	Adopting product modularity in house building to supply mass customisation	√	√	√	√	√	√
Piroozfar and Frank (2016)	Mass customisation and personalisation in architecture and construction	√	√	√	√	√	√
Vinodh et al. (2010)	Amalgamation of mass customisation and agile manufacturing concepts: the theory and implementation study in an electronics switches manufacturing company	√					√
Viana et al. (2017)	Using modularity to reduce complexity of industrialised building system for mass customisation	√	√	√			√

Table 3.1 offers an insight into the application using mass customisation with the modularity method and identifies mix-&-add-in modularity as an alternative. This is because the cement industry involves a lot of mixing, grinding, and adding in of other raw materials during the production process to meet customer expectations. But these steps are part of traditional cement production processes and are not related to productivity optimisation improvements such as new technologies.

Table 3.2 examines simulation modelling methods in relation to individual machine performance for optimistic processes and outcome data under a variety of customised small lot on-time delivery conditions in the virtual production environment. Its output is one of the sources used to develop the empirical stochastic frontier analysis equation.

3.1.2 Measure productivity with assistance of simulation

This section discusses the relevant articles for the productivity measure and simulation modelling methods. The simulation model validating optimisation process is commonly used in virtual manufacturing to address a bottleneck (Grigoryev, 2018). It also can generate a series of data, namely panel data, with quantities obtained from multiple individuals at time intervals commonly used in the stock market (see Chapter 4, Section 4.2.5.3) for statistics and econometrics for the trend of business performance of a target company, determining the market values at the right time to make money. But Agrawal et al. (2015) used simulation method for trickling the production facilities' performances, determining the fault location, and formulating repair and maintenance strategies. Baek et al. (2009) used panel data from simulation models to identify machine performances. Meanwhile, Das et al. (2019), Chiang (2014) and Cai et al. (2016) used panel data from the simulation model to deformation models in the early stage of product development.

Chan's (2018) also developed a method to make a factory's operation more advanced using a new production technology that is environmentally friendly and can optimise productivity. This new technology includes the use of hydrogen fuel in a kiln combustion chamber (Appendix A4), wave technologies to fully mix fly ash with sodium hydroxide solution pool (Appendix A8) and so on. However, Chan's plant involves significant work to develop the stochastic frontier equations and technical data because this approach differs from traditional cement production (Appendix A5).

Xing et al. (2019) probed further based on a new method for cement production. As a result, Gosling (2011), Griffin (2011), Kumbhakar et al. (2015), Liu and Park (2007), and Ma et al. (2018) found new technologies involving productivity measures. However, this method needs a large amount of data to convert function to linear regression equation for the empirical stochastic frontier analysis methods. In order to collect data, one of the methods is the simulation model (see Chapters 5 and 6), which can provide all production processes and optimal data in the virtual environment (see Chapters 4 to 6 for further discussion). Table 3.2 reviewed what current researchers have achieved previously and the proposed framework being developed based on their findings.

Table 3.2 Measure Productivity with Assistance of Simulation and Panel Data

Authors	Titles	Productivity and Efficiency Measures: Productivity: CDPF	Productivity: SFA	Efficiency	Simulation
Aigner et al. (1968)	On estimating the industry production frontier		√		
ACM (2014)	Elements of hybrid simulation model: a case study of the blood supply in low-and-middle income country				√
Argrwal et al. (2015)	Review of control fault diagnosis methods applied in coal mills				√
Behr (2015)	Production and efficiency analysis with R			√	√
Bhatt (2014)	Productivity in small and medium enterprise of India: a Cobb–Douglas production function	√			
Biddle (2012)	The introduction of the Cobb–Douglas regression	√			
Chen et al. (2011)	Empirical analysis on the construction workers' contribution to Chinese construction industry economics growth sharing of economic gain		√		
Cheng et al. (2014)	A modified Cobb–Douglas production model and its application	√			
Chiang (2014)	Estimating contractors' efficiency with panel data-comparison of the data envelopment analysis, Cobb–Douglas and translog production function method	√	√	√	
Cheng and Han (2003)	A modified Cobb–Douglas production function model and its application		√		
Hasan et al. (2018	Factors affecting construction productivity: a 30-year systematic review	√	√		

Table 3.2 Measure Productivity with Assistance of Simulation and Panel Data (Continued)

Coelli et al. (2005)	An introduction to efficiency and productivity analysis	√	√	√	√
Das (2019)	Econometrics in theory and practice, analysis of cross section and time-series and panel data with STATA™ 15.1	√	√	√	√
Deniz and Umunc (2013)	Application of statistical process control for coal particles size			√	√
Doum et al. (2011)	Numerical study of the flow field in vertical roller mills				√
Dundar et al. (2011)	Simulation assisted capability improvement of cement grinding circuit: case study in cement plant			√	√
Dzeng et al. (2013)	Efficiency measurement of the construction industry in Taiwan: a stochastic frontier cost function approach		√		√
Farrell (1957)	The measurement of productivity efficiency	√		√	
Gao et al. (2017B)	Optimisation control of a pulverising system based on the estimation of the outlet coal powder flow of coal			√	√
Gao et al. (2017A)	Modelling of a medium speed mill			√	√
Ghosh et al. (2006)	Method and system for small lot orders to optimise production runs in the steel industry			√	
Greens (2002)	Alternative panel data estimators for stochastic frontier models		√		
Griffins (2011)	Bayesian clustering of distributions in stochastic frontier analysis		√		
Grigoryev (2018)	AnyLogic™ in the three days			√	√
Gupta and Sharma (2014)	Analysis of ball mill grinding operation using mill power specific kinetic parameters			√	√
Hasan et al. (2012)	A Cobb–Douglas stochastic frontier model on measuring domestic efficiency in Malaysia	√	√	√	√
Jacka and Keller (2010)	Business process mapping-improvement satisfaction				√
Harrison (2007)	Can measurement error explain the weakness of productivity growth in Canadian construction industry	√	√		√

Table 3.2 Measure Productivity with Assistance of Simulation and Panel Data (Continued)

Oggioni et al. (2011)	Eco-efficiency of the world cement industry: a data envelopment analysis.			√	
Johannes et al. (1985)	Estimating regional construction cost difference: theory and evidence	√	√		√
Kumbhhakar et al. (2015)	Practitioner’s guide to stochastic fronter using STATA™ 15.1		√		
Lai and Kumbhakar (2018)	Panel data stochastic frontier with determinants of persistent and transient inefficiency		√	√	
Liu and Park (2007)	The logarithm-linear relationship of the occurrence frequency to the duration of sand-dust storm	√	√		
Lin and Du (2014)	Measuring energy efficiency under technologies using a latest class stochastic frontier approaches-an application to Chinese energy economy		√	√	
Ma et al. (2018)	Combined cutting stock and lot-sizing problem with pattern set			√	
Merit (2015)	A note on the relationship among the shape of the production possibility frontier, ‘return to scale’ and ‘returns to factors’ under Cobb–Douglas production function	√			
Mintzberg et al. (2014)	The strategy process: concepts, context, cases			√	
Naghiloo et al. (2011)	Using developing PM to optimise the production productivity in cement industry	√	√	√	
Nobil et al. (2020)	A multiproduct single machine economic production quantity (EPQ) inventory model with discrete delivery order; joint production policy and budget constraint			√	
Robert et al. (2004)	Monte Carlo statistical methods			√	√
Palucci and Scaile (2014)	Agent-based manufacturing and control system			√	√
Panhwar et al. (2016)	Profit optimisation through Cobb–Douglas production function.	√			
Rocha et al. (2015)	Adapting product modularity in house building to support mass customisation			√	

Table 3.2 Measure Productivity with Assistance of Simulation and Panel Data (Continued)

Pellicer et al. (2009)	A macroeconomic regression analysis of the European construction industry	√			
Savidis and Mills (1999)	Labour productivity in the construction industry	√			
Samara (2015)	ERP and information system				√
Schotter (2018)	On estimating efficiency effects in stochastic frontier model		√		
Selikh (2012)	Labour productivity and rice production in Bangladesh a stochastic approach		√		
Sharma and Sehgal (2010)	Impact of infrastructure industry	√			
Shen et al. (2016)	Multi-objective time-cost optimisation using Cobb–Douglas production function and hybrid genetic algorithm	√			
Song and Tang (2016)	Simulation and optimisation of logistics distribution for engine production line			√	
Song et al. (2017)	Fix-and-optimize and variable neighbourhood search approaches for stochastic multi-item capacitated lot-sizing problems	√		√	
Song et al. (2016)	Simulation and optimisation of logistic distribution for an engine production line	√		√	
Tan et al. (2017)	A simulation study of capability utilisation to predict future capability for manufacturing system sustainability	√	√		
Toledo et al. (2015)	The synchronised and integrated two-level lot sizing and scheduling problems: evaluating the generalised mathematical model			√	
Vanzela et al. (2017)	The integrated lot sizing and cutting stock problem with saw cycle constraints applied to furniture production			√	
Yao et al. (2013)	Stochastic modelling and optimisation with application in queues		√		
Yeon (1977)	Estimation of the Cobb–Douglas and CES production functions in Korea	√			
Zhang et al. (1990)	Green QFD-II; life cycle approach for environmentally conscious manufacturing by integrating LCA and LCC into QFD metric	√			
Zhang et al. (2017)	On the use of stochastic resonance processing perspective		√		

Table 3.2 identified the classic Cobb–Douglas production method to measure productivity for various industries. The second-best approach is the empirical stochastic frontier analysis, which is commonly used in the financial and manufacturing industries. When developing the empirical stochastic frontier analysis method model, it needs significant quantities of data to support building a model. Therefore, simulation can generate a set of panel data, which is longitudinal or cross-sectional time-series data of entities' behaviour for the observing cross times (see Appendix A7). The relationship of mass customisation to different productivity measures with a variety of modularity discussed in Table 3.3.

3.1.3 Measure different productivity methods with various modularity

This section identifies six modularity and two productivity tools for simulation model development. Adapting and extending their methods becomes part of the proposed framework, as detailed below:

- Six modularity tools:
  1) Component
  2) Component-swapping
  3) Cut-fit
  4) Mix-&-add-in
  5) Bus
  6) Sectional

  see Section 3.1.1

- Two productivity tools:
  1) Classic Cobb–Douglas production function
  2) Empirical stochastic frontier analysis

The above items are approaches to constructing the voices of the house of deployment in the mass customisation matrix. The modularity preference outcome provides a roadmap for the simulation model, resulting in data for further study of the classic Cobb–Douglas production function equation, including resource use, size of the labour force and so on, and the development of the empirical stochastic frontier analysis. This uses XLMiner™, which is a mining tool associated with Excel™ (see Table 3.3 for further discussion).

Table 3.3 Measure Different Productivity Methods with Various Modularities

Authors	Titles	Productivity: CDPF	Productivity: SFA	Modularity: Component sharing	Modularity: Component-swapping	Modularity: Cut-to-fit	Modularity: Mix and Add-in	Modularity: Bus	Modularity: Sectional
Rocha et al. (2015)	Adapted product modularity in house building to support mass customisation			√	√	√		√	√
Anderson (2004)	Build-to-order and mass customisation—the ultimate supply chain management and lean manufacturing strategy for low-cost, on-demand product without forecasts or inventory			√		√			√
Aigner et al. (1997)	Formulation and estimation of stochastic frontier function model		√						
Andújar et al. (2015)	A construction management framework for mass customisation in the traditional construction			√	√				√
Bellemare (2014)	Managing complexity	√							√
Nadi (2019)	Construction labour productivity benchmarking: a comparison between on-site construction and prefabrication		√						
Savidis and Mills (1999)	Labour productivity in the construction Industry	√							
Shi et al. (2015)	Manufacturing productivity and efficiency: a stochastic efficiency analysis		√						

Table 3.3 Measure Different Productivity Methods with Various Modularities (Continued)

Authors	Titles	Different Productivity Methods with a Variety of Modularities							
		Productivity		Modularity					
		CDPF	SFA	Component sharing	Component-swapping	Cut-to-fit	Mix and Add-in	Bus	Sectional
Satya and Sriram (2018)	On estimating efficiency in stochastic frontier model		√						
Hong Kong Government (2021)	Modular integrated construction	√	√						√

3.1.4 Measure small lot productivity with various modularity

Section 3.1.1 discussed the relationship between various modularity and two productivity measures given in the black box of Table 3.4. This study adapted Chan et al. (2005d) and Zhang et al. (1990) methods and extended them to build the voices of the house of the deployment in the mass customisation matrix for the cement industry and the two voices criteria. The first voice is for the customer; the second is for manufacturers' modularity. As a result, a simulation models have been developed based on these results and is detailed below:

- Voice from manufacturers' modularity
  1) Various modularity for small lot cement fabrication

- Voice of the customers (e.g., nine items)
  1) Customer requirements (see Chapter 4, Table 4.3)
  2) Customers' importance rating (see Appendix A11)
  3) Competitive analysis (see Appendix 11)
  4) Technical requirement, including
     - wear resistance
     - sink expanded
     - low carbon emission
     - heat resistance
     - acidic resistance
     - early strength

     see Chapter 4, Table 4.3
  5) Relationship matrix (see Appendix A11)
  6) Engineering analysis (see Chapter 2, Table 2.1 and Chapter 4, Table 4.3)
  7) Importing rating (see Appendix A11)
  8) Target values (see Appendix A11)
  9) Correlation matrix (see Chapters 5 and 6)

Table 3.4 shows related articles on what researchers have done. Therefore, adapting and extending their methods becomes the proposed framework.

Table 3.4 Measure Small Lot Productivity with Various Modularity

Authors	Titles	Small Lot Productivity Various Modularities							
		Productivity		Modularity					
		CDPF	SFA	Component sharing	Component-swapping	Cut-to-fit	Mix -&- add-in	Bus	Sectional
Bazaz et al. (2020)	The prediction method of tool life on small lot turning process development of digital twin for production			√		√			
Chan et al. (2005d)	Implementation of case-based reasoning in DMAIC for six sigma	√							√
Vanzela et al. (2017)	The integrated lot sizing and cutting stock problem with saw cycle constraints applied to furniture production								√
Więcek et al. (2019)	Cost estimation methods of machine elements at the design stage in unit and small lot production conditions				√				
Nobil et al. (2020)	A multiproduct single machine economic production quantity (EPQ) inventory model with discrete delivery order, joint production policy and budget constraint			√	√				
Toledo et al. (2015)	The synchronised and integrated two-level lot sizing and scheduling problems: evaluating the generalised mathematical model	√	√						√

Table 3.4 Measure Small Lot Productivity with Various Modularity (Continued)

Authors	Titles	Small Lot Productivity Various Modularities							
		Productivity		Modularity					
		CDPF	SFA	Component sharing	Component-swapping	Cut-to-fit	Mix -&-add--in	Bus	Sectional
Li et al. (2017)	Fix-and-optimise and variable neighbourhood search approaches for stochastic multi-item capacitated lot-sizing problems	√		√	√		√		√
Ma et al. (2018)	Combined cutting stock and lot-sizing problem with pattern setup			√					
Desai et al. (2014)	An empirical investigation of composite product choice		√						
Gauri (2013)	Benchmarking retail productivity considering retail pricing and format strategy	√	√						
Ding and Sickles (2018)	Frontier efficiency, capital structure, and portfolio risk: an empirical analysis of US banks	√							
Carroll et al. (2011)	A comparison of stochastic frontier approaches for estimating technical inefficiency and total factor productivity	√							

Different modularity applications were discussed using the comparison method. One finding is Zhang et al. (1990) to use the voice of manufacturers and clients' needs in mass customisation matrix to measure modularity capability.

Table 3.4 Measure Small Lot Productivity with Various Modularity (Continued)

Authors	Titles	Small Lot Productivity Various Modularities							
		Productivity		Modularity					
		CDPF	SFA	Component sharing	Component-swapping	Cut-to-fit	Mix -&- add-in	Bus	Sectional
Kiadaliri et al. (2013)	Frontier-based techniques in measuring hospital efficiency in Iran: a systematic review and meta-regression analysis	√	√						
Liu (2006)	Model selection in stochastics frontier analysis: maize production in Kenya	√							

Summarising the findings from Tables 3.1 to 3.4 requires a comparison method that studies the numerous researchers' achievements. Li et al. (2017) used the fix-and-optimise method. This is classified as a modified empirical stochastic frontier analysis approach (Desai, 2014) to solve various small lot steel production productivity measures. Chen et al. (2011), Liu (2006) and Battese and Coelli (1995) also addressed the use of the empirical stochastic frontier analysis method to capture lot-sizing production problems such as backlogging production, setup carryovers, machine downtime and more using mining tools. However, this means that a calculation mistake can easily be made after long calculation work. Further, the development of the empirical stochastic frontier analysis method needs multiple-source data to reorganise the format function into regression equations using XLMiner™, which also studies any new production technologies, including machine performances that set data to examine statuses of technical efficiency, although it has a format function. XLMiner™ also provides data for further study of the classic Cobb–Douglas production equation.

As the cement plant manufacturing process labour, machines and various types of cement products, the current cement fabrication makes it very hard to effectively collect a variety of customised geopolymer-based and Portland-based multiple-sources data (CIF, 2019). One of the sub-tools is the role of the simulation method in collecting data for the optimisation process. Therefore, this study can select the main tools and sub-tools to develop the proposed framework, providing expert opinions for decision-makers that can enable them to maximise profit.

Further discussion of the proposed framework is in Section 3.2.1.

3.2 Methodology

This chapter has developed a proposed framework using in-depth study of two main tools concerning productivity measures: the classic Cobb–Douglas production function and the development of empirical stochastic frontier analyses associated with sub-tools surveys, simulation, and modularity preference. The methodology used is as follows:

1) Collect initial data via survey (questionnaire) of the target companies
2) Collect optimisation data for cement production processes, including new technologies via a simulation model, and compare them with traditional methods
3) Develop and used the voice of the house deployment in mass customisation for modularity preference, enhancing popular tool selection
4) Examine the classic Cobb–Douglas production function by changing the parameters of elasticates, α and β, concerning capital, labour and developing empirical stochastic frontier analysis equations for productivity measures
5) Compare the two tools' advantages, disadvantages, and applications.

3.2.1 Proposed framework

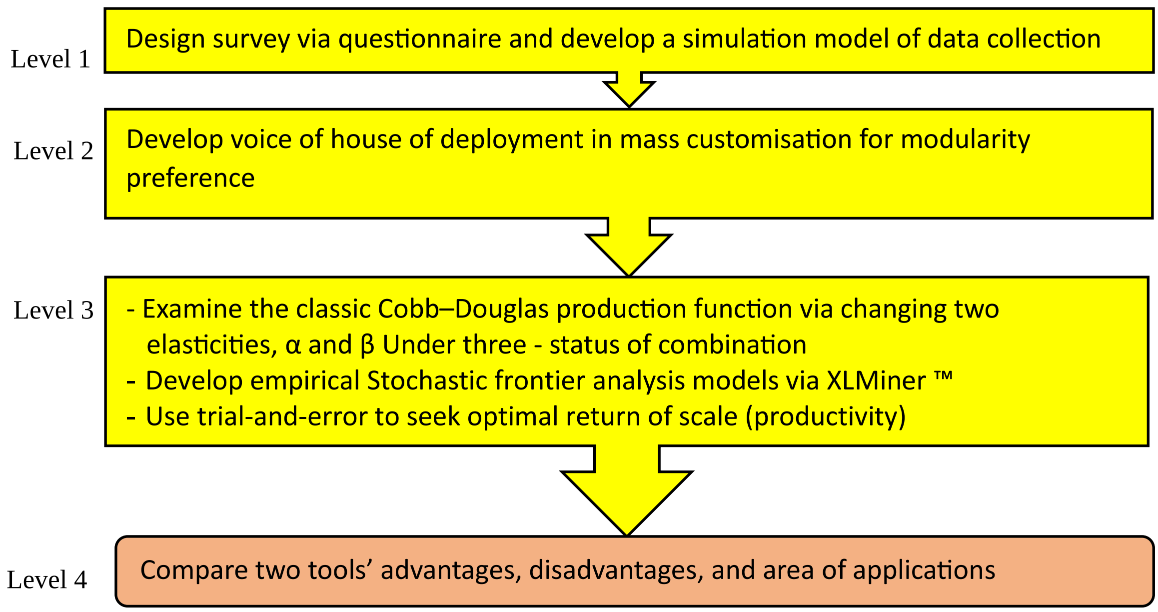


Figure 3.1 Proposed Framework to Measure Total Productivity for a Variety of Customised Cement Manufacturing

Figure 3.1 illustrates four levels of the proposal frameworks to measure a variety of small lot customised cement productivity technique. Each level function is listed below:

(a) *Level 1:* design survey via questionnaire and a simulation model of data collecting

(b) *Level 2*: develop the voice of house deployment in mass customisation for modularity preference based on the voice of manufacturers and clients with nine items: customer requirement, importance rating, competitive analysis relationship matrix, importance rating, target values, engineering analysis and correlating matrix.

(c) *Level 3*: examine:

- Classic Cobb–Douglas production function by changing two elasticities, α and β, under three statuses of combination by changing α, β parameters based on the Cobb–Douglas production function with the constants of capital and labour
- Develop the stochastic frontier analysis equations based on XLMiner™, which derives suitable equations, such as linear regression equations, instead of the function status of one of the elements in the empirical stochastic frontier analysis equation
- Use both productivity tools to measure new technologies involving the customised cement plant.

(d) *Level 4*: compare:

1) The classic Cobb–Douglas production function and the empirical stochastic frontier analysis outcome and application, seeking customised strategies (Xiao and Shao, 2018; Ma et al., 2018).

See Section 3.3 for further discussion.

3.3 Simulation models and survey (level 1)

3.3.1 Simulation models

One way of obtaining the initial data in optimisation processes is through the unlimited use of simulation models. Compared with various simulation models, AnyLogic™ is user-friendly, as shown in Figure 3.2.

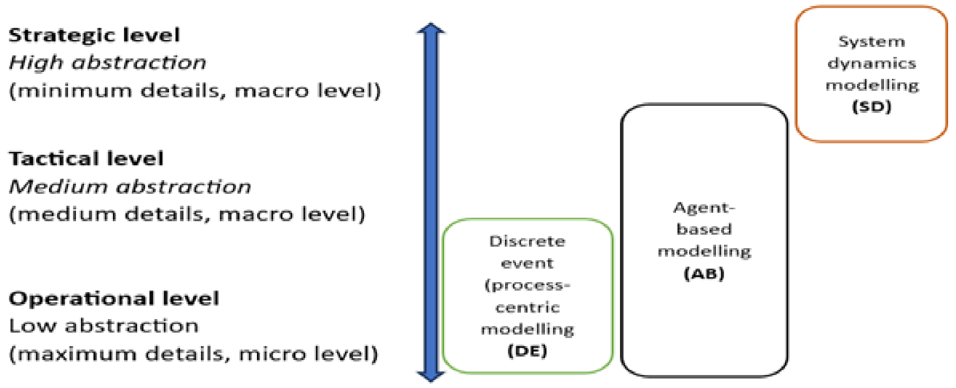


Figure 3.2 Three Types of Modelling Methods Using AnyLogic™ (Grigoryev, 2018)

This was by Grigoryev (2018) and extended in the cement industry:

a) System dynamics (SD) is a high abstraction level and is typically used for strategy modelling and casually closed structure and defines its behaviours.
b) Discrete event (DE) is either a medium- or low-level abstraction. As a result, it is a discrete production process.
c) Agent-based models (AB) have low to high abstraction levels, resulting in works that collaborate with items 1) and 2) models. The expected outcomes are as follows:

   a) Use of resources (e.g., machine performances data)
   b) Time spent in the system (e.g., optimal process time data)
   c) Waiting time (e.g., downtime data)
   d) Queue length (e.g., production priorities data)
   e) Systems throughput (e.g., paralleling run two similar process cement such as GP, GB and so on)
   f) Bottleneck (e.g., production facilities efficiency measure)

Therefore, the agent-based simulation model (see Figure 4.2 and Section 4.2.2) is more suitable for the cement and concrete industries because of its icon-driven functions, which is referring to the now-standard computer design that enables the user to transfer, copy, open, close, and manipulate files and software program while in the computer's root directory, by pointing and clicking on an icon. As a result, it is easy data exchange with other software, such as Excel™, as shown in Figure 3.3. It is also easily customised to each process through JavaScript™, which is website-based software and can monitor the process in the virtual environment.

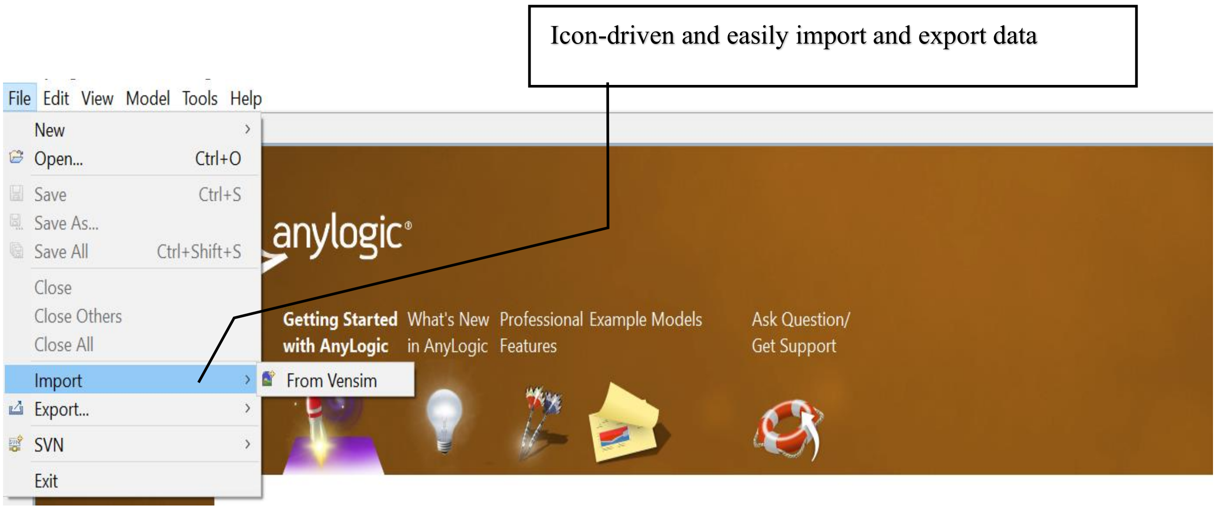


Figure 3.3 Snapshot of AnyLogic™

Due to effective simulation development, this study adopted and extended Grigoryev's (2018) method. Below items need to be identified:

a. Attribute independence (e.g., Table 2.1): the raw materials, such as the amount of clay, limestone/lime, sand, slag, fly ash, metakaolin, gypsum and so on
b. Process independence (see Appendices 1 to 5): production facilities
c. Process similarity independence (see Appendix 7): the processes are related to one another. This is an easily relocated production process in virtual manufacturing.

Chapters 5 and 6 discussed building a traditional cement process simulation model for optimisation. The expected outcomes are one of the sources of providing data for the empirical stochastic frontier analysis development using intensive examining production processes.

3.3.2 Survey

The purpose of the survey has been to capture initial data from the cement industry using state-of-the-art technology to fabricate cement. Based on the outcome, the in-depth trial-and-error method can be used to study the three statuses of change two elasticity, α and β combination and keeping capital and labour constant, seeking optimisation of returns to scale (see Section 3.4.2.1). This is one of the sources to develop the empirical stochastic frontier analysis equation in a format function status. Although the literature review and related associations can provide traditional cement production data, this research directly collects target companies' data because of new technologies involved in manufacturing.

Two scenarios were used to examine the business performances of three target companies based on outcome data (Companies X, Y and Z). This is because their interests are in the customised-cement business, involving new technologies for optimum productivity. The detailed survey questions can be found in Appendix A10.

3.3.3 Voice of the house of deployment mapping mass customisation (level 2)

Development of the voice of house of deployment in the mass customisation matrix is for modularity preference to enhance the selection of popular tools, such as those in Tables 3.1 to 3.4. Adapted and extended Zhang et al. (1990), Gonzalez et al. (2011), Kassala (2016), Bolar et al. (2017) and Chan et al.(2005d) methods with a nine-item selection criteria matrix for the modular candidate, as shown below:

Voice of the House

of Deployment in Mass Customisation Matrix for Cement Industry

Voice of customers' needs	Voice from manufacturers' capability	
1. Customer requirement	2. Customers' voice score	3. Modularity voice score 3.1 Six modular candidates for Preference
4. technical matrix 5. relationship matrix 6. importance rating 7. target values 8. engineering requirement 9. correlation matrix		

Table 3.5 Voice of the House of Deployment in Mass Customisation (Nadi, 2019; Zhu, 2003; Trappey et al., 2017; Chan et al., 2005d, Zheng et al., 1990, Aartsengel et al., 2015)

1) Customer requirement (see Table 2.1 aligned with AS 3972:2010 standard)

2) Customers' voice score (see Appendix A11 and survey outcome)

3) Modularity voice score

3.1) Six modularity candidates for preferences

4) Technical requirements (see AS 3972:2010 or SA TS 199:2023 standards)

5) Relationship matrix: it concerned price offer and delivery schedule

6) Engineering analysis (see AS 3972:2010 or SA TS 199:2023 standard)

7) Manufacturers' importance rating (see Appendix A11)

8) Target values (see Table 4.16)

9) Correlation matrix: this concerned the data correction error.

3.4 Classic Cobb-Douglas production function and empirical stochastic frontier analysis level 3)

3.4.1 Classi Cobb-Douglas production function

Several versions of the Cobb–Douglas Production Function are identified in Chapter 2. However, only the classic Cobb–Douglas production function equation is illustrated in Equation (3.1) for the cement industry study. This is because the earlier outcome of Cobb–Douglas gave the guideline of elasticity and can vary. Here are the adapted three combinations of elasticity, α and β, concerning capital and labour. The expected outcome can provide expert opinions on the status of the returns to scale (Merit, 2015, Lebacque et al., 2007; Lin et al., 2014; Long et al., 2015; Biddle, 2012). Based on its outcomes, reorganising manufacturing strategies for better productivity, including new production methods to maximise profit and minimise capital investment, can be undertaken:

$$\text{F (K, L)} = AK^{\alpha_i}L^{ß_j} = \begin{cases} \alpha_i + ß_j = 1 & \text{i,j are variables} \\ \alpha_i + ß_j \leq 1 & \text{i,j are variables} \\ \alpha_i + ß_j \geq 1 & \text{i,j are variables} \end{cases} \quad \ldots\ldots\ldots\ldots(3.1)$$

where A = productivity factor, K = capital, L = labour and α_i, $ß_i$ = elasticity variables (see Abbreviations)

Because of one of the elements, the capital (K) parameter in the classic Cobb–Douglas production function conjugates with the working capital test ratio, as illustrated in Equation (3.2). This process would further determine whether a healthy investment is required for customised cement production business performance in Australian-owned companies instead of sub-contracted overseas cement companies. This is expressed in mathematical format below:

$$\text{Working Capital Ratio} = \frac{\text{Current Assets}}{\text{Current Liability}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.2)$$

3.4.2 Change elasticity parameters in the classic Cobb-Douglas production function

3.4.2.1 Change Elasticities α and β

Equations (3.3) to (3.4) illustrate changing α and β parameters using increasing α and corresponding to decreasing β at ±0.01 intervals (Xue and Zhang, 2018; Panhwar et al., 2015) to examine the three statuses of the returns to scale, which provides alternative optimisation and productivity scales, as below:

3.2.2.1.1 When $\alpha + \beta = 1$

Let $q = \frac{Q}{L}$ and $k = \frac{K}{L}$

Then $$Q = A\left(\frac{K}{L}\right)^{\alpha} L^{\alpha}L^{1-\alpha} = ALk^{\alpha} \Rightarrow q = \frac{Q}{L}\ Ak^{\alpha} \quad \text{……………………………(3.3)}$$

3.2.1.1.2 When $\alpha + \beta \leq 1$ and $\alpha + \beta \geq 1$ (Merit, 2015; Shen et al., 2016) as obtained

$$Q_i = AK^{\alpha+\Delta\alpha}L^{\beta-\Delta\beta} \quad \text{…………………………………………………………(3.4)}$$

Where $\Delta\alpha = \alpha_i + \alpha_{i+1} = 0.01$ and $\Delta\beta = \beta_i - \beta_{i+1} = 0.01$

Adapted from Cobb's earlier work (Farrell, 1957; Coelli et al., 2005), this results in the elasticity, α, equalling 0.75 for the exponents on labour(L) used in the car industry for productivity measures and extended to the cement plant, which is one of the process plants. However, the nature of the business is not labour-intensive. Therefore, the expression in mathematical format below using the trial-and-error method complies with equations (3.4) and (3.5), seeking optimisation of returns to scale (e.g., close to Qi equals 100):

- $\alpha + \beta \leq 1$
- $\alpha + \beta \geq 1$
- $\alpha + \beta = 1$

Further discussion is in Chapters 5 and 6, Scenarios 1 and 2.

3.5 Empirical stochastic frontier analysis

Farrell (1957), who studied the frontier production function, is a pioneer who motivated Aigner and Chu (1968) to extend the Cobb–Douglas production function model to probe further frontier models of various manufacturing methods' productivity measures. As a result, Aigner, Lovell, Schmidt, Meeusen and Van Den Broeck (1977) developed the empirical stochastic frontier analysis method in Equation (3.6), as shown by the two yellow brackets, which identifies its function as follows:

$$q_i = \underbrace{f(x_i;\beta)}_{\text{Function status}} \times \underbrace{TE_i}_{\substack{\text{Technical efficiency, TEi, is the ratio between} \\ \text{maximum feasible result (e.g., specification) and production facilities output}}} \qquad (3.5)$$

In addition, Anderson (2004) enabled new production technologies and speedy measuring of each productivity process in a virtual production environment.

Legend

$f(x_{i,}\beta)$ — a function and solves x_i and β statues using intensive examination production processes and their data, resulting in XLMiner™ derived multiple sources of data into a regression equation for the empirical stochastic frontier analysis. i=variable for 1,..,x

TE_i — technical efficiency is the ratio between actual and specificities production facilities output under mass customisation downfall of production facilities, such as loading and unloading time of material handling unit, admixture process and so on. i = variable for 1,…,x_i

One element is the empirical stochastic frontier analysis equation in format function $f(x_{i,}\beta)$, as shown in Equation (3.6). To solve this equation, XLMiner ™ (Chan, 2018) derived multiple sources of data in the regression equation to study production facilities' operational procedures (see Table 4.7) according to new production technologies to process flow, such as a slide feed valve system to improve raw material handling, replacement bulk belts, and wave technology for accelerating the interaction of fly ash and sodium hydroxide. Thus, the findings for all proposed production facilities are linear regression equations for the empirical stochastic frontier analysis in a productivity measure.

Multiple sources data are from the following:

- First data:
  - simulation model outcome data
- Second data:
  - survey
  - related articles and conference papers
  - related associations

Additionally, Shi et al. (2015) and Satya and Sriram (2018) addressed $f(x_{i,}\beta)$, a regression equation (Chapter 2, Figure 2.5) derived from a set of input(panel) data, a longitudinal or cross-sectional time-series data, from simulation results. This is because of new cement technologies involving for productivity improvement (see Appendix A6, Appendix A8, Appendix A11 and Appendices A13 and A15). Further, technical efficiency, TE_i, also has three statuses, as shown in Equation (3.7), because the production facilities are considered 100% efficient and equal to 1, as illustrated in the black box in Equation (3.7). This is when 0.5 value means conditional repair and maintenance tasks, and the worst is equal to 0% as the machine-down being down. This is expressed mathematically as follows:

$$q_i = f(x_{i,}\ \beta) \times TE_i = \begin{cases} TE_i = 0 \\ \boxed{TE_i \leq 1 \ldots\ldots} \\ TE_i \geq 1 \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.6)}$$

Legend

q_i = stochastic frontier analysis productivity measure outcome
$f(x_{i,}\beta)$ = function for a linear regression equation
TE_i = technical efficiency

As shown in equations (3.6) and (3.7), two elements in the empirical stochastic frontier need much more data to formulate the function status into regression equations and more data to determine efficiency status. Thus, XLMiner™ plays an active role in this research (see Chapters 5 and 6 for further discussion).

3.6 Compare classic Cobb-Douglas production function and empirical stochastic frontier analysis for productivity measure (level 4)

Lin et al. (2014) addressed the classic Cobb–Douglas production function as a simple form of empirical stochastic frontier analysis (Coelli et al., 2005) in the financial industry, which is classified as a service industry. Further, the equation is used in the cement industry and is not correct. This is because the cement plant is a chemical process industry and needs many production facilities to perform its assigned tasks. It is machine-intensive, and this is illustrated in Appendices A1 to A5. Additionally, the two tools use different approaches:

- The Cobb–Douglas production function equation has been evolving since 1927 and 1947, but a few versions have been used in other industries like bank industry for productivity measures (Weber and Lippiatt, 1983). This research is based on a classic trial-and-error method in-depth study and optimises cement productivity by changing the three statuses of the elasticity combination and seeking suitable a return to scale rather than maximising profit. One element of the capital of the equation is associated with the working capital ratio test, ensuring a healthy investment for customised cement production.

  The ability of equations to measure productivity for the empirical stochastic frontier analysis method has relied on XLMiner™ to derive the multiple dimensions data into various regression equations. A different form of regression equation has a variety of productivity outcomes.

- Two elements are the components of the empirical stochastic frontier analysis equations. The first is the main equation, $f(x_i, \beta)$, and the second is technical efficiency: TE_i. Therefore, it needs a lot of data for equation development. The TEi is concerned with machine efficiency, such as the production facilities' breakdown frequency. Therefore, this method is suitable for measuring the productivity of new technology and is not related to labour force scale.

Both the above methods require considerable calculation, resulting in easily made mistakes.

4. SUMMARY

This chapter has discussed the proposed framework, including:

- Undertaking an in-depth study of Cobb–Douglas production optimisation to maximise resources and profit with respect to three-statuses of scale assessment, including under, normal and over the returns to scale using changing of two elasticities. Further, α and β concerns for capital and labour are as follows:

  - $\alpha+\beta \leq 1$
  - $\alpha+\beta = 1$
  - $\alpha+\beta \geq 1$

- Developing the empirical stochastic frontier analysis equation using XLMiner™ (Chan, 2018) for multiple data resources involving new production technologies for traditional cement manufacturing. It also introduces three stages of technologies, and TE_i to closely examine Portland-based and geopolymer-based cement production productivity.

This chapter also introduced two sub-tools, simulation, and the voice of house of deployment in the mass customisation matrix, to assist with the modularity preference using quantitative approaches that enhance the popular manufacturing selection methods deployed by current researchers. It also provides an entity identification method to select attribute independence, process independence and similarity independence in the data collection process, leading to the development of an optimisation process using simulation modelling methods. The expected outcome is for visual management, a form of communication used to snapshot manufacturing operations. This then translates shop-floor processes and production statuses into easy-to-understand overviews (Cudney et al., 2015), helping decision-makers better understand their business performances. Comparing the two tools' results shows that a company should easily be able to justify their manufacturing and business strategies.

CHAPTER 4: DATA COLLECTION AND ANALYSIS

4.1 Introduction

This chapter discusses the collection methods for the first and second data from multiple sources to develop two main and two-sub tools for optimising productivity measures under new production technologies that involve manufacturing environment and validate the proposed framework. The two main tools are as follows:

- Tool 1: use XLMiner™ to develop the sub-tools, which can derive data into a regression equation for the empirical stochastic frontier analysis productivity measure under technology-intensive conditions, including the machine manufacturing environment.
- Tool 2: examine the classic Cobb–Douglas production function by changing two elasticities, α and β, with three combinations, such as $\alpha + \beta \leq 1, \alpha + \beta \geq 1$ and so on, with respect to under, normal, and above returns to scale outcomes concerning capital and labour for the productivity optimisation measure and validating the proposed framework.

Additionally, two sub-tools are discussed:

- Sub-tool 1: The aim of the voices of the house of deployment for a mass customisation technology matrix is for a modularity preference that enhances popular use choices from current researchers. The voices are customer needs and manufacturer capability (e.g., modularity).
- Sub-tool 2: The development of simulation models, including traditional manual process flow methods, following the first and second data to enrich the items for the main tool decisions and is expected to provide process optimisation data.

The two scenarios optimise productivity measures using the trial-and-error method, study individual production facilities' performance and compare the two tools' application areas.

4.2 Data collection

Three types of data are collected for this research to enrich the sub-tool functions and assist with the development of the main tools; these types are listed below:

4.2.1) Simulation method: this research uses AnyLogic™ (e.g., agent-based model) for the simulation sub-tools to develop the optimisation process in a virtual manufacturing environment. This is because AnyLogic™ is friendly and icon driven, particularly when examining how to optimise the process flow for new production methods.

4.2.2) Survey: this direct method collects the target companies' data (Company X, Company Y and Company Z) for further equation study and to develop simulation models. Details of the survey questions (see Appendix A11).

4.2.3) Literature review and related association: this is classified as secondary data. These target data are as follows:

- Production facilities' capability for mass production
- Scheduling for major/minor overhaul
- Resources use, workforce arrangement and number of shifts
- The interim balance sheet of a target company
- Cement associations and institutions
- New production technologies.

The sub-tools use the above data to further investigate the classic Cobb–Douglas production equation and investment strategy in customised cement production facilities. The data are also used to develop the regression equation for the empirical stochastic frontier analysis method.

4.2.1 Simulation method

This study identified AnyLogic™ as one of the integrated simulation tools (see figures 3.2 to 3.3) suitable for research. Grigoryev (2018) discussed AnyLogic™ and its outstanding functions, and it must:

1) Allow analysis of systems and find solutions where methods such as analytic calculations and linear programming fail
2) Develop a simulation process model faster than an analytical model that is scalable, incremental, and modular
3) Measure values and track entities within the level of abstraction, enabling additional measurements and statistical analysis at any time
4) Enable play and animation of system behaviour over time and use this for demonstration, verification and debugging
5) Exchange data with Excel™ spreadsheets, as Excel™ only uses numbers and graphics (see Figure 4.1); this data exchange can present a dynamic animation that can attract stakeholders' attention when it comes to achieving optimisation.

The study has adapted Grigoriev's (2018) approaches above and extended one of the modelling methods, agent-based using AnyLogic™, to develop Portland-based and geopolymer-based series production processes through a tailored-made model for data collection and analysis. This can develop optimisation processes because it allows the user unlimited parameter changes. Further, AnyLogic™ embeds three types of simulation models, but an agent-based simulation model in a blue rectangle as shown in Figure 4.1 suits research need. This is because it enables sharing of data with Excel™ and other simulation models. Each simulation model's role is as follows:

(a) System dynamics: abstract and strategic modelling (Seddon, 2004)
(b) Discrete event: supports medium and medium-low abstraction (Seddon, 2004)
(c) Agent-based: can vary from very detailed models (Grigoryev, 2018)

Attribute Independence	Process Independence/ Process Similarity

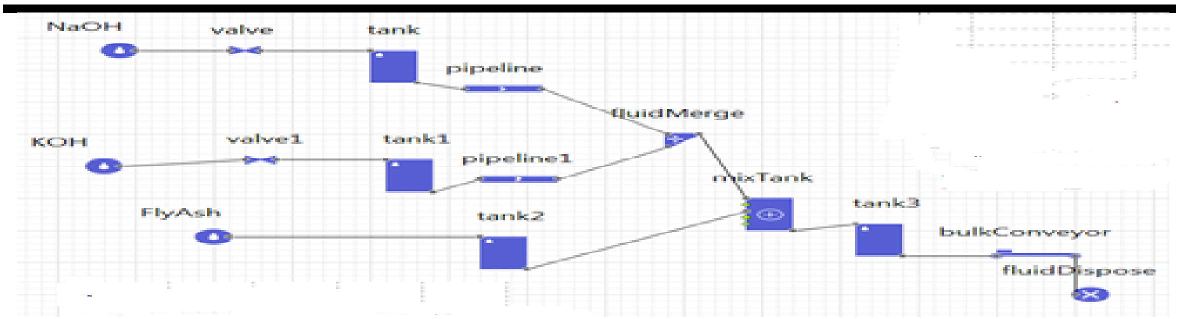


Figure 4.1 Agent-based Simulation Model of FA-based Geopolymer Cement Manufacturing

Figure 4.1 shows the traditional FA-based geopolymer cement agent-based simulation production model, resulting in Figure 4.2. This method is suitable for mass production in standard time. Facing customised small-lots cement production challenge, a cement entrepreneur based on their outcomes of these model could improve their process flow and resolve bottlenecks meeting production schedules (see Scenarios 1 and 2, Tables 5.1 and 5.2, Table 6.1).

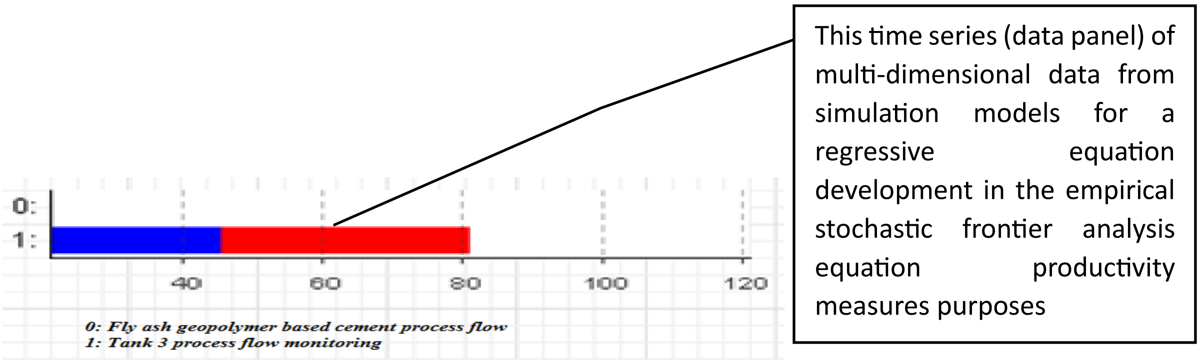


Figure 4.2 Agent-based Simulation Model of FA-based Geopolymer Cement Manufacturing Process Monitoring Result

Further, the black box in Figure 4.3 shows agent-based model development using a process monitoring library icon, which capture data that can help achieve optimal cement production.

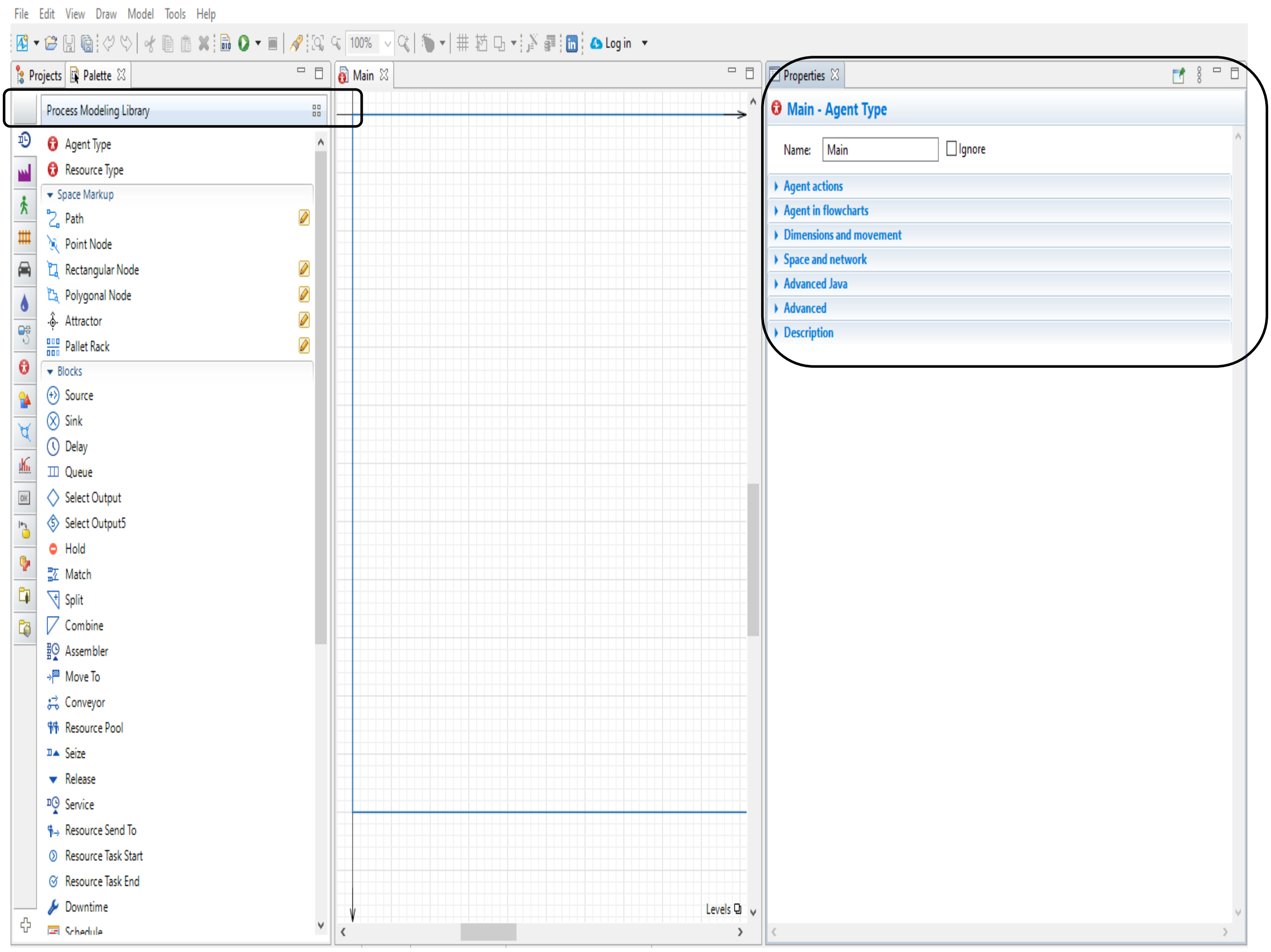


Figure 4.3 Insight from AnyLogic™

Further, the black box in Figure 4.3 illustrates a parameter setting for optimal operation (see Chapters 5 and 6, Scenarios 1 and 2 for further discussion of the model development).

4.2.2 Data from simulation model

The outcome data from simulation are used to examine the optimisation process flow in cement manufacturing by adding or eliminating specific processes for optimal production via classic Cobb–Douglas production function performances, such as reorganising a workforce. In addition, the result provides data for the empirical stochastic frontier analysis equations to measure small lot productivity under new manufacturing technologies.

Two statisticians, Ross Ihaka and Robert Gentleman, created R (RStudio™) programming language for statistical computing and graphics supported by R Core Team and R Foundation for statistical computing and launched this to the public. It provides a free tutorial, thus attracting more users, (see Chapter 5, Section 5.4, Figures 5.1 to 5.2, for further discussion), of how R or RStudio™ can offer better data analyses and minimise calculation mistakes.) In terms of collecting and analysing functions, it can replace ERP, which is the integrated management of main business processes, often in real time and mediated by software and technology. As a result, R or RStudio™ is suitable for small/micro-scaled companies but requires intensive training.

4.2.3 Data design

The following sections discusses what kind of data would be suitable for this research, particularly in relation to customised Portland-based and geopolymer-based cement production. Examining the classic Cobb–Douglas production function equation and developing the linear regression equations for empirical stochastic frontier analysis is based on the quantitative gathering of machine-intensive efficiency (see Chapter 3).

4.2.4 Data from survey method

The E-survey questionnaire (Appendix A11) using internet technologies to determine the target company's production methods and status. The contents consisted of parts A to C. Part A is a question about various tailor-made cement production processes. Parts B and C are about gathering manufacturing data for customised Portland-based and geopolymer-based cement. The expected result can be imported/exported to Excel™ for further analysis, and one of the data sources for the simulation model is discussed in the scenario outlined in Chapters 5 and 6.

4.2.5 Data from literature review, related associations, and financial reports from target cement companies

Clinker production in Australia was 5.6 million tonnes from 2018 to 2019, up to 2 per cent year on year, and clinker imports were 4.1 million tonnes in 2018–19, a 4 per cent increase on the year before (CIF, 2020). Imported cement was 0.9 million tonnes in 2018–19, a drop of around 7 per cent compared with 2017–18. However, these data are for overall cement production in Australia, including geopolymer-based cement. Therefore, periodically examining the yearly financial and quarterly interim reports develops an understanding of the target company's business strategies. Further, most cement companies use mass production methods to fabricate popular cement types such as ordinary Portland cement, and a few have introduced new manufacturing technologies for customised cement that maximises profit.

One finding show that these technologies have seldom been studied various types of small lot cement production in optimisation to satisfy clients' needs and achieve just-in-time (JIT) delivery with minimal resources (see Chapters 5 and 6 for further discussion).

4.2.5.1 Data from Literature Review

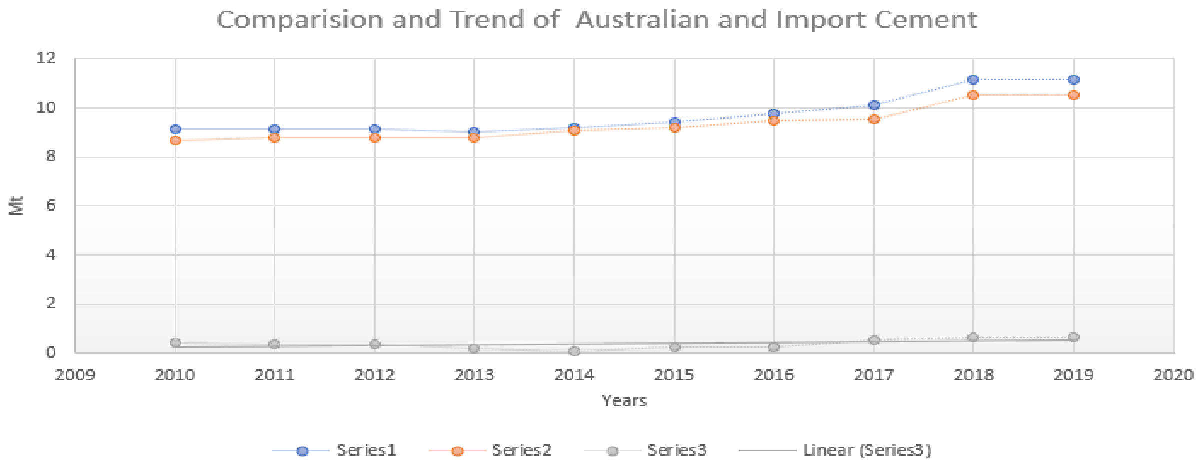


Figure 4.4 Clinker Production and Clinker Imports from Overseas in 2020 (CIF, 2023)

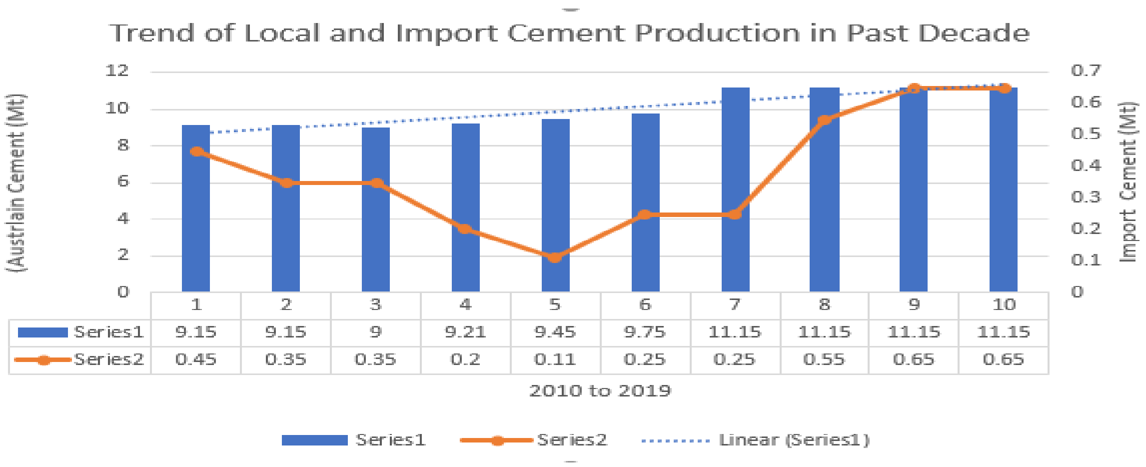


Figure 4.5 Cement Production and Imports in Australia in 2020 (CIF, 2023)

Figure 4.4 illustrates the trend of clinker production in 2020 in Australia, showing that process parts (e.g., sectional modularity) produced in offshore cement factories. This because the operational cost, including raw material cost, is cheaper than for Australian-owned cement factories (ABS, 2020; CIF, 2023). As a result, a slight rise subcontracted overseas is shown in Figure 4.5 (dotted blue line).

Because of its cost-driven strategy, Company X (2021) used the built-in-stock production method and did not satisfy various clients' needs. This was due to numerous problems with changing product lines. To determine bottlenecks at an earlier stage, simulation technology can solve tailor-made cement process problems using virtual manufacturing technologies. However, developing simulation models requires lot of data, and reorganising a regression equation for the empirical stochastic frontier analysis creates the same problem. Therefore, data are the backbone of whether the equation succeeds for alternative productivity measures.

4.2.5.2 Data from Related Associations

This study identified one of the public organisation, Cement and Concrete Aggregation Association, somewhere else in Brisbane city providing valued data in cement manufacturing research such as Australian cement standards (AS), American Standard of Test Materials (ASTM) and so on. Examples of the standard are below:

- AS3972 (2010): general Portland (GP) and blend Portland (GB) cement
- AS 2350.14 (2006): methods of testing Portland and blended cements, with the length change of cement mortars exposed to sulphate solution
- ASTM C150: specification for Portland cement
- ASTM C-595: specification for blended hydraulic cement
- ASTM C-57: performances specification for hydraulic cement

The above standards provide a guideline for organising a virtual manufacturing environment, identifying bottlenecks earlier and seeking optimal workflow. This is because previously customised cement was contracted overseas and could not maintain quality standards (ABS, 2022; Rozhkov et al., 2022). As a result of the COVID-19 pandemic, Australian-owned cement factories suffered time-to-market delivery and a shortage of fast-moving production data. Therefore, there is industry momentum in modelling to collect and analyse data for the optimisation process at an affordable price that meets company interests and client needs.

4.2.5.3 Data from Financial Reports from Target Cement Companies

Figure 4.6 Historical Price of Company X (Company X, 2021)

	CONSOLIDATED GROUP			
	30 JUN 20 POST AASB 16 $'000	30 JUN 20 PRE AASB 16 $'000	30 JUN 19 PRE AASB 16 $'000	CHANGE PRE AASB 16 $'000
Current assets	84,552	84,552	69,124	15,428
Non-current assets	245,438	152,949	131,707	21,242
Total assets	329,990	237,501	200,831	36,670
Current liabilities	64,295	61,923	53,251	8,672
Non-current liabilities	163,288	70,227	84,975	(14,748)
Total liabilities	227,583	132,150	138,226	(6,076)
Net assets/(liabilities)	**102,407**	**105,351**	**62,605**	**42,746**

Figure 4.7 Balance Sheet of Company X (Company X, 2021)

The black box in Figure 4.6 illustrates Company X's (2021) dynamic business performance in the stock market. It is a typical example of Australian-owned businesses, which is representative of the industry during the COVID-19 pandemic in terms of its ability to meet customer needs steadily declining. Due to boundary closure, this trend become worse, and domestic-made is an alternative (Company X, 2021), but needs upgrading production facility and investment. The capital test ratio demo in Equation (4.1) is the well-known method complied with Figure 4.7 outcome to measure financial performance (see p.71). Its result shows whether it is a worthy investment for productivity improvement and solving bottlenecks. A cement entrepreneur using the classic Cobb–Douglas production function and the empirical stochastic frontier analysis methods determines whether the company's capability time-to-market of customised cement works out.

	Consolidated Group 30 Jun 2019 $'000	Debt drawdown	Impact of the offer	Proforma Balance Sheet
Current Assets				
Cash and cash equivalents	6,101	367		6,468
Trade and other receivables	42,661	4,907		47,568
Inventories	19,515			19,515
Derivative instruments	368			368
Other assets	479			479
Total Current Assets	**69,124**	**5,274**	**-**	**74,398**
Non-current Assets				
Other financial assets	7			7
Property, plant and equipment	123,520	2,718		126,238
Intangible assets	2,638			2,638
Deferred tax assets	5,542			5,542
Other assets	-			-
Total Non-current Assets	**131,707**	**2,718**	**-**	**134,425**
Total Assets	**200,831**	**7,992**	**-**	**208,823**
Current Liabilities				
Trade and other payables	28,242			28,242
Borrowings	14,673			14,673
Derivative instruments	1,474			1,474
Current tax liabilities	3,714			3,714
Provisions	5,148			5,148
Total Current Liabilities	**53,251**	**-**	**-**	**53,251**
Non-current Liabilities				
Borrowings	81,749	7,992	- 39,455	50,286
Derivative instruments	2,856			2,856
Provisions	370			370
Total Non-current Liabilities	**84,975**	**7,992**	**- 39,455**	**53,512**
Total Liabilities	**138,226**	**7,992**	**- 39,455**	**106,763**
Net Assets/(Liabilities)	**62,605**	**-**	**39,455**	**102,060**
Equity				
Issued capital	371,334		40,000	411,334
Pre IPO distributions to related entities	- 354,613			- 354,613
Reserves	- 397			- 397
Retained earnings	46,281		- 545	45,736
Total Equity	**62,605**	**-**	**39,455**	**102,060**

Figure 4.8 Detailed Balance Sheet of Company X (Company X, 2019)

Company X (2019) has a detailed balance sheet for the year 2019 as shown in Figures 4.7 to 4.8. The company was interested in a wealth balance using a ratio test. The asset and liability data are as follows:

- Asset value is A$15,428,000
- Liability value is A$8,672,000

Extracting data from Figure 4.7 into a working capital ratio test obtains the following result:

In year 2019:

Total working Capital Ratio $= \frac{\text{Current Assets}}{\text{Current Liabilities}} = \frac{15428000}{8672000} = 1.79$ …..……………….…………(4.1)

The ratio based on Figure 4.8 using Equation 4.1 measures working capital performance. If the outcome value is less than one, it results in business risk. But too much could be a sign of mismanagement. Bayne and Wee (2019) determined that the acceptable working capital ratio (current ratio) is 1.5 to 3. Company X's (2020) financial statement is healthy in 2019 because the outcome equals 1.79 based on Equation (4.1). However, the working capital is slightly above the standard ratio of 1.5 and needs to improve to 2 (Pellicer et al., 2009; Wacker, 1975; Merit, 2015; Dasu, 1998) for customised cement business to maximise profit and resource uses.

According to Equation (4.1) outcome result, Company X needs to be careful in terms of its business performance, particularly productivity performance that maximises profit. Therefore, the classic Cobb–Douglas production function further examines the three statuses of scale using trial-and-error with respect to $\alpha + \beta \leq 1; \alpha + \beta \geq 1$ and $\alpha + \beta = 1$ methods for the productivity optimisation measure. Further, Company X also controls better new production facilities investment for the customised cement business using the empirical stochastic frontier analysis method because of machine efficiency (see Chapters 5 and 6 for further discussion).

Figure 4.10 explores Company Y (2021) using a time series for data collection and analysis of business performance. As in, increasing security price upward trend in the dark box of Figure 4.7 is due to improved manufacturing strategies using cost control of raw materials and labour and attaining more construction infrastructure businesses nationwide in 2021. Company Y (2021) suffered from a customised small lot production problem that offered opportunities to competitors. Company Y to consider new technologies and methods for their next lot of cement production.

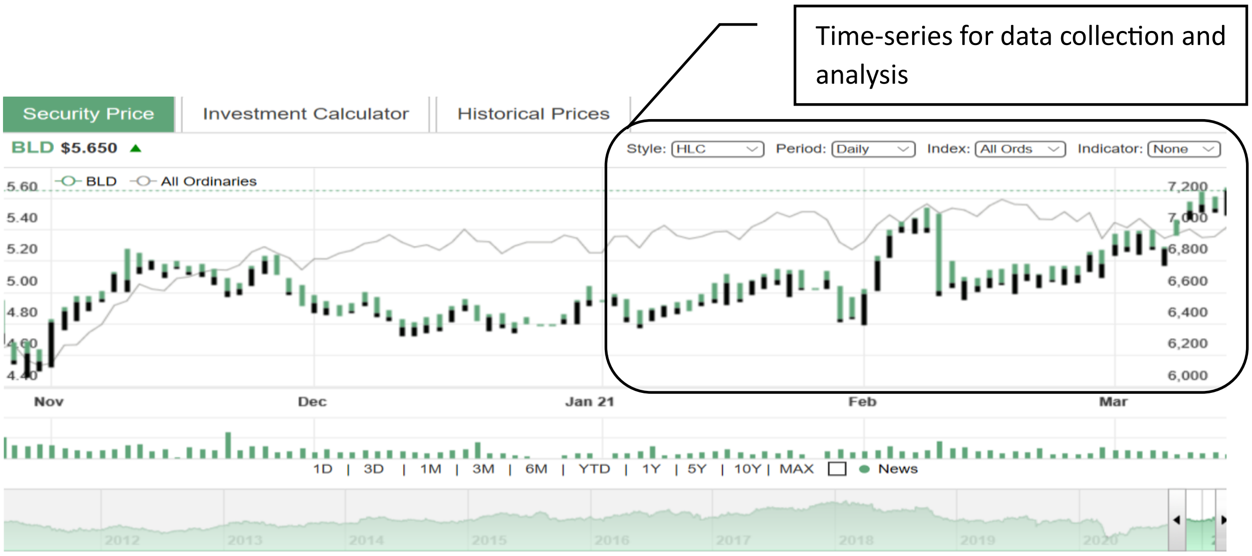


Figure 4.9 Trend of Security Price (Company Y, 2021)

CCAA (2020) and Company Y (2021) also addressed the loss of business demand for small lot cement construction infrastructure in the domestic and worldwide markets. For a long-term cement business, new production facilities and technologies can assist Australian-owned factories rather than contracted overseas facilities, thus maximising the Australian Government stimulus plan fund, and involving investment in manufacturing facilities (see Appendices A6 to A8, Appendix A11, Appendices A13 to A15). The working capital current ratio test, when combined with the main tools and sub-tools, can assist with challenges of trying to optimise business performances.

Table 4.1 Bogue Compounds of Ordinary Portland Cement (CCAA,2020)

Name of Raw Materials	Weight by Percentage (%)
Lime (CaO)	60 to 67%
Silica (SiO_2)	17 to 25%
Alumina (AI_20_3)	3 to 8%
Iron oxide (Fe_2O_3)	0.5 to 0.6%
Magnesia (MgO)	0.1 to 4%
Sulphur trioxide (SO_3)	1 to 3%
Soda and/or Potash (Na_2O+K_2O)	0.5 to 1.3%

Expected outcome data

Analysing the production optimisation of different types of Portland-based cement, such as blend Portland (GB) and high early strength (HE) cement, Anderson's approaches can improve productivity if they are used with the simulation modelling methods based on Bogue's compounds outcome (see Appendix A5 and Appendix A14) for fast-moving customised cement and market demand. Tables 4.1 to 4.2 show the fundamental composition of ordinary Portland cement.

Table 4.2 Composition and Compound Content of Portland Cement (CCAA, 2020)

	Normal	Rapid Hardening	Low Heat
Composition (%)			
Lime	63.1	64.5	60
Silica	20.6	20.7	22.5
Alumina	6.3	5.2	5.2
Iron Oxide	3.6	2.9	4.6
Compound (%)			
Tricalcium silicate(C_3S)	40	50	25
Dicalcium silicate (C_2S)	30	21	35
Tricalcium aluminate, $3CaO.Al_2O_3$,(C_3A)	11	9	6
Tetraclcium aluminoferrite, $4CaO.Al_2O_3.Fe2O_3$, (C_4AF)			

Further, the black box in Table 4.2 shows that Portland-based cement has less tricalcium silicate (C_3S), higher ultimate strength, less generation of heat, and less cracking in clinker based on the AS 2350.2:2006 requirement. Time control and the correct proportion of raw material are the key factors in fabricating target cement regarding the cement production process for clinker, which uses the mix-&-add-in modularity of mass customisation technologies.

As a result of the simulation of the Portland-based cement (e.g., GP) manufacturing model, similar composition and characteristics (homogeneous), as shown in Table 4.3, would be captured in the set stage using icon-driven prompts in the AnyLogic™ system; the system would then compile and examine the results until an optimal result is achieved. There are eight phases and limitations in the development of the simulation models, as shown below:

1) *Phases:*

Phase 1: creating cement factory layout drawing in digital format (Chan, 2018)

Phase 2: uploading this drawing to AnyLogic™ via the import function

Phase 3: selecting essential independent attributes, including grinding, process tank, mixed tank, clinker, piping and valves

Phase 4: setting parameters for each independent attribute and process independence

Phase 5: simulating all necessary raw materials that arrive at the job shop and silos

Phase 6: expanding the model by adding material handling devices to be delivered various production facilities

Phase 7: exanimating the processes using a wide range of parameters

Phase 8: reorganising production processes to meet the requirements of a small lot of cement fabrication, as shown in Table 4.5, in a virtual reality manufacturing environment via simulation.

2) *Limitations:*

- Assume good quality throughout the production and do not consider any rework
- Using mass and mass customised production methods

(see Chapters and 6 for further discussion).

Table 4.3 Chemical and Physical Properties of Ordinary Portland Cement (CCAA, 2020)

Variety cement (homogeneous)

AS3972 (2010) requirement		Type of Cement						
		GP	GB	GL	HE	SL	SR	LH
Physical properties	Max(hr)	6	10	10	6	10	10	10
	Min (minutes)	45	45	45	45	45	45	45
Soundness	Max expansion(mm)	5	5	5	5	5	5	5
Compressive strength (MPa)	Min at 3 days	-	-	-	25	-	-	-
	Min at 7 days	35	20	20	40	(b)	(b)	10
	Min at 28 days	45	35	35	-	(b)	(b)	30
Peak temperature rises	Max (℃)	-	-	-	-	-	-	23
Drying shrinkage	Max (microstrain) 16 weeks	-	-	-	-	750	-	-
Sulphate expansion	Max (microstrain) 16 weeks	-	-	-	-	-	750	-
Chemical limitations	MgO in clinker less than (%)	4.5	4.5	4.5	4.5	4.5	4.5	4.5
	SO_3 content Max (%)	3.5	3.5	3.5	3.5	3.5	3.5	3.5
	Chloride ion Max (%)	0.1	0.1	0.1	0.1	0.1	0.1	0.1

(a) when determined in accordance with the methods set out in AS2350
(b) strength shall comply with the type with type GP or GB requirement depending on the cement composition

Legend

A. Type general Portland (GB) cement = two methods of producing blend Portland (GB):
   a1) cement may be produced using either (a) a post-blending operation where the supplementary cementitious material (SCM) is blended with previously milled material
   a2) clinker and SCM may be inter-ground together with gypsum and mineral to form the blend (typical for slag blends).
B. Type high early strength (HE) cement:
   b1) typical blended cement made by either post-blending or inter-grinding depending on the SCM type used
   b2) type HE cement is usually compositionally like type GP but milled to a higher level of fineness.
C. Type general Portland (GP) or general lime (GL)= cement clinker is then ground, in ball mills or vertical roller mills, with gypsum and generally one or more forms of mineral addition to form. These may be used alone or in combination up to the maximum allowable 7.5% of the 7.5% mineral addition allowance.
D. Type low heat (LH) is low heat cement used where the exothermic cement hydration reaction concrete temperature may lead to structural issues. LH cements are typically used in mass concrete structures (e.g., concrete dams, plinths, and large footings)
E. Type SL cement or Type SR cement is a special purpose cement complying with AS 3972. It is manufactured from specially prepared Portland cement clinker and gypsum. SL cement may contain up to 7.5% of AS3972 approved additions.

Further, Table 4.3 shows the physical and chemical properties of various Portland cement parameters for cement types including general Portland (GP), blend Portland (GB), general lime (GL), high early strength (HE), shrinkage limited (SL), shrinkage resistance (SR) and low heat (LH), with general requirements from Standards Australia AS3972-2020 in general Portland (GP) and general blend (GB) Cement. The types of GP, GB and HE cement have the same independence attributes and similar processes, process independence and homogeneous composition characteristics. Table 4.3 also provides general specifications that serve as the voice of customer needs to develop the voice of house of deployment in the mass customisation matrix (see Section 4.3.1).

To simultaneously satisfy the three homogeneous characteristics of cement (e.g., GP, GB, HE) and optimum production, this study uses modelling methods that maximise the use of production facilities, meeting just-in-time delivery (see Chapter 5, Table 5.1, and Chapter 6.1).

When producing general blend Portland (GB) cement, a certain amount of slag is added to the contents and mixed just after the general Portland (GP) production process has finished, resulting in the same blended cement characteristics. This is one of the significant differences between general blend Portland (GB) and general Portland (GP) cement.

HE has fine cement particles compared with general Portland (GP) and general blend Portland (GB) cement. A ball roller grinding process just after GP mixing is finished or mixing before with gypsum to ensure high early strength (HE)-grade cement. This means that the traditional method of HE fabrication is time-consuming. As a result of the optimisation process, ultra-sonic linear vibration production facilities undertake mixing and grinding cement production instead of traditional vertical roller mills or horizontal ball mills, resulting in speedy and easy-to-produce HE cement because of the two-to-one process (see Appendices A1 to 2).

The efficiency of all the production methods discussed here are validated by simulation model. (see Chapters 5 and 6 for further discussion).

4.2.5.4 Classic Cement Plant Operational Data

Table 4.4 shows the standard production process and capability for classic Portland cement (Chan, 2018). This method is suitable for mass production because of the regular scheduling of repair and maintenance plans, expected quantities and time to market, resulting in outcome data that suits typical dynamic simulation model development (Anderson, 2005). Further, ordinary Portland (GP) and blend Portland cement (HE) cement have homogenous structures as the type shown in Table 4.2, which means these types of cement share process characteristics and the agent-based simulation model can seek optimal productivity approaches for all of them.

300 workdays facing agile small-lots-based production

Table 4.4 Classic Cement Plant Yearly Capability (Chan, 2018, p.125)

Productivity / Process	**Capability (Tonne/year)**	**Machine (24 hours/day)**	**300 workdays**
Coarse grinding	1,500,000	1 mill	432,000 minutes
Mixer	1,200,000	2 mixers	432,000 minutes
Admixture (SCM)	400,000	1 conveyor	432,000 minutes
Fine grinding	1,500,000	1 mill	432,000 minutes
Clinker (Cement)	1,600,000	1 clinker	432,000 minutes
Packing	1,700,000	bulk bag	432,000 minutes
Silo	46,000	300 cycle times	432,000 minutes
Transport	26,000,000km	by train/vehicles	432,000 minutes

In developing a simulation model to customise different cement types and synchronise production, mixed batches must be avoided because of similar process characteristics. To improve productivity, linear actuator valves, whether interlock devices or sequence-control systems (see Appendix A6 and Appendix A13), are fixed at both ends of production facility itself using top-bottom production methods (Appendix 14), minimising downtimes, avoiding mixed batches, and ensuring that correct grades of quality cement are delivered to customers (see Chapters 5 and 6 for further discussion).

Tables 4.5 to 4.6 show classic ordinary Portland cement (GP) and FA-based geopolymer-based cement production. They identify the homogeneous and heterogeneous structures of ordinary Portland and geopolymer-based cement and share similar processes; the same simulation modelling method can be used for both.

Table 4.5 Raw Materials Composition to Produce One Tonne of Ordinary Portland Cement (Huntzinger and Eatmon, 2009; Chan, 2018, p. 159)

Name of Raw Materials	Amount to Produce One Tonne of Ordinary Portland Cement
Limestone/lime	1.41
Gravel	0.002
Sand	0.034
Clay	0.139
Slag	0.015
Gypsum	0.05

Table 4.6 Raw Materials Composition to Produce One Tonne of FA-Based Geopolymer Cement (Davidovits, 2013)

Name of Raw Materials	Amount to Produce One Tonne of FA-based Geopolymer Cement
Fly Ash	2.1
NaOH Solution	1
KOH Solution	1
Sand	0.68
Clay	0.001

Table 4.7 The Fundamental Formulation of Linear Regression Equations for Ordinary Portland Cement

Items / **Name Raw Materials**	**Capability Variables** a_i	**Attributes Independence Variables** X_i	**Proposed Linear Regression Equations** $\sum Q_i = \sum a_i X_i$
Limestone/lime	a_1	X_1	$Q_1 = a_1 X_1$
Clay	a_2	X_2	$Q_2 = a_2 X_2$
Sand	a_3	X_3	$Q_3 = a_3 X_3$
Gypsum	a_4	X_4	$Q_4 = b_4 Y_4$
Silica	a_5	X_5	$Q_5 = b_5 Y_5$
Slag	a_6	X_6	$Q_6 = b_6 Y_6$

Table 4.8 The Fundamental Formulation of Linear Regression Equations for Geopolymer-based Cement

Items / **Name Raw Materials**	**Capability Variables** b_i	**Attributes Independence Variables** Y_i	**Proposed Linear Regression Equations** $\sum Q_i = \sum b_i Y_i$
Fly ash/MK/GBBFS	b_1	Y_1	$Q_1 = b_1 Y_1$
NaOH/KOH solutions	b_2	Y_2	$Q_2 = b_2 Y_2$
Sand	b_3	Y_3	$Q_3 = b_3 Y_3$

Legend

a_i, b_i, c_i, X_i, Y_i, Q_j are available, where i and j = 1 to n

$$Q_i = a_i X_i + C_i \text{ or } Q_j = b_j Y_j + C_j \qquad (4.4)$$

Tables 4.7 to 4.8 and Equation (4.4) are proposed linear equations for Portland-based and geopolymer-based cement, converting the functional status of the empirical stochastic frontier into productivity measure (see Chapters 5 and 6 scenarios 1 and 2 for further discussion).

Further, adapting and extending Satya and Sriram (2018), Shi et al. (2015) and XLMiner™ approaches, Tables 4.7 and 4.8 use data from multiple sources to derive linear regression equations in a new cement production involvement environment in a wide range of elastic study for optimising three-scaled of under, normal, and over of return assessment; compared to in traditional cement production methods to assess which approach offered better productivity.

Table 4.8 shows the fundamental formulation of FA-based geopolymer cement. Metakaolin (MK)-based geopolymer is an alternative to this that arose because of the closure of coal-fired power stations (ABS, 2020) and higher prices as a usual offer to the fly ash users (Chan, 2018). Because of the similar process characteristics of fly ash and metakaolin, the finding is that metakaolin's chemical reaction with sodium hydroxide solution takes an extra 0.3 hours longer when it is undertaken using fly ash particles as shown in Table 4.9, results in better technical efficiency, TE_i.

Table 4.9 Chemical Reaction Timing Including Sodium Hydroxide for Either Fly Ash or Metakaolin and Mixed with Sand and Others (Chan, 2018, p. 159)

Item / Process	**Unit processing time (tonne / hour)**		**Availability (hour)**
	FA	**MK**	
Chemical reaction of sodium hydroxide (NaOH) with either fly ash or metakaolin (mixer)	3	3.3	2400
Mixed with sand	3.3	3.3	2400
Pack (pneumatic bulk tanker)	3	3	2400
Total processes yield	9.3	9.6	7200

Additionally, Table 4.9 shows a class of individual production processing in the unit of tonne/hour, available hour for fly ash, and the metakaolin chemical reaction of sodium hydroxide for geopolymer-based cement production. This method is either fly ash or metakaolin (mixer) 3 and 3.3 tonne/hour and is available for 2,400 hours. It is suitable for mass production of a single cement product, and it improves expected productivity. It adapts mass production manufacturing performances and extends customised Portland-based and geopolymer-based cement for small lot cement production (see Section 4.4 for further discussion).

Table 4.10 Plant Capability for Producing Ordinary Portland Cement with Supplementary Continuous Materials (Chan, 2018, p. 159)

Re-organising available work hours for small-lots-based of production

Standard / **Process**	**Unit Processing Capability (tone/hour)**		**Availability (hr)**
	OPC (tonne/hr)	OPC with SCM (tonne/hr)	
Crushing	3.1	3.1	3,000
Vertical roller mill (coarse grinding)	2.6	2.6	7,200
Additive (SCM)	0	1	7,200
Clinker	3	3	7,200
Additive (gypsum)	1	1	7,200
Ball mill (fine grinding)	2.99	2.99	7,200
Packing	3	3	7,200

Further, Tables 4.10 to 4.12 show the classic capabilities needed to produce ordinary Portland cement-based and geopolymer-based cement using the mass production manufacturing method. This is a continuous fabrication of Portland cement with minor changes to any production status. Therefore, it is straightforward to develop a standard time of fabrication cement, resulting in constant income, stable workforces, and outstanding productivity. The time for delivery to various contractors worldwide is not a problem, fulfilling the mass customisation scope.

Table 4.11 Machine, Material and Energy Costs Distribution for Ordinary Portland Cement with Supplementary Cementitious Material in Traditional Cement Plant Production (Chan, 2018, p. 145)

Item / Cost	OPC	OPC with SCM Cement	Unit (A$ / tonne)
Total machine cost	150	155	A$/tonne
Total material cost	106.9	111.5	A$/tonne
Total energy cost	43.1	23.5	A$/tonne
Subtotal total cost	300	290	A$/tonne
Revenue	345	348	A$/tonne
Profit	45	58	A$/tonne

Table 4.12 Standard Time and Availability of Classic Geopolymer-based Cement Plant Operational Data (Chan, 2018, p. 159)

Item / Process	Unit processing time (tonne / hour)		Availability (hour)
	FA	MK	
Chemical reaction of sodium hydroxide (NaOH) with either fly ash or metakaolin	3	3.3	2400
Mixed with sand	3.3	3.3	2400
Material handling unit	3	3	2400
Total processes yield	9.3	9.6	7200

Tables 4.9 to 4.12 discuss machine capability for mass production. They show that there is room to fabricate a more tailor-made variety of small lot cement, considering 300 working days across the year and rest days for repair and maintenance machines (Chan, 2018). As a result of having a better understanding of both voices of customers' expectations and manufacturers' capabilities, using the house of deployment of the mass customisation matrix can provide two voices of feedback, and then parallel use of customised and mass cement production can satisfy customer needs; this improves services and modularity preference based on quantitative measure outcomes and enrichment of choices only from expected cement products (see Section 4.2.5.4.1 and Section 4.3).

Further, the expected outcome of the house of the voice of deployment of the mass customisation matrix offers customer satisfaction and modularity preference for a manufacturer (see Section 3.3.37). This is for the following reasons:

- Cudney et al. (2015) addressed the voice of the house of deployment for customers commonly used in Japanese approaches to operations management. This is adapted and extended to the voice of house of deployment in the mass customisation matrix and used in the Australian-owned cement industry because of market demand. The approach positions the first voice as prioritising customer needs and the second voice as the manufacturers' strategy, ensuring the ability to meet new business challenges and achieve better modularity preference using a quantitative measuring method (see Table 4.13).
- The voice of the house of deployment of customers matrix uses nine items (criteria) to measure modularity preference from the manufacturer and customer needs based on the cement data specification sheet, which includes customer orders (see Table 4.16 and Figure 4.11).
- Two scenarios discussed in chapters 5 and 6 show that various companies call their cement products different names even though they have the same function and composition. For example, Company X (2021) classifies ordinary Portland cement with supplementary cementitious materials (SCMs) as high early strength (HE) cement because of its composition, which is similar to general Portland cement and blend Portland cement, resulting in a higher level of fineness (CCAA, 2020). It needs more testing to ensure that its particles reach the required standard and to minimise CO_2 emissions during the production process. Therefore, the role of the mass customisation matrix in prioritising customer needs and less influence on the environment ensures correct comparison.

Further, the result is needed to develop a simulation model and explore the Cobb–Douglas production function of the productivity optimisation measure of the development of the voice of the house of deployment in mass customisation (see Section 4.2.5.4.1 and Chapters 5 and 6, Scenarios 1 and 2 for further discussion).

4.2.5.4.1 The Voice of the House of the Deployment in Mass Customisation

This section discusses adapting the quality function deployment voice of the customer (Mazur, 2015; Anderson, 2004; Nadi,2019; Zhang et al., 1990) and extending it to the voice of the mass customisation matrix, ensuring that a preference for mix-&-add-in modularity is correct. The nine items include two voices, customer concerns and manufacturer concerns (see Section 3.3.3), as listed below:

1. Customer requirement: a variety of Portland-based and geopolymer-based cement based on Table 2.1, Table 4.3, and related Australian standard (AS) cement standards
2. Customers' importance rating uses multiple sources of data, including benchmarks from customers, surveys, etc.
3. Competitive analysis in modularity for mass customisation: clients and manufacturers, as per Table 2.2, etc.
4. Technical requirement: cement that is early strength, wear resistance, etc., based on Table 2.1, Figures 2.1 to 2.2, Australian standard AS3972, AS1478, AS3582.2, AS3582.3, AS3972
5. Relationship matrix: associated with various attributes based on raw material names, etc.
6. Manufacturers' importance rating: various benchmarks from manufacturers (modularity) and machines' capability, etc.
7. Target values: expert opinion from the ranges 1 to 5
8. Engineering analysis: homogeneous materials, process similarity using a simulation model based on related AS cement standards, etc.
9. Correlation matrix: the variety of geopolymer-based or Portland-based cement characteristics based on Table 2.1 and related standards and associations

For further discussion development of the house of deployment for mass customisation, see Section 4.2.5.4.1.1 and Section 4.3.

4.2.5.4.1.1 Construction of the House of Deployment

This study focuses on four steps to construct the mass customisation matrix, including cement characteristics (Table 4.14) and their properties, such as geopolymer-based, Portland-based cement and so on. The four steps are listed below:

A. Step 1: derive data using XLMiner™ (Chan, 2018) to develop a customer needs matrix, as shown on the far left of Table 4.13.
B. Step 2: develop manufacturing importance associated customers with need matrix, as shown in the middle of Table 4.13.
C. Step 3: weight the benchmark results of the matrix
D. Step 4: examine the benchmark result for customers and manufacturing.

Table 4.13 Voice of the House of Deployment in Mass Customisation (Nadi, 2019; Zhu, 2003; Trappey et al., 2017; Mazur, 2015; Anderson, 2004; Zhang et al., 1990)

Voice of the House of the Deployment in Mass Customisation Matrix

Scores / **Criteria**	**Customer Needs Voice Score**					**Modularity Important Voice Score**				
Customer Needs (nine items)										
Manufacturer Capability, Including Modularity										
Manufacturing Cost										
Time to market										
Subtotal										

4.3 Voice of mass customisation and productivity measures for small lot batch production

The voice of the house of deployment in quality has been commonly used in Japanese manufacturing firms to meet customer needs and achieve quality assurance (Kassela, 2016) because it is one of the communication quality control platforms with internal and external stakeholders. However, this method does not consider the voices of customers and manufacturing methods for cement production, thus creating a gap. The house of the voice of mass customisation method thus builds a bridge between customer and manufacturer, generating more confidence in the on-time delivery of customers' desired cement at an affordable cost. It adapts the house of quality function deployment (QFD) Deming's quality principles (e.g., Father of Quality) to the field of new innovative services in a particular field (Mazur, 2015) and extends this to the mass customisation (modularity) matrix to satisfy both voices' needs. Deming's 14 points for management excellence (Aartseng et al., 2015) are as below:

1) Create constancy of purposes for improving products and services (e.g., time-to-market)
2) Adopt the new philosophy (e.g., time-to-market)
3) Cease dependence on inspection to achieve quality (e.g., product specification)
4) Minimise total cost (e.g., voice of house in deployment in mass customisation matrix)
5) Improve constantly and forever every process for planning, production, and service
6) Institute training on the job
7) Break down barriers between staff areas (e.g., customer relationship)
8) Eliminate slogans, exhortations, and targets for the workforce
9) Drive out tear
10) Adopt and institute leadership
11) Eliminate numerical quotas for the workforce and numerical goals for management
12) Concern pride of workmanship, and eliminate the annual rating or merit system
13) Institute a vigorous program of education and self-improvement for everyone
14) Put everybody in the company to work accomplishing the transformation

Summarises all data from multiple sources, including parts of Deming's principles for the house of deployment of mass customisation matric development discuss in Section 4.3.1.

4.3.1 Mass customisation related to manufacturer voices and demand for geopolymer-based cement

Table 4.14 shows a geopolymer-based cement matrix for modularity preference as below:

A. Voice of the customer: the left column lists customer needs for three types of geopolymer-based cement with similar processes and structures: AS types of FA-based, MK-based and GBBFS-based geopolymer-based cement

B. Voice of manufacturer: the upper row shows six characteristics of geopolymer-based cement: early strength, acidic resistance, low carbon emission, sink/expand and water resistance

C. Score board: the right column is for evaluating modularity preference; the score is 1 to 5 in each row.

A. Voice of the customers: three types of geopolymer-based cement (see Table 2.2):

C) FA-based geopolymer

D) Mk-based geopolymer

E) GBBFS-based geopolymer

B. Voice of the manufacturers (see Table 2.1 and Table 4.3):

- Early strength
- Acidic resistance
- Heat resistance
- Low carbon emission
- Sink/expand
- Wear resistance

C. Six modularities: the assessment scale is from 1 to 5 for each column:

- ‘a’ is component-sharing modularity
- ‘b’ is component-swapping modularity
- ‘c’ is cut-in-fit modularity
- ‘d’ is mix-and add-in modularity
- ‘e’ is bus modularity
- ‘f’ is sectional modularity.

Table 4.14 Matrix Measure of the Mass Customisation with Customer and Manufacturer Voices and Demand for Geopolymer-based Cement Demand (Nadi, 2019; Zhu, 2003; Kassela, 2016; Trappey et al., 2017; Cudney et al., 2015; Zhang et al., 1990)

Voice of the House of the Deployment in Mass Customisation for Geopolymer-based Cement Matrix

Voice of the Customer Needs								Voice of Manufacturer Capability										
Specifications / Cement		Early strength	Acidic Resistance	Heat Resistance	Low Carbon Emission	Sink Expand	Wear Resistance	Customer Needs Voice Score					Modularity Important Voice Score					
								1	2	3	4	5	a	b	C	d	e	f
Manufacturing Cost		●	●	●	●	●	●					5				5		
Delivery Just-in-Time		●	●	●	●	●	●					5				5		
MK-based	Geopolymer Cement	●	●	●	●	●	●					5				5		
FA-based		○	○	○	○	○	○				4					5		
GBBS-based																		
Subtotal												24				25		

Homogeneous material and have a process similarity

Legend

●= Need

○ = Plan; Scale = 1 to 5; 1 = Less Demand and 5 = Strong Demand

a = component-sharing modularity
b = component-swapping modularity
c = cut-to-fit modularity
d = mix-&-add-in modularity
e = bus modularity
f = sectional modularity

The black box in Table 4.14 illustrates the two scores of the customer and the manufacturer voices of the house of deployment in mass customisation of the geopolymer-based matrix outcome. A survey outcome finding is machine capability. According to Rozhkov et al. (2022), COVID-19 border closure issues over the past two years mean that client needs for on-time delivery cannot be met, resulting in a score of 24 out of 25. The voice of the manufacturers is 25, which is a full mark due to the satisfaction of manufacturing skill (modularity). Option d is the best—it meets the voice of manufacturers' capability in the modularity preference because of maximising resources.

One finding is that FA-based, MK-based and GBBFS-based geopolymer cement types are homogeneous materials based on Australian Standards (2020) Part 1 to Part 2 assessment. As a result, there are similar independence characteristics, providing opportunities for modelling different types of geopolymer in each batch production and minimising machine idling and resource use. Therefore, the geopolymer-based manufacturing processes—including fly ash, metakaolin and GGBFS—enable adding or eliminating processes according to manufacturing need, thus satisfying various customers' expectations (see Chapters 5 and 6, and Table 4.14 for further discussion).

4.3.2 Voice of mass customisation and productivity measures for small lot batch production for Portland-based cement

Table 4.15 Mass Customisation with Customer and Manufacturer Voices and Demand for Portland-based Cement (Nadi, 2019; Kassela, 2016; Cudney et al., 2015; Zhang et al.,1990)

Voice of the House of the Deployment in Mass Customisation for Portland-based Cement Matrix

Voice of Customer Needs								Voice of Manufacturer Capability										
Specifications / Cement		Early strength	Acidic Resistance	Heat Resistance	Low Carbon Emission	Sink Expand	Wear Resistance	Customer Needs Voice Score					Modularity Important Voice Score					
								1	2	3	4	5	a	b	c	d	e	f
Manufacturing Cost		●	●	●	●	●	●			3						5		
Delivery Just-in-Time		●	●	●	●	●	●					5				5		
Variety of Portland-based Cement	GP	●	●	●	●	●	●					5				5		
	GB	●	●	●	●	●	●				4					5		
	HE	●	●	●	●	●	●				4				3			
	GL	○	○	○	○	○	○				4				3			
	SR	○	○	○	○	○	○					5				4		
	LH	○	○	○	○	○	○					5				4		
Subtotal												35				34		

Homogeneous material and have a process similarity characteristic

Legend

● = Need
○= Plan; Scale = 1 to 5; 1 = Weak Demand and 5 = Strong Request
a = component-sharing modularity
b = component-swapping modularity
c = cut-to-fit modularity
d = mix-&-add-in modularity
e = bus modularity
f = sectional modularity

Table 4.14 method is adapted and extended to Table 4.15 in building the house for Portland-based cement for the modularity preference matrix as below:

A. Voice of the customer: the left-hand column details the customers' needs for six types of Portland-based cement
B. Voice of manufacturer: the upper row describes six characteristics of Portland-based cement
C. Scoreboard: the right column is for evaluating modularity preference. The scores are from 1 to 5 in each row.

A. Voice of the customer (see Table 2.2):

- The six types of AS standard Portland-based cement are:
  - General Portland (GP), general blend (GB), general lime (GL), high early strength (HE), sulphate resistance (SR), low heat (LH)
- Because of market demand based on survey outcomes and easily constructed optimisation processes using simulation, there is a similar process and homogeneity structure. Therefore, the matric considers GP, GB and HE for further study.

B. Voice of the manufacturers (see related Australian cement standard):

- Early strength
- Acidic resistance
- Heat resistance
- Low carbon emission
- Sink/expand
- Wear resistance

C. Score board for six modularity: the assessment scale is from 1 to 5 for every column:

- 'a' is component-sharing modularity
- 'b' is component-swapping modularity
- 'c' is cut-in-fit modularity
- 'd' is mix-&-add-in modularity
- 'e' is bus modularity
- 'f' is sectional modularity.

In Table 4.15, the black box red wordings illustrates that the overall scores are 35 out of 40 and 34 out of 40. Therefore, the mix-and-add-modularity, option d, is the option that represents the most popular modularity choice.

Chapters 5 and 6 detail further study based on the above outcome and using a scenario method.

The development of Chapters 5 and 6 used the data collection and analysis of multiple sources to study the geopolymer-based productivity, including manual and simulation modelling methods, and the voice of house of deployment in mass customisation matrix for modular preference. Thus, this research undertakes an in-depth study using trial-and-error methods to examine the classic Cobb–Douglas production function concerning the change of two elasticities, α and β, regarding capital and labour parameters and the empirical stochastic frontier analysis for optimal measures. Three types of return of scale are as follows:

- Score *below* is less than 100 whether a customer or capability issue
- Score *normal* means close/equal to 100, optimal productivity that maximises profit, and minimises resource use
- Score *over*-represents larger than 100 misuses of resources and minimises profit

In order to measure technology-intensive in fast-moving small lot customised cement businesses in manufacturing productivity, examination of a state-in-the-art factory using the empirical stochastic frontier analysis function method is one solution to measure productivity problems. However, $f(x_i, \beta)$ and technical efficiency, TEi, are in text formats. To solve these issues, systematic analysis of their motions for production adopts the survey method, related articles, and simulation modelling data. XLMiner™ (Chan, 2018) derives multiple data such as manufacturing methods, technical efficiency, TE_i., with the three statuses and so on data into one linear regression equation based on Chapter 4, Table 4.7 displays the empirical stochastic frontier analysis equations, which are intended to promote optimal resource use (see Scenarios 1 and 2 for further discussion). The scenarios are as follows:

- Scenario 1 examines FA-based and MK-based geopolymer cement productivity measures using two main tools associated with sub-tools discussed in this Chapter.
- Scenario 2 examines productivity measures for ordinary Portland cement, blend Portland (GB) and early strength Portland (HE) cement using two main tools associated with sub-tools (see Chapter 6).

The expected results cannot affect the mass production of ordinary Portland businesses.

CHAPTER 5: SCENARIO 1

Scenario 1 is one of the two case studies for the manufacturing strategy of target companies using proposed methods. As such, Company X (2021) is obliged to develop a manufacturing strategy to meet the new Australia's infrastructure stimulus plan (2019) projects (Australian Infrastructure Audit, 2019). The survey finding shows that various small lot customised geopolymer-based cement businesses are overloading the current plant in the Southeast Queensland areas. Therefore, a factory intended for simultaneous production methods fulfils the customer expectations of an Australian-owned company. Reorganising the factory operational procedures, as a result, is less investment and validated a tactic of the proposed framework. It also compares the advantages and disadvantages of traditional cement production methods.

5. SCENARIO 1

The market demand for the three types of geopolymer-based cement produced by Company X (2021) is as follows:

Table 5.1 Small Lot Batch Production Plan of Geopolymer-based Cement Production Order in Year 2021 (Company X, 2021)

Overload of the customised cement production

Geopolymer-based Cement	Quantities (Tonnes)	Delivery Time Status
FA-based	450,000	Quarters 1 and 4
MK-based	350,000	Quarters 1 and 3
GBBFS-based	180,000	Quarters 3 and 4
Subtotal (Tonnes)	980,000	

In 2021, the total amount of cement produced was around 1 million tonnes (Company X, 2021). FA-based cement dominated delivery in quarters 1 to 4. MK-based cement dominated quarters 1 to 3. As a result, this situation is similar to a traffic jam, causing poor downstream production performance and total productivity that does not meet expectations based on both the classic Cobb–Douglas production function and the empirical stochastic frontier analysis results.

The finding shows that significant time was taken up by material handling using the conventional production method (see Appendices A1 to A5). A proposed new technology and a new production method, including vertical integration manufacturing and improving productivity by using drop-down finished front process semi-product to downstream for further treatments, could save time. The empirical stochastic frontier analysis method can assist the measurement. However, a linear regression equation, including technical efficiency assessment involving production facilities instead of function status, must be developed to validate the proposal methods (see Section 5.1.5 for further discussion).

Another finding from the above is that geopolymer-based cement faces logistics and supply chain challenges (Rozhkov et al., 2022) due to fly ash being one of the by-products of coal-fired power stations in North Queensland. The problem is that the suppliers of sodium hydroxide solutions are based overseas (Australian Federation Cement, 2019). Raw material occupies 40% of the manufacturing cost (Chan, 2018), slowing growth. The electrolysis technology of seawater (Chan, 2018) can provide enough hydrogen gases for combustion to heat the kiln temperature to 1270°C for the chemical reaction of cement production (e.g., Appendix 4) and a large amount of sodium hydroxide solution mixed with fly ash to fabricate FA-based cement (e.g., Appendix 4) can save costs. Chan (2018) also addressed the plant, as shown in Chapter 2, Section 2.4, Figure 2.4, cost can be reduction by introducing new technologies that can directly collect fly ash etc., as shown in Appendices A14 and A15, that can directly collect fly ash from the power station and mix it with sodium solutions to achieve a chemical reaction and produce FA-based cement using a mobile container that minimises resource use, including labour, machine down-time and new technology involved. To mass produce FA-based geopolymer cement, a large enough sodium hydroxide solution pool is an alternative to more traditional methods because the factory can then supply cement to various clients' needs worldwide, achieving better time to market. To validate the innovative fabrication method, an agent-based simulation model is one of the tools that can change the minds of those in the industry and persuade them of the benefits them of virtual manufacturing. This is because it can be used unlimited times to revise the process until optimisation is achieved. Cement entrepreneurs can thus reorganise manufacturing strategies earlier to maximise production facility use and direct labour involvement.

Further, accelerated market demand considers new technologies and creates a more environmentally friendly environment, such as the vertical top-bottom manufacturing method, which starts produced from the top-bottom using vertical integration manufacturing methods of the factory (see Appendix A8, Appendices A13 to A14) that new technology can introduce this approach. As such is to examine maximising the use of a linear actuator valving system instead of a conventional conveying belt for raw material delivery that saves time and energy. The special-design fly ash vessel directly collects fly ash from a power station and generates a chemical reaction within the sodium hydroxide solution pool instead of using classic methods (see Appendix A8 and Appendix A15). The new technologies involved in the optimisation process to satisfy market demand are summarised below:

- Adapted and extended Chan's (2018) mini advanced integrated cement manufacturing plant. This is because this plant is a vertically integrated manufacturing and sustainable cement factory, maximining resources use and minimising carbon dioxide emissions.
- Use seawater and undertake electrolysis for a chemical process that generates the sodium hydroxide solution that is released on the anion electrode side. Hydrogen gas emits from the catholic electrode side. Sodium hydroxide solution is one of the raw materials that has a chemical reaction with fly ash, providing FA-based geopolymer cement, and hydrogen gases are an alternative fuel in the kiln, raising temperatures for a chemical reaction that changes limestone to lime instead of fossil fuel, thus minimising carbon dioxide emissions in Portland-based production and reducing energy costs.
- Be capable of recycling special fly ash vessels for the next production.
- Provide the same production conditions for the fabrication of geopolymer-based and Portland-based cement to measure productivity using the classic Cobb–Douglas production function and the empirical stochastic frontier analysis methods. Examine new manufacturing strategies for changing labour and production facilities allocation that easily reorganises a manufacturing process and maximises the use of machines for small lot cement production.
- Use sub-tools such as those adapted from Anderson (2004) and Viana et al. (2018) to develop simulation models in a mass customisation (modularity-based) work environment (see Section 3.1.1).

5.1 Formulating the classic Cobb-Douglas production function and developing the empirical stochastic frontier analysis equations for demand market

This section reviews the current production facilities and production methods of Company X (2021). Summarised below collected from Chapter 4: Data Collection and Analysis as follows

1. Mixer: mix correct portions of sodium hydroxide/potassium hydroxide solution with a constant amount of fly-ash (FA) particles
2. Tank, including valve, electrical actuator, and pneumatic actuator: store sodium hydroxide and potassium hydroxide, fly ash powder, metakaolin powder, etc.
3. Material handling unit, including pipeline: delivery of raw materials from one process to another
4. Horizontal ball mill: grinding ground granulated blast furnace slag (GBBFS) into desired particle sizes
5. Vertical grinding mill: grinding the bottom ash into desired particle sizes
6. Silos and packing machines: store FA-based and MK-based geopolymer cement.

A typical labour-intensive operation like the one outlined above occurs because many resources are involved in traditional production facilities. The result is for mass-producing one type of geopolymer-based cement. Formulating Figure 5.1 time-to-market strategy and introducing below manufacturing technologies:

1). Use large-scaled ultra-sonic with vibration technology to break down raw materials to the desired particle size instead of a vertical or ball mill grinding process

2). Contain sodium hydroxide solution equipped with ultra-sonic mobile vessel, resulting in collecting fly ash from a power station directly, quicker chemical interaction with it

3). Consider vertical integration (drop-down) methods (see Appendix A13) instead of a conveying belt of raw materials delivery from one process to a downstream process to minimise idle time.

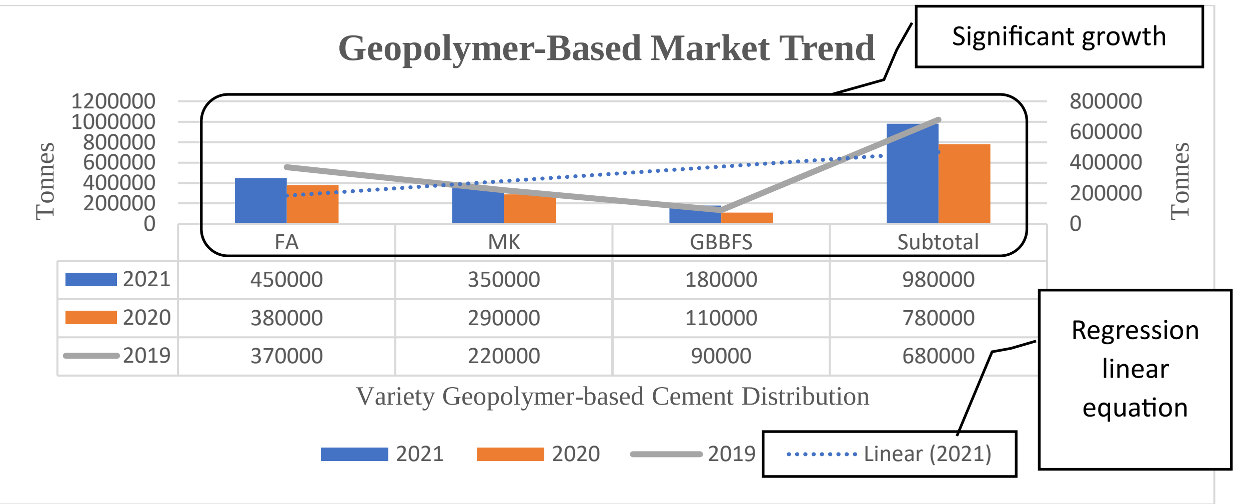
4). Apply valving systems using sequential control valving system control amount batch to batch fly ash or metakaolin to downstream processes for quality control (see Appendix A12).

5). Modify silo sizes to satisfy fast-moving small lot of customised cement business.

5.1.1 Formulating the classic Cobb-Douglas production function for demand and manufacturer capability

5.1.1.1 Demand

Fly ash and metakaolin geopolymer-based production capabilities are illustrated in Table 5.1 and Figure 5.1. As a result of this capability, three types of geopolymer-based cement are in market demand worldwide. Company X needs to reorganise manufacturing methods, including introducing new machines instead of labour-intensive ones, to respond to the voices of customer needs and manufacturer capabilities.



	FA	MK	GBBFS	Subtotal
2021	450000	350000	180000	980000
2020	380000	290000	110000	780000
2019	370000	220000	90000	680000

Figure 5.1 Demand for Geopolymer-based Production Orders from 2019 to 2021

5.1.1.2 Manufacturer Capability

The trend for fly ash and metakaolin-based geopolymer customised cement grew from 2029 to 2021. This is classified as a linear regression equation, as shown by the grey straight line in Figure 5.1. Facing this challenge, minimising downtimes and investment are successful factors—for example, using new technologies to change the classic valve to a linear actuator valving system, where fly ash raw material directly contacts the sodium hydroxide pool using a vibration method (Appendix A8) instead of a rotation-type mixer (Kuzmichev and Verstov, 2018), and so on. The modelling method is one of the outstanding tools for validating manufacturing tactics because it is changing parameters until they become optimum.

Table 5.2 Standard Time and Availability of Classic Geopolymer-based Cement Plant: Operational Data (Chan, 2018, p. 159)

Process \ Item	Unit processing time (tonne / hour)		Availability (hour)
	FA	MK	
Bulk mix with sand, fly ash and m Metakaolin, sodium hydroxide (NaOH)	3	3.3	2400
Chemical reaction of NaOH with either fly ash or metakaolin (mixer)	3.3	3.3	2400
Actuator valving system using feed control	3	3	2400

Table 5.2 illustrates the mass production of geopolymer-based cement using traditional methods, resulting in fast-moving customised geopolymer-based cement time-to-market delivery that cannot solve issues. To satisfy small lot business just-in-time (JIT), Company X (2021) extended shift-based operations from two hours to four hours, as shown in Table 5.3, they could make better use of existing workers instead of hiring new ones. This is the most economical way of using state-of-the-art technology. One of the limitations of the classic Cobb–Douglas production function does not offer an efficiency measure. The empirical stochastic frontier analysis method has this function. Therefore, in measuring reorganising productivity, the classical Cobb–Douglas production function is the right tool because of its well-defined equation for changing capital and labour parameters to seek optimisation of returns to scale outcomes using the trial-and-error method.

Table 5.3 Enrichment and Reorganising Various Working Hours

Process \ Item	Unit Capability (ton/ hr)			Various Work hour per day(hr/d)			
	FA	MK	GBBFS	8	12	16	24
Chemical reaction of sodium hydroxide (NaOH) with either fly ash or metakaolin (mixer)	3	3.3	3.34	2400	3600	4800	7200
Mixed with sand	3.3	3.3	3.37	2400	3600	4800	7200
Material handling unit	3	3	3.3	2400	3600	4800	7200

Since the empirical stochastic frontier analysis is a functional equation (see Chapter 3, Equation 3.6), this study uses step-by-step methods to identify proposed production facilities and equipment characteristics based on the survey outcome to develop a suitable equation. Some production processes need particular focus because of machine-intensive methods for optimistic productivity instead of traditional production methods, as listed below:

- To examine the traditional grinding method and proposed ultra-sonic with vibration technologies' operational characteristics and manufacturing processes in grinding the raw up to fine material ground granulated blast furnace slag (GBBFS) or metakaolin (MK) material. It is because the mill uses a frictional force between the roller and crushes the material into small pieces. The ultra-sonic devices generate a high frequency to break down the material into particles with vibration technologies using left and right, up and down motions, whether the operation is in linear movement for further particle separation and screening (Si et al., 2009; Woywadt, 2017; Tang et al., 2018a and 2018b) addressed using large and small ultra-sonic production facilities, avoiding operation in resonance frequency due to a phenomenon in which an external force or vibrating system forces another system around it to vibrate with greater amplitude at a specified frequency of operation like the Tacoma Bridge Collapse. Here is the same principle using wave technology that is a chance to cause machine failure early. Therefore, the key to success is to check raw material and production facilities' acceptable frequency, avoiding unnecessary machine malfunction and downtime. It is one of the limitations of applying natural (resonance) frequency to break down raw materials.
- To minimise breakdown events and ensures productivity optimisation, a skilful royalty worker is one of the keys to success (Si et al., 2009; Jenson et al., 2011; Jufri and Siswanto, 2020; Aartseng et al., 2015), resulting in the technical efficiency, TE_i, of the empirical stochastic frontier analysis is improved being kept to a maximum (e.g., 100).

5.1.2 Development of regression linear equation for fly ash/metakaolin mixer, mixer with sand, material handling unit

5.1.2.1 Development of Regression Linear Equation for Fly Ash/Metakaolin/GBBFS Mixer

Figure 5.1 shows the high market demand for geopolymer-based customised cement. The finding is that new cement production technologies involve vertical integration manufacturing management, linear vibrating screen, wave, and vibration for the mixing process and more; methods to optimise productivity either satisfying customers' needs or do not. Therefore, the linear regression equation for the empirical stochastic frontier analysis methods can develop an in-depth understanding of innovative production methods with working principles and survey outcomes in machine-intensive manufacturing environments. This requires identifying distance equals velocity in multiple time domains. It is one of the classic linear regression equations (see Chapter 4, Table 4.8).

- A linear actuator valving system is used instead of a conveying belt for material handling and the production methods change from top-down integration manufacturing methods to minimise raw material handling times (see Appendix A14). The first process takes place on the top of the building and then raw material is dropped down by the force of gravity the valving system. It is a linear motion and is reflected in the linear regression equation.
- A special-design enclosure (see Appendix A14) is directly transported from a power station to a cement factory and sinks gradually in a sodium hydroxide solution pool. Ultra-sonic vibration technologies and artificial waves move forwards and backwards and then left to right inside a chemical solution pool instead of the traditional rotational-type method. Raw materials have more time and space to interact and achieve the correct proportion, ensuring the internal layer is wholly mixed and minimising agglomerate. All motion is linear motion.
- A mobile container with sodium hydroxide solution and auxiliary equipment are used to collect fly ash from a power station and chemical action is then undertaken. This method involves bulk buying one container. It is a linear motion.

5.1.2.2 Development of Regression Linear Equation for Mixer with Sand

The special enclosure is mixed with sand for further processing using a linear ultrasonic vibrating motion instead of traditional rotational mixers. The finding from the survey is that this is the more efficient and reliable device, resulting in the linear regression equation.

5.1.2.3 Development of Regression Linear Equation for Material Handling Unit

This section discusses two devices for handling the raw materials: the linear actuator, and the raw material drop-down from top to bottom downstream process.

5.1.2.4 Actuator Systems

These systems involve raw material in a top-to-bottom manufacturing operation using a special-design linear actuator valving system to control the raw material flow (Company Z, 2021) for optimal productivity. They have two problems:

- fly ash, metakaolin, and ground granulated blast furnace particles can mix in the change production batch because of residue of them somewhere in the enclosure. The valving system can separate the raw material in and out amount in early stage of process for better quality control.
- fly ash particles can spread through the air in changing batches, causing respiratory system problems. Introducing the actuator's valving system is quickly slide horizontally open/close motion. But it has a chance breakdown. Conditional maintenance can minimise machine idle time due to scheduling machine trimming of the actuator speed parameters (see Section 5.1.5, Table 5.23 for further discussion).

5.1.2.5 Drop-Down Process

Raw material is stored at the top of the building using a vertical integration manufacturing method. After the front process is complete, it falls vertically due to opening the actuator valve system by its weight. Identified as a linear regression equation.

5.1.3 Traditional and simulation modelling method for data collection

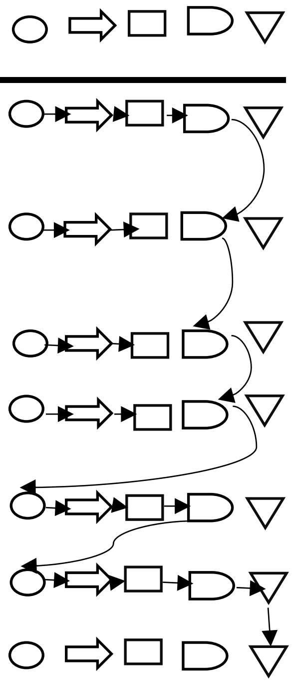
The aim of this section is to use simulation models to reorganise the plant layout using the top-down (see Appendix A13) manufacturing process, minimising material handling idle time and the probability of production facilities breaking down, using state-of-the art technologies, maximising total productivity in process flow while minimising investment and satisfying worldwide contractor needs. There are two parts to studying geopolymer-based process flow:

- Section 5.1.3.1 Manual method: a classic tool that is hard to use to capture dynamic data.
- Section 5.1.3.2 Modelling (simulation) method: an advanced tool to capture dynamic and static processes generating panel data, which are collected by observing particular variables over a while of time at a regular frequency. Customised cement production frequently changes production as one of the applications of collecting such data.

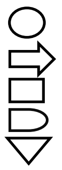
5.1.3.1 Manual Method to Develop Geopolymer-Based Cement Process Flow Chart for Data Collection

Table 5.4 Manual Geopolymer-based Cement Flow Process Chart

	Labours	Capitals		Flow Processes	
		Raw Materials	Production Facilities	Process	
1	3	Fly ash	silos, pipeline, valves, blower	mixer 1	
2	2	NaOH solution	vessels, pipeline, valve, pump		
3	2	KOH solution	vessels, pipeline, valve, pump		
4	3	sand	silos, material handing unit	grinding	
5	4	Mixed items 1 to 4		mixer 2	
6	3			pack	
7	2			delivery	
Subtotal	19				



Legend



Assembles
Process
Inspection
Flow forward
Stop

The manual geopolymer-based cement manufacturing flow chart is in static operation and collects dynamic data at time intervals using a bookkeeping method (Aartsenger et al., 2015; Emvalomatis, 2012; Sau, 1998). Therefore, this method is suitable for mass production. It is because it is standard traditional operational time. In facing dynamic production challenges, the system considers introducing new manufacturing technologies and monitors geopolymer-based cement fabrication. Simulation is an alternative because it speedily gathers both static and dynamic data.

5.1.3.2 Agent-Based Modelling

This study identifies that agent-based modelling efficiently gathers data, as opposed to the manual modelling of process flow methods. This is because it can more quickly capture and manipulate dynamic and discreet event modelling outcomes with unlimited change parameters, which is particularly suitable for various customised cement production under the mix-and-add-in modularity. Further, each agent can perform its assigned goal properly and systematically by collecting time domain data (Company X, 2021).

Additionally, Grigoryev (2018) used agent-based and system dynamic modelling (AnyLogic™) methods to capture job-based dynamic data for optimisation process measures. Data are the time-series domain in spreadsheet format monitored the flow performances in virtual reality technologies from which overseas wherever else sub-contracted overseas small-sized cement companies or domestic manufacturing performances.

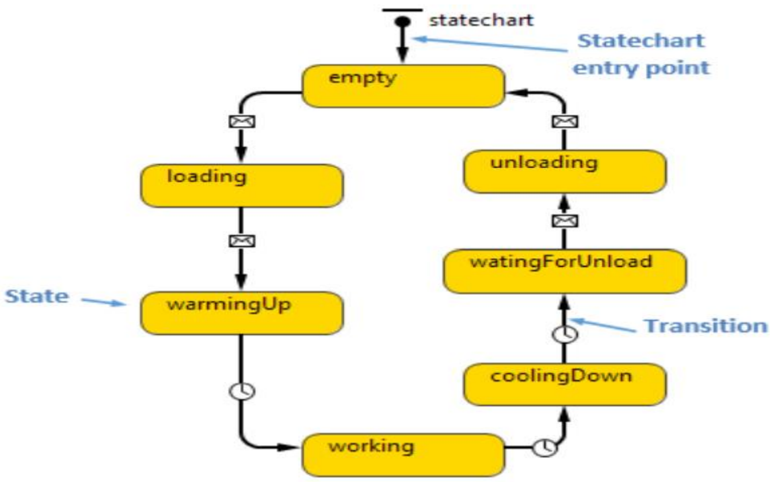


Figure 5.2 Example of System Dynamic Process Flow from AnyLogic™ (Grigoryev, 2018)

The finding is that both agent-based and system-dynamic models can work collaboratively to capture multiple-dimension data and measure the proposed workflow until optimisation is achieved (see Chapters 5 and 6, Scenarios 1 and 2 for further discussion).

5.1.3.2.1 Identified Independence Attributes, Process Independence, Process Similarity and Modularity (Anderson, 2005; Viana et al., 2017)

As a result of market demand, reorganising plant performances is based on frequently changing factors, including attribute independence, process independence and similarity mechanism parameters that need more data, ensuring time to market. Therefore, by changing the shift-based workforce, the outcome data is used to examine the three statuses of elasticity concerning capital and labour. To accurately forecast workload in terms of both production facilities' utilisation rate and labour use, more elastic data can organise the simultaneous fabrication of homogeneous structures and geopolymer-based concrete. In addition, the cement plant is not labour-intensive, but it relies on machine performance or technical efficiency, $TE_{i,}$ to measure the manufacturing environment under new technologies.

Table 5.5 Identified Independence Attributes, Process Independence, Process Similarity and Modularity Based on Anderson (2005) and Viana et al. (2017) for Development of Geopolymer-based Cement Simulation Models—AnyLogic™

Name / Item	Mass Customisation Technologies			
	Independence Attributes	Process Independence	Process Similarity	Modularity
1	FA-based geopolymer MK-based geopolymer GBBFS-based geopolymer	Tank, Linear Actuator with Valving Function with Feeding Systems	Mixing	Mix-& Add-in Modularity
2	Sodium hydroxide	Mixer and Tank		
3	Potassium hydroxide			

In order to ramp up small lots of batch production, relocation appropriate of production facilities, including adding or eliminating the processes flow to meet the new challenges. The modified feeding system (e.g., material handling) of the linear actuator valving system is just one of the examples until optimisation.

The black box in Table 5.5 includes three mechanisms to illustrate attributes independence, process attributes and process similarity for the fabrication of geopolymer-based cement. Based on Zhang et al. (2017), the ratio to design the mixture for modelling is as follows:

- Fly ash with the ratio of 100% sodium hydroxide solution
- Metakaolin with the ratio of 95% sodium hydroxide and 5% potassium hydroxide solution. 100% sodium hydroxide also works but requires a long time for mixing and chemical reaction
- GBBFS with 90% sodium hydroxide and 10% potassium hydroxide solution. 100% sodium hydroxide also works but requires a long time for mixing and chemical reaction.

The traditional fabrication method for geopolymer-based cement uses the correct ratio of sodium hydroxide and potassium hydroxide solution for fly ash or metakaolin for chemical reactions. Figure 5.1 shows market demand; the company considered a new manufacturing method. Thus, in Company X's (2021) use of the top-bottom integration manufacturing method, the upper part represents upstream processes, and the lower chamber represents downstream processes. To prevent unnecessary mixing of batches with raw materials in production, a series of valving systems (e.g., Appendix 12) with a blower or high-speed compressed air, including electric motor type actuators, pneumatic type actuators, mechanical type valves, pressure control valves and more, are placed between two vessels to control the flow of those raw materials into the downstream processes that are easily batch-by-batch quality control, in case of the non-conformality product using the valving systems open/close service advantages separated different raw material mixing in the changing batches One of the characteristics of small lot production is frequent changes in production status, aiming of compressed air is at the clear pipeline, minimising the expected residues elsewhere in the production system. Thus, the valving system is a reliable device, and a routine inspection is necessary to prevent unnecessary idle time, breakdowns and a shortage of raw material downstream; this keeps the technical efficiency at a maximum using empirical stochastic frontier analysis productivity measures.

The essential geopolymer-based operation considers using virtual reality technologies and is discussed in the next section.

5.1.3.2.1.1 Mass Customisation Method for Developing Geopolymer-Based Simulation Models

Table 5.6 shows a traditional mix-&-add-in modularity (Liu et al., 2017) model method for mass customisation of tracking small lot batch production (Aartsengel and Kurtoglu, 2015; Anderson, 2004; Bellemare et al., 2015; Cunha et al., 2010; Dolores et al., 1993). Geopolymer-based cement production involves mixing the fly ash with the correct proportion of sodium hydroxide solution for chemical reaction, as shown in most left of the table. Company X (2021) consuming time collected production data and resources to construct manual models compared with a simulation method. The simulation model can automatically generate once the system is compiled (see Section 5.1.3.2.1.2). So, it is not suitable for fast-moving customised cement manufacturing management-minimising profit.

Table 5.6 Using Mass Customisation Modularity Method to Develop Geopolymer-based Manual Simulation Models

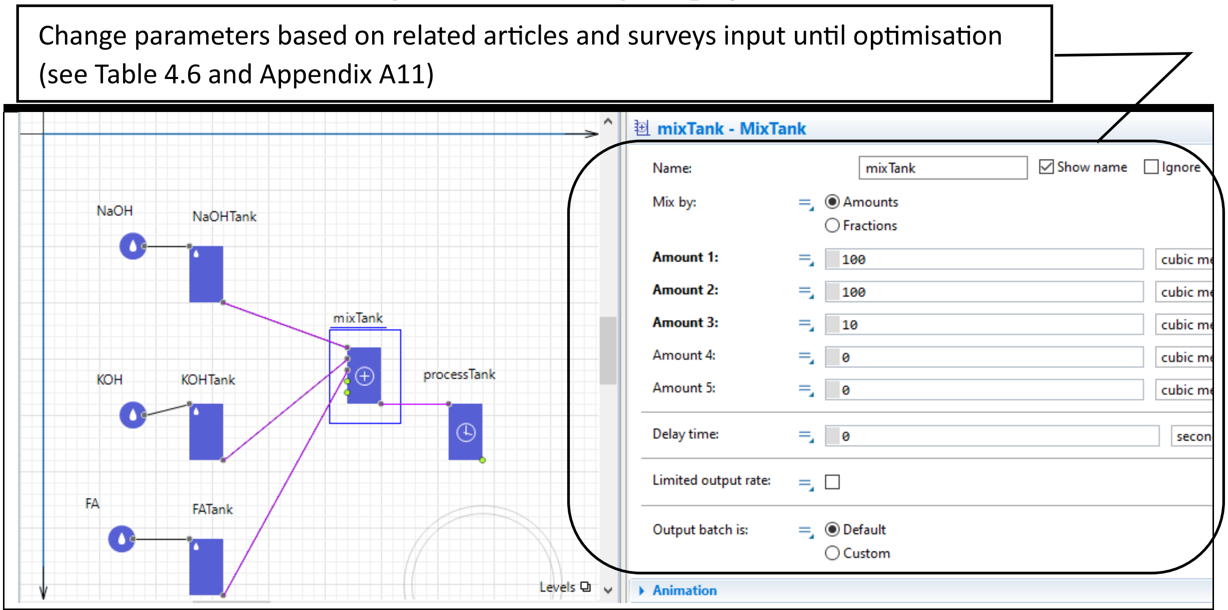
Modularity / **Processes**					**Mix-&-Add-in Modularity (Liu et al. 2017)**				
Attributes Independence						**Process Independence**			**Similarity Process**
Raw Materials					Production Facilities	Work hours	Flow Rates	Idle Time	Produce homogeneous geopolymer-based cement
FA	MK	GBBFS	NaOH	KOH	Mixers, Piping, Different sized Tanks, Valves (Actuator),	ST	ST	ST	

Legend

FA = fly ash
MK = metakaolin
GBBFS = ground granulated blast furnace slag
NaOH = sodium hydroxide
KOH = potassium hydroxide
ST = standard times

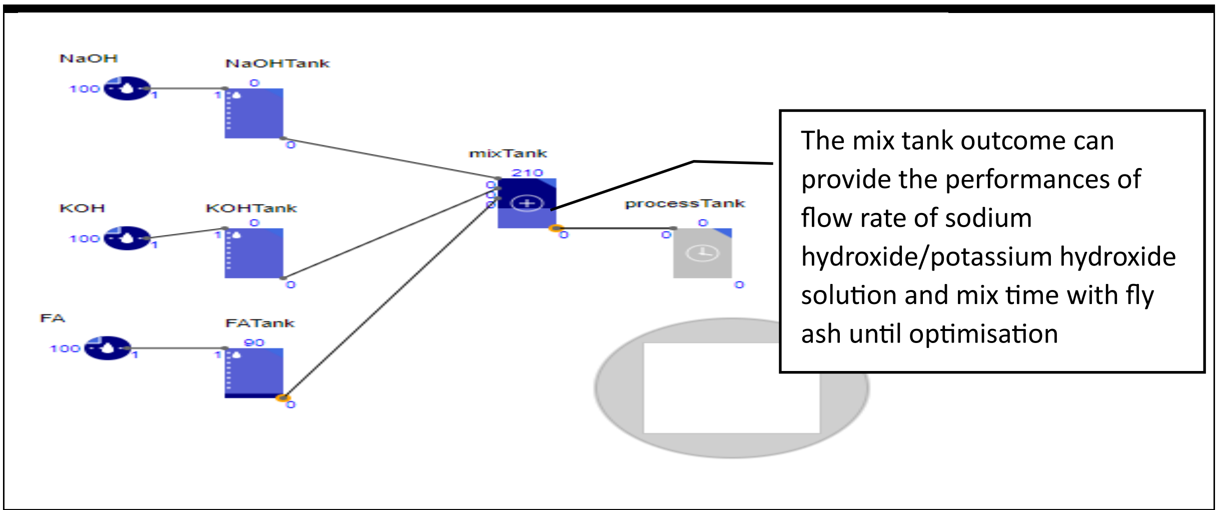
This method can provide production facilities performance data to develop regression equations for stochastic frontier analysis via manual data collection but is time-consuming (see Appendix A8, Appendices 13 and 14, Table 4.8).

5.1.3.2.1.2 Simulation Model for Fabrication of Geopolymer-based Cement



Attributes Independence	Process independence: providing space for data justification until optimisation

Figure 5.3 Justified Parameters (Not to Scale)



Attributes Independence	Process Independence: providing space for data justification until optimisation

Figure 5.4 The Classic Result of Fly Ash–Based Geopolymer Cement Production (Not to Scale)

Figures 5.3 and 5.4 show the classic simulation model and can provide expert opinions on optimisation. However, this model is suitable for mass production of one type of geopolymer-based cement. To meet the production schedule (Table 5.1), Figure 5.5 further models two types of geopolymers in paralleling customisation manufacturing.

Additionally, Figure 5.3 uses the simulation modelling method to bring real-world classic FA-based geopolymer cement production into virtual manufacturing. The steps are outlined below:

1) Step 1: the orange box in the top-right corner illustrates the parameter's setting procedures for every single attribute's independent flow, from front to downstream processes, and then the completion of the preliminary layout, as shown in Figure 5.4.
2) Step 2: most left entity is the three source tanks containing fly ash, sodium hydroxide and potassium hydroxide solutions in separate vessels. These tanks are placed at the top of the building. The flow down speed is controlled by step 1 via the valving systems.
3) Step 3: the middle is the mixing of fly ash, sodium hydroxide and potassium solutions with an assigned flow rate from step 1. The expected output is FA-based geopolymer cement solution that is stored in a day tank.
4) Step 4: most right entity is the last process tank, ready for delivery to the silo or to the treatment tank.

As a result of market demand for FA-based geopolymer and GBBFS-based geopolymer-based cement, extra production facilities can modify these processes. Therefore, Figure 5.4 illustrates two types of geopolymer-based cement fabrication processes simultaneously that minimise downtimes, extra tank, mixer, valve, pipeline, etc.

Facing the challenges going back to step 1 procedures, adjusting input data the rightest corner box. This is the advantage of the agent-based simulation model. This set of outcome data is for closely examining the elasticity of capital and labour in the classic Cobb–Douglas production function; it also provides data to XLMiner™ (Chan, 2018) for technical efficiency, TEi, and the linear regression to develop the empirical stochastic frontier analysis equation.

To achieve just-in-time (JIT) delivery of FA-based and MK-based geopolymer cement, Figure 5.5 uses the modelling method in paralleling the production of similar processes using mix-&-add-in modularity methods of mass customisation technologies. To achieve the different ratios of sodium hydroxide and sodium hydroxide solutions, Figure 5.3 shows steps 1 to 4 to justify the flow parameters of each single entity's technique. Therefore, the model outcome is promising because it shows that valve systems can be installed in every single pipeline to achieve flow control making it happen in virtual production environment.

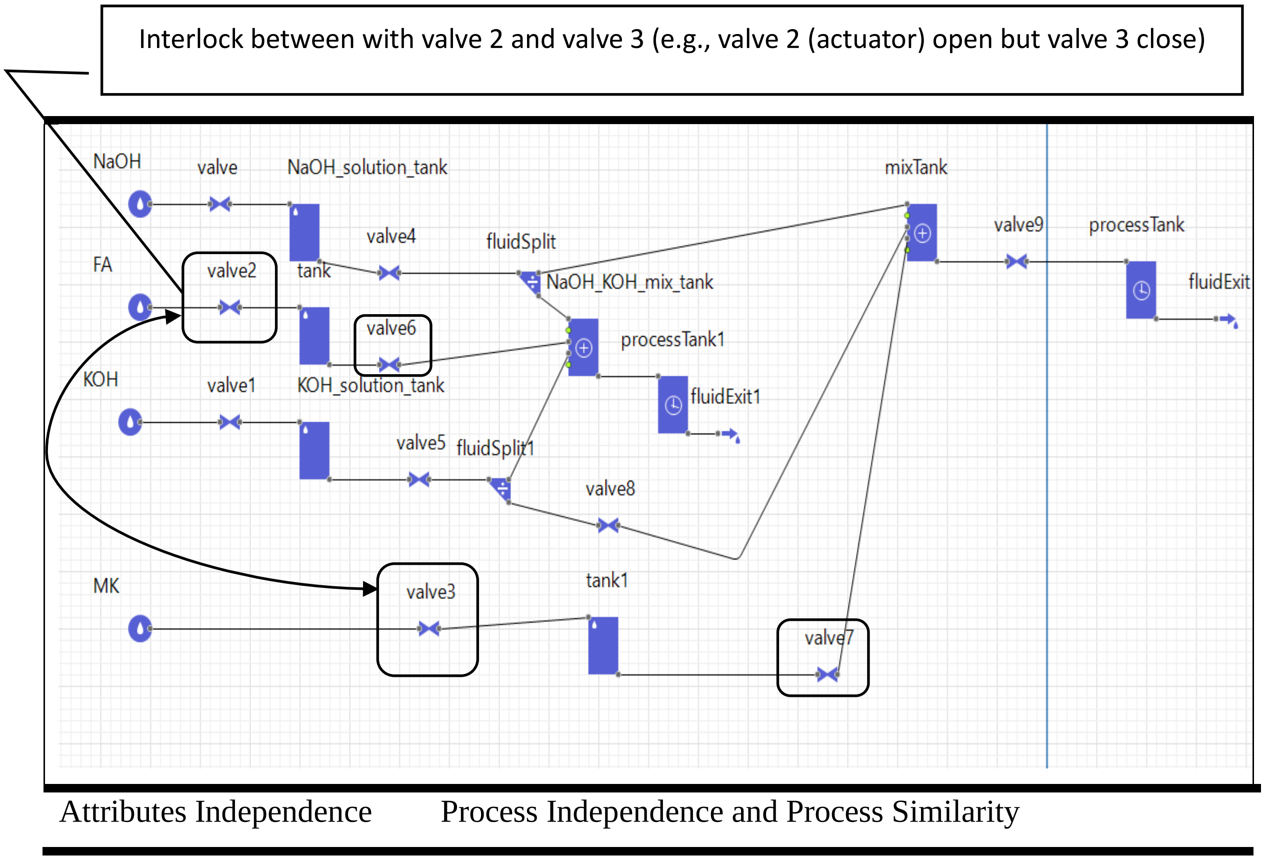


Figure 5.5 Extra Production Facilities Minimising Downtime (Not to Scale)

The design also achieves the below:

- Controls the flow sequence: the raw materials for FA-based and MK-based geopolymer are shown in the red and green boxes of Figure 5.5. The double-arrowed green line represents an interlock between valves 2 and 3. When valve 2 is open, valve 3 is closed and vice-versa, avoiding incorrect proportions in the cement mix.
- Minimises downtimes: changing production lines and using extra production facilities can help to meet market demand at short notice for to meet market demand, avoiding incorrect proportions in the cement mix, minimising resources. Time-to-market expectations.

One of the sub-case studies used the classic Cobb–Douglas production function for Company X's (2021) productivity measures via the trial-and-error method, as detailed below:

- Examine geopolymer-based cement small lot production in one factory, providing the same conditions to compare the empirical stochastic frontier analysis productivity measure results. Since the two tools focus on different areas, the empirical stochastic frontier analyses production facilities' performance and the classic Cobb–Douglas Production Function Measures concerning capital and labour with an exponential function for elastics.
- Consider two to three shifts per day, seven days a week for 365 days using new technologies to increase productivity (see Appendix A8, Appendices A13 to A14).
- Examine the productivity by changing elasticities, seeking return to scale of three combinations α and β within defined limits:

$$f(K,L)=AK^{\alpha}L^{\beta}=\begin{cases}\alpha+ß=1 & \alpha=0.7;\beta=0.3\\ \alpha+ß\leq 1 & \alpha=0.6;\beta=0.3\\ \alpha+ß\geq 1 & \alpha=0.7;\beta=0.5\end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5.1)$$

where A = productivity factor, K = capital, L = labour and α, ß = elastic variables

Liu et al. (2018) have set $\alpha = 0.7, \beta = 0.3$ of the classic Cobb–Douglas production function in bank industry productivity measures. It is suitable for the cement industry, adapted from Cobb–Douglas' earlier result and extended in change $\alpha = 0.3, \beta = 0.7$ as shown in Equation (5.1), due to considering the machine-intensive and flexible labour force, obtained as follows:

$$f(K,L)=AK^{\alpha}L^{\beta}=\begin{cases}\alpha+ß=1 & \alpha=0.3;\beta=0.7\\ \alpha+ß\leq 0.9 & \alpha=0.3;\beta=0.6\\ \alpha+ß\geq 1 \text{ to } 1.2 & \alpha=0.5;\beta=0.7\end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5.2)$$

However, Equation (5.2) does not mean α and β settings are optimal and extended to vary elasticity based on Merit (2015) and Shen et al. (2016) in Chapter 3 Equation (3.5) approaches, increasing α=0.01 and decreasing the same amount of β= –0.01 at the intervals and vice versa, as capital and labour are in constant, seeking scale of the return status for maximum productivity. Further discussion is in Section 5.1.4.

5.1.4 Productivity measure using Cobb-Douglas production function method

Table 5.7 organises data from multiple sources using the classic Cobb–Douglas production function to study productivity as below:

Table 5.7 Classic Cobb–Douglas Production Function Measures Productivity for Fabrication of Geopolymer-based Cement (Company X, 2021)

Parameters / **Classic Cobb–Douglas Production Function**	**Reorganising Variety Workforce in Two Shifts for Agile Small Lot Customised Geopolymer-based Production**			
Total Productive Factor (A)	1			
Total Input Labours, L (e.g., by Shift)	Number of persons in morning shift		Number of persons in evening shift	Subtotal (persons)
	4		4	8
Capital, K (Measure Individual Production Facilities' Capital, including Pipeline)				
Individual Production Facilities / Process	US$'000			
1 Tank for in/out (Appendix A14)	20	20	20	20
1 Sodium Hydroxide Solution Pool (Appendix A14) with special design vessel	110	110	110	110
2 Linear Vibration Screen (Equipped with Ultra-Sonic) with Wave Provider (Appendix A10)	40	40	40	40
3 Linear Actuator Valving System (Appendix A12)	20	20	20	20
Capital Subtotal	180	180	180	180
Classic Cobb–Douglas Production Function	$\boldsymbol{f(L^{\beta}, K^{\alpha})}$ **is variety combination of elasticities**			

Table 5.7 organises the breakdown of plant facilities' financial data from one of the popular procurement websites (Alibaba, 2019). This data is suitable for use by Company X (2021) to optimise productivity for a variety of small lot customised cement businesses. Four investment areas in production facilities are as follows:

A. Tank
B. Sodium hydroxide pool with special-design vessel
C. Linear vibration screen (equipped with ultra-sonic) with wave provider
D. Linear actuator valving system

A. Tank (silo): this device is a mobile vessel that directly collects fly ash from a power station and delivers it to a cement plant (see Appendix A15). It uses a chemical reaction with sodium hydroxide solution with the assistance of wave and vibration technologies. The company only considers one set of it at an initial cost of US$20,000.
B. An electrolysis process can separate seawater, resulting in the production of hydrogen, chlorine, oxygen gases and sodium hydroxide solution (Chan, 2018). Each chemical is pumped separately through a specially designed piping system into silos for storage. Sodium hydroxide solution is stored in the mobile vessel for future chemical reactions with fly ash whenever collecting fly ash. Hydrogen and oxygen gas silo can supply fuels for kiln combustion, which is an environmentally friendly fuel compared with fossil fuel diesel. It costs US$110,000 for Company X (2021) and is considered one set of sodium hydroxide-generating devices.
C. Linear motion screen (equipped with ultra-sonic technology) with wave provider: this device has two functions, one for grinding and one for mixing accelerating chemical reactions and wholly mixed with fly ash and sodium hydroxide solution. It costs US$40,000 and is considered two sets for the demand market.
A. Linear actuator valving systems: this device uses a faster open/close valve to deliver massive fly ash bulk from the top and bottom processes, avoiding fly ash particles running everywhere. It costs US$20,000 and is considered three sets for the demand market.

The process in Table 5.7 is significantly capital- rather than labour-intensive, as Company X (2021) only has eight direct workers.

Here is a further study of the Cobb–Douglas production function that changes two elasticities and is based on Chapter 2, Section 3.4.2 .1, equations 3.4. to 3.5. Table 5.7 illustrates the $\alpha,$ ß combination statuses in dark boxes. This has been adapted by numerous researchers, such as Li and Park (2017), Panhwar et al. (2016), Paolucci and Sacile (2014), Naghiloo (2011), Liu and Park (2007) and Li et al. (2017). It extends the earlier Cobb–Douglas result and varies the α, β range data, in which α keeps the range at 0.21 to 0.29 instead of being equal to 0.3, and the corresponding β values also change under the three statuses of the combination of α and β, such as $\alpha_i + \beta_j \leq 1$, $\alpha_i + \beta_j = 1$, and $\alpha_i + \beta_j \geq 1$.

By contrast, the purpose of keeping α_i at the range of 0.21 to 0.29 via equations (4.10) to (4.15) is because all production facilities (assets) are either amortised from the financial institutions or need to have the ability to create wealth for a company and then return it portion by portion to a bank at a time interval (Liu et al., 2018; Company X, 2021).

Due to the new technologies involved and the machine-intensive work, changing the elasticities α_i , β_j based on three statuses of a combination α_i , β_j status with one increasing interval of 0.01 and another decreasing interval of 0.01 using the trial-and-error method seeks to optimise the return to scale (e.g., closed to 100%). As a result, a productivity score less than 100% is the below return of scale and above 100% is the over return of scale. Examined below are three case studies as obtained:

1) Case A when $\alpha_i+\beta_j = 1$ (see Section 3.4.1)
2) Case B when $\alpha_i + \beta_j \leq 1$ (see Section 3.4.1):
   - $\alpha_i+\beta_j\leq0.7$
   - $\alpha_i+\beta_j\leq0.8$
   - $\alpha_i+\beta_j\leq0.9$
3) Case C when $\alpha_i + \beta_j \geq 1$ (see Section 3.4.1):
   - $\alpha_i+\beta_j\geq1.1$
   - $\alpha_i+\beta_j\geq1.2$
   - $\alpha_i+\beta_j\geq1.3$

Derivative further of elasticises from Equation (5.2), Equation (3.9) and Equation (3.10) include three cases seeking productivity optimisation with reasonable three statuses of the returns to scale. This research considers two decimal points because of involving exponential calculation, $(K, L) = AK^{\alpha}L^{\beta}$, using the classic Cobb–Douglas Production Function Measures as follows:

$$f(K,L)=AK^{\alpha}L^{\beta}=\begin{cases}\text{Case A}\\ \text{Cases B1 to B3}\\ \text{Cases C1 and C3}\end{cases} \quad \text{(5.3)}$$

Probing further Equation (5.3) for cases A to C as obtained:

A. Case A = $\alpha + ß = 1$, $\begin{cases}\alpha\text{=0.21 to 0.29}\\ \beta\text{=0.79 to 0.71}\end{cases}$ ……………………………………………………(5.4)

B. Case B

B1. Case B1 $\alpha + ß = 0.7$, $\begin{cases}\alpha\text{=0.21 to 0.29}\\ \alpha\text{=0.21 to 0.29}\end{cases}$……………………(5.5)

B2. Case B2 $\alpha + ß = 0.8$, $\begin{cases}\alpha\text{=0.21 to 0.29}\\ \beta\text{=0.59 to 0.51}\end{cases}$ ……………………(5.6)

B3. Case B3 $\alpha + ß = 0.9$, $\begin{cases}\alpha\text{=0.21 to 0.29}\\ \beta\text{=0.69 to 0.9}\end{cases}$ ……………………(5.7)

C. Case C

C1. Case C1 $\alpha + ß = 1.1$, $\begin{cases}\alpha\text{=0.21 to 0.29}\\ \beta\text{=0.89 to 0.81}\end{cases}$……………………..(5.8)

C2. Case C1 $\alpha + ß = 1.2$, $\begin{cases}\alpha\text{=0.21 to 0.29}\\ \beta\text{=0.99 to 0.91}\end{cases}$ ……………………(5.9)

C3. Case C2 $\alpha + ß = 1.3$, $\begin{cases}\alpha\text{=0.21 to 0.29}\\ \beta\text{=1.09 to 1.01}\end{cases}$ …………………(5.10)

Legend

- productivity factor, A = 1 (Shen et al., 2016; Dzeng and Wu, 2013)
- capital, K = 180,000 (Company Z, 2021; Hasan et al., 2012)
- labour, L = 8 in two shifts due to workmanship issues (Company Z, 2021; Nadi, 2019)
- α is from the ranges of 0.21 to 0.29 and changes corresponding $\beta, f(\alpha, \beta)$, with 0.01 increasing/decreasing with corresponding values under the three statuses, examining the returns to scale and productivity optimisation.

Further, the reason Equation (5.4) differentiated into Equation (5.3), as shown in Figure 5.6, is a result of developing Equations (5.4) to (5.10), seeking optimum results as follows:

- This is a classic setting, where $\alpha + \beta = 1$ and α= 0.3 and β=0.7 for Equation (5.2). However, the score is 161.71, as shown in the dark box in Figure 5.6. This is not an optimal solution and cannot provide a roadmap for the three statuses of optimum return to scale that maximises capital use but maximises productivity.
- Because of seeking the optimum three combinations of the three statuses, including $\alpha+\beta<1$, $\alpha+\beta=1$ and $\alpha+\beta>1$. As such, keeps on elasticity for $f(\alpha_i,\beta_j)$ calculation that minimises resources.

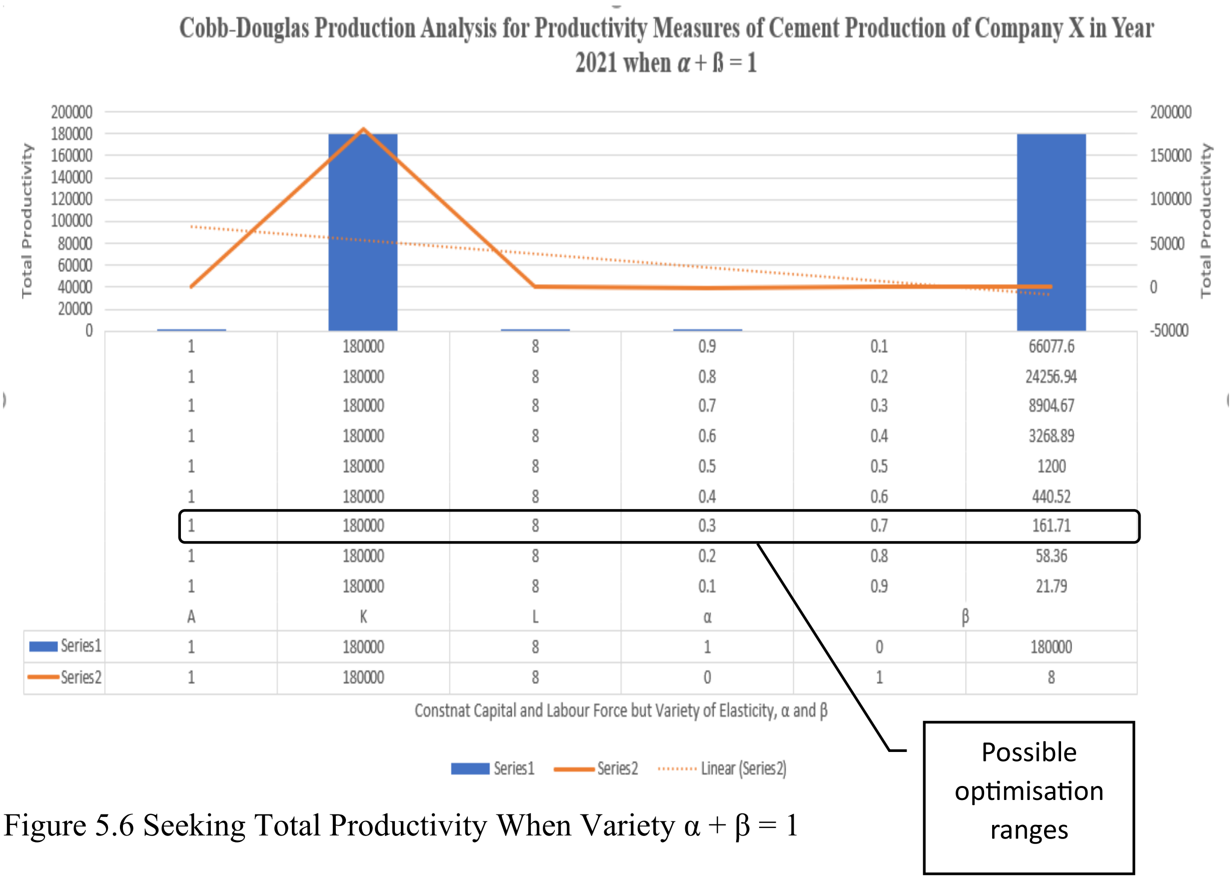


Figure 5.6 Seeking Total Productivity When Variety α + β = 1

Examining various combinations of α_i = 0.21 to 0.29 associated with β_i = 0.79 to 0.21 ranges when $\alpha_i + \beta_j = 1$ uses the trial-and-error method to seek possible productivity optimisation.

5.1.4.1 Application of the Classic-Douglas Production Function to Cement Industry

A. Case A: Equation (5.4) - Case A $\alpha+\beta = 1$ when $\begin{cases}\alpha=0.21 \text{ to } 0.29\\ \beta=0.79 \text{ to } 0.71\end{cases}$

The range α = increasing interval from 0.21 to 0.29 and justifying corresponding β values from the decreasing interval from 0.79 to 0.71 at the intervals 0.1, when the status α + β = 1, which is all production facilities, productivity factor and workforce, are well defined (Company X, 2021). After a careful calculation, the normal return of the scale is 97.98 and close to 100% productivity; below or above this solution achieves less profit and moves away from the voices of the house of deployment in mass customisation concerning customer expectations and manufacturer capability, as shown in the dark bold box in Table 5.8.

Table 5.8 Considering Close to 100% Total Productivity When α + β = 1 Using Classic Cobb-Douglas Production Function Measures

Classic Cobb- Douglas Production Function Method ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 1$ α_i=0.21 to 0.29 and β_j=0.79 to 0.71									
A	1	1	1	1	1	1	1	1	1
K	180000	180000	180000	180000	180000	180000	180000	180000	180000
L	8	8	8	8	8	8	8	8	8
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.79	0.78	0.77	0.76	0.75	0.74	0.73	0.72	0.71
Q_i	65.62	72.54	80.64	88.64	97.98	108.31	117.26	132.34	146.29
	Below				Normal	Over			

Legend
below = below return of scale
normal = normal return of scale
over = over return of scale
α_i=variables increasing from 0.21 to 0.29; β_j=variables decreasing from 0.79 to 0.71

To seek optimisation of the returns to scale status, using the trial-and-error method considers the combination $\alpha_i + \beta_j$, as expressed below:

The solution to $\alpha + \beta = 1 \rightarrow \{\alpha, \beta\} \rightarrow \{0.25, 0.75\}$ is obtained as follows:

$Q_i = f(K, L) = (1) * (180{,}000)^{0.25} 8^{0.75} = 97.98$……………………………………..(5..11)

Further, three black brackets at the bottom of Table 5.8 are as follows:

- The left-most bracket is under the return of the scale
- The middle dark bold bracket is normal the return of the scale that is optimum productivity
- The right-most right bracket is over the return of the scale

Additionally, Table 5.8 presents a series of results using Equation (5.4). As a result, the middle bracket shows the optimum normal returns to scale operation for the capital and labour use of the target company.

Equation (5.11) fails to achieve productivity optimisation for customised cement production. Therefore, there is a need to continuously seeking the combination of α_i and β_j to maximise machine-intensive use.

The trial-and-error method can continue being used for the classic Douglas production function analysis to measures three statuses of scale until productivity optimisation is achieved.

B. Three cases, B1 to B3, are differentiated from Case B by these combinations of α and β when $\alpha + \beta \leq 1$ is obtained:

B1) Case B1 when α+β=0.7
B2) Case B2 when $\alpha + \beta = 0.8$
B3) Case B3 when $\alpha + \beta = 0.9$

B1) Case B1 when $\alpha + \beta = 0.7$

There are several studies in setting α_i, β_j

- α_i = from 0.21 to 0.29
- β_j = from 0.49 to 0.41

Tableaux results are achieved using the trial-and-error method, as shown in Table 5.9.

Table 5.9 Considering Close to 100% Total Productivity When $\alpha_i + \beta_j \leq 0.7$ Using Classic Cobb–Douglas Production Function Measures

Classic Cobb- Douglas Production Function ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 0.7$ α_i=0.21 to 0.29 and β_j=0.49 to 0.41									
A	1	1	1	1	1	1	1	1	1
K	180000	180000	180000	180000	180000	180000	180000	180000	180000
L	8	8	8	8	8	8	8	8	8
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.49	0.48	0.47	0.46	0.45	0.44	0.43	0.42	0.41
Q_i	35.17	38.87	42.97	47.5	52.51	58.04	64.16	70.92	78.4

Below

Normal

Legend
below = below return of scale
normal = normal return of scale

Table 5.9 illustrates the outcomes using trial-and-error methods for the classic Cobb–Douglas production function equation, seeking productivity optimisation. Compared with another outcome, figure 78.84 closes of maximising productivity as obtained:

The solution of $\alpha + \beta \leq 0.7 \rightarrow \{\alpha, \beta\} \rightarrow \{0.29, 0.41\}$:

$f(K, L) = (1) * (180{,}000)^{0.29} 8^{0.41} = 78.4$……………………………………….…………..(5.12)

Additionally, Equation (5.12) does not represent ideal small lot customised cement production. This is because:

- All results at the bottom of rows, Q_i, they show decreasing return to scale. In Table 5.9, the figure in the far-right column is 78.4 of the return to scale, which is a far away from optimisation.
- It cannot provide any opportunity to maximise the advantages of machine-intensive work for time to market.

Therefore, continuing to use the trial-and-error calculation method for the classic Douglas production function equation seeks an optimal result.

B2) Case B2 when $\alpha + \beta = 0.8$

Equation (5.12) cannot provide productivity optimisation, and using trial-and-error for the class Cobb–Douglas production analysis function method via continuous calculation is obtained as follows:

Table 5.10 Considering Close to 100% Total Productivity When $\alpha_i + \beta_j \leq 0.8$ Using the Classic Cobb–Douglas Production Function Measures

Classic Cobb–Douglas Production Function Measures ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 0.8$ α_i=0.21 to 0.29 and β_j=0.59 to 0.51									
A	1	1	1	1	1	1	1	1	1
K	180000	180000	180000	180000	180000	180000	180000	180000	180000
L	8	8	8	8	8	8	8	8	8
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.59	0.58	0.57	0.56	0.55	0.54	0.53	0.52	0.51
Q_i	43.3	47.86	52.9	58.48	64.64	71.46	78.99	87.31	96.52
	Below								Normal

Legend
below = below return of scale
normal = normal return of scale

The trial-and-error calculation method for the classic Cobb–Douglas production function calculation equation seeks productivity optimisation, as shown in Table 5.10. Compared with other outcome, the figure 96.52 closes to maximising productivity at a value of 100 (e.g., normal returns to scale):

The solution of $\alpha + \beta \leq 0.8 \rightarrow \{\alpha, \beta\} \rightarrow \{0.29, 0.51\}$ is obtained as follows:

$f(K, L) = (1) * (180{,}000)^{0.29} 8^{0.51} = 96.52$……………………………………………..(5.13)

Additionally, Equation (5.13) does not represent ideal small lot customised cement production. This is because:

- All results at the bottom of rows, Q_i, they show decreasing return to scale. In Table 5.10, the far-right column is 96.52 of the return of the scale, which is close to the optimistic value of 100 (e.g., the normal return of scale), resulting in a close to optimisation.
- It cannot provide any opportunity to maximise the advantages of machine-intensive work for time to market.

Therefore, continuing to use the trial-and-error calculation method for the classic Douglas production function equation seeks an optimal result.

B3) Case B3. $\alpha + \beta = 0.9$

Equation (5.13) only provides close productivity optimisation, and using trial-and-error for the class Cobb–Douglas production analysis function method via continuous calculation and obtained as follows:

Table 5.11 Considering Close to 100% Total Productivity When $\alpha_i + \beta_j \leq 0.9$ Using Classic Cobb–Douglas Production Function Measures

Classic Cobb–Douglas Production Function Measures ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 0.9$ α_i=0.21 to 0.29 and β_j=0.69 to 0.61									
A	1	1	1	1	1	1	1	1	1
K	180000	180000	180000	180000	180000	180000	180000	180000	180000
L	8	8	8	8	8	8	8	8	8
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.69	0.68	0.67	0.66	0.65	0.64	0.63	0.62	0.61
Q_i	53.3	58.92	62.13	71.2	79.58	87.97	99.29	107.49	118.83
	Below						Normal	Over	

Legend
below = below return of scale
normal = normal return of scale
above = above return of scale

The trial-and-error calculation method is used for the classic Cobb–Douglas production function equation to seek productivity optimisation, as shown in Table 5.11. Compared with other outcome, the figure 99.29 closes to maximising productivity at a value of 100 (e.g., normal return to scale):

The solution of $\alpha + \beta = 0.9 \rightarrow \{\alpha, \beta\} \rightarrow \{0.27, 0.63\}$ is obtained as follows:

$f(K, L) = (1) * (180{,}000)^{0.27} 8^{0.63} = 99.29$…………………………………………..(5.14)

Additionally, Equation (5.14) provides close to maximum productivity optimisation. This is because:

- Can provide close to maximum productivity with three cases of return to scale as shown in Table 5.11, obtained as follows:

  - the most left figure in the bottom row is under the return to scale
  - the middle figure in the bottom row is normal return to scale (optimal)
  - the rightest figure in the bottom row is over the return to scale.

- Lin et al. (2014) stated that normal returns to scale is in considering optimistic operation when the combination is $\alpha + \beta = 1$. However, one finding based on Equation 4.19 is the value of 99.29, it is 0.01 closer to the optimum valued of while as $\alpha + \beta = 0.9$ with α=0.27 and β =0.63.

Therefore, continuously using the trial-and-error calculation method for the classic Douglas production function analysis equation seeks another optimum result. Decision-makers use expert advice to formulate a customised cement business strategy, resulting in reorganising shift-based workers; they do not necessarily want to invest in more facilities fulfil customer needs because they want to save money.

C. Three cases, C1 to C3, are differentiated from Case B of combinations of α and β when $\alpha + \beta \geq 1$:

C1) Case C1 when $\alpha + \beta = 1.1$
C2) Case C2 when $\alpha + \beta = 1.2$
C3) Case C3 when $\alpha + \beta = 1.3$

C1) Case D1.$\alpha + \beta = 1.1$

Equation (5.14) provides one of the closer optimisation productivities (e.g., 99.29) using the trial-and-error method for the classic Cobb–Douglas production analysis function in a continuous calculation, seeking alternative obtained as follows:

Table 5.12 Considering Close to 100% Total Productivity When $\alpha_i + \beta_j \leq 1.1$ Using Classic Cobb–Douglas Production Function Measures

Classic Cobb–Douglas Production Function Measures ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 1.1$ α_i=0.21 to 0.29 and β_j=0.89 to 0.81									
A	1	1	1	1	1	1	1	1	1
K	180000	180000	180000	180000	180000	180000	180000	180000	180000
L	8	8	8	8	8	8	8	8	8
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.89	0.88	0.87	0.86	0.85	0.84	0.83	0.82	0.81
Q_i	80.79	89.3	98.72	109.12	120.63	133.34	147.4	162.93	180.1
	Below		Normal	Over					

Legend
below = below return of scale
normal = normal return of scale
over = over return of scale

Table 5.12 illustrates the trial-and-error calculation method for the classic Cobb–Douglas production function equation to seek productivity optimisation. Compared with other outcomes, the figure 98.72 closes to maximising productivity at a value of 100 (e.g., normal return to scale):

The solution of when $\alpha + \beta \leq 1.1 \rightarrow \{\alpha, \beta\} \rightarrow \{0.23, 0.87\}$ is obtained as follows:

$f(K, L) = (1) * (180{,}000)^{0.23} 8^{0.87} = 98.72$…………………………………………..(5.15)

Additionally, Equation (5.15) provides close to maximum productivity. This is because:

- Can provide close to maximum productivity with three cases of returns to scale as shown in Table 5.12, obtained as follows:

  - the most left figure in the bottom row is under the return to scale
  - the middle figure in the bottom row is normal return to scale that is optimisation
  - the rightest figure in the bottom row is over the return to scale.

- Lin et al. (2014) stated that normal returns to scale is in considering optimum operation when the combination is $\alpha + \beta = 1$. However, one finding based on Equation 5.15 is the value of 98.72, which is 1.27 above the optimisation valued of 100 while as $\alpha + \beta = 1.1$ with α=0.23 and β =0.87 and these results can satisfy customer needs, leading to extra resource use and higher than expected operational costs.

Therefore, continuously using the trial-and-error calculation method for the classic Douglas production function analysis equation seeks an optimum result. Decision-makers use expert advice to formulate a customised cement business strategy, resulting in reorganising shift-based workers; they do not necessarily want to invest in more production facilities to fulfil customer needs are not necessarily interested in further investing in production facilities because they want to save money.

$C2. \alpha + \beta = 1.2$

Equation (5.15) provides one of the close optimisation productivities using the trial-and-error method for the classic Cobb–Douglas production analysis function method in a continuous calculation obtained as follows:

Table 5.13 Considering Close to 100% Total Productivity When $\alpha + \beta \leq 1.2$ Using Classic Cobb–Douglas Production Function Measures

Classic Cobb–Douglas Production Function Measures ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 1.2$ α_i=0.21 to 0.29 and β_j=0.99 to 0.91									
A	1	1	1	1	1	1	1	1	1
K	180000	180000	180000	180000	180000	180000	180000	180000	180000
L	8	8	8	8	8	8	8	8	8
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.99	0.98	0.97	0.96	0.95	0.94	0.93	0.92	0.91
Q_i	99.46	109.95	121,54	134.35	148.51	164.16	181.47	200.59	221.74

Normal Over

Legend
normal = normal return of scale
over = over return of scale

Table 5.13 illustrates using the trial-and-error calculation method for the classic Cobb–Douglas production function equation to seek productivity optimisation. Compared with other outcomes, the figure inside the most left black box is 99.46, close to maximising productivity at a value of 100 (e.g., normal return to scale):

The solution of $\alpha + \beta \leq 1.2 \rightarrow \{\alpha, \beta\} \rightarrow \{0.21, 0.99\}$ is obtained as follows:

$f(K, L) = (1) * (180{,}000)^{0.21} 8^{0.99} = 99.46$…………………………………………..(5.16)

Additionally, Equation (5.16) provides closer to maximum productivity optimisation (e.g., 99.46). This is because:

- Can provide close to maximum productivity with three cases of return to scale as shown in Table 5.13, obtained as follows:

  - the middle figure in the bottom row is normal return to scale
  - the rightest figure in the bottom row is the over return to scale.

- Lin et al. (2014) stated that normal returns to scale is in considering optimistic operation when the combination is $\alpha + \beta = 1$. However, one finding based on Equation (5.16) is the value of 99.46, which is 0.54 below the optimisation value of 100 while $\alpha + \beta = 1.2$ with α=0.21 and β =0.99. These results can satisfy customers' needs, leading to extra resource use and higher than expected operational costs.

Therefore, continuously using the trial-and-error calculation method for the classic Douglas production function analysis equation seeks an optimum result. Decision-makers use expert advice to formulate a customised cement business strategy, resulting in reorganising shift-based workers; they do not necessarily want to invest in more production facilities to fulfil customer needs are not necessarily interested in further investing in production facilities because they want to save money.

$C3. \alpha + \beta \leq 1.3$

Equation (5.16) provides one of the close optimisation productivities and using the trial-and-error method for the classic Cobb–Douglas production analysis function method in a continuous calculation obtained as follows:

Table 5.14 Considering Close to 100% Total Productivity When $\alpha + \beta \leq 1.3$ Using Classic Cobb–Douglas Production Function Measures

Classic Cobb–Douglas Production Function Measures ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 1.3$ α_i=0.21 to 0.29 and β_j=1.09 to 1.01									
A	1	1	1	1	1	1	1	1	1
K	180000	180000	180000	180000	180000	180000	180000	180000	180000
L	8	8	8	8	8	8	8	8	8
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	1.09	1.08	1.07	1.06	1.05	1.04	1.03	1.02	1.01
Q_i	122.45	135.36	168.88	165.4	182.84	202.11	223.42	246.96	272.99
	Normal	Over							

Legend
normal = normal return to scale
over = over return to scale

Table 5.14 illustrates using the trial-and-error calculation method for the classic Cobb–Douglas production function equation to seek productivity optimisation. Compared with other outcomes, the figure inside the most left box is 122.45 close to maximising productivity at a value of 100 (e.g., normal return to scale). But it is overuse resources.

The solution of $\alpha + \beta \leq 1.3 \rightarrow \{\alpha, \beta\} \rightarrow \{0.21, 1.09\}$ is as follows:

$f(K, L) = (1) * (180{,}000)^{0.21} 8^{1.09} = 122.45$……………………………………………..(5.17)

Additionally, Equation (5.17) provides close to maximum productivity. This is because:

- Cannot provide close to maximum productivity with three cases of returns to scale, as shown in Table 5.14, due to both capital and labour in the controllable situation
- Lin et al. (2014) stated that normal returns to scale is in considering optimistic operation when the combination is $\alpha + \beta = 1$. However, one finding based on Equation (5.17) is the value of 122.45, which is 22.45 above the optimisation value of 100 while as $\alpha + \beta = 1.3$ with α=0.21 and β =1.09 and these results can satisfy customers' needs, leading to extra resource use and higher than expected operational costs.

Using the trial-and-error computing method for the classic Douglas production function analysis equation completes the assigned calculations work. Therefore, decision-makers organise a customised cement business strategy based on expert advice that maximises profit. The outcomes are summarised in the next section.

Summaries of the trend of the various combinations of $\alpha_i + \beta_j$ to seek the productivity optimisation of Q_{ij} are shown in the far-right column of Table 5.15.

Table 5.15 Summary of Findings

CBPF / α_i,β_j,Q_{ij}		Optimisation Parameters and Results based on A=1, K=180000, L=8			Status of the Return to Scale
		α_i	β_j	Q_{ij}	
$\alpha + \beta \leq 1$	$\alpha + \beta = 0.7$	0.29	0.41	78.4	below
	$\alpha + \beta = 0.8$	0.29	0.51	96.52	below
	$\alpha + \beta = 0.9$	0.29	0.61	$\boxed{99.29}$	**normal**
$\alpha + \beta = 1$		0.25	0.75	97.98	below
$\alpha + \beta \leq 1.3$	$\alpha + \beta = 1.1$	0.23	0.87	98.72	below
	$\alpha + \beta = 1.2$	0.21	0.99	$\boxed{99.46}$	**normal**
	$\alpha + \beta = 1.3$	0.21	1.09	122.45	above

Legend

A = productivity factor

K = capital

L = labour

below = below return of scale

normal = normal return of scale

above = above return of scale

Q_{ij} = total productivity, q is available

α_i, β_j = elasticities parameters, i and j are available

5.1.4.1.1 Performances of Change α, β Parameters

The two results of 99.29 in Table 5.15 with $\alpha_i + \beta_j \leq 0.9$ and 99.29 and when $\alpha_i + \beta_j \leq 1.2$ is 99.49. Both figures close to the optimisation value of 100. As a result, there is a variation of Lin et al. (2014) addressed that the normal returns scale is in considering optimistic operation when the combination is $\alpha + \beta = 1$ as the outcome is 100. Summarised the trial-and-error findings as below:

1) $\alpha_i + \beta_j = 0.7$: a combination of two elasticities using the parameters $\alpha_i = 0.27$ *and* $\beta_j = 0.43$, resulting in 97.3 and identified as under normal return to scale and 2.73 below the optimisation value of 100. More production facilities and workers can help companies achieve optimum productivity. Additionally, the outcome shows that more effort is required to satisfy customer expectations for time to market.
2) $\alpha_i + \beta_j = 0.8$: a combination of two elasticities using the parameters $\alpha_i = 0.29$ *and* $\beta_j = 0.51$, resulting in 96.52 and identified as under normal returns to scale and 3.48 below the optimisation value of 100. More production facilities and workers can help companies achieve optimum producitvity. Additionally, the outcome shows that more effort is required to satisfy customer expectations for time to-market.
3) $\alpha_i + \beta_j = 0.9$: combines two elasticities based on the parameters $\alpha_i = 0.29$ *and* $\beta_j = 0.61$, resulting in a score of 99.28, which is closer to the optimisation value of 100. As a result, this is an alternative because it maximises resource use and profit and is classified as normal return to scale.
4) $\alpha_i + \beta_j = 1$: it is the traditional solution for normal return to scale. However, this does not achieve productivity optimisation because of the 97.98 score, which does not satisfy client needs. This score variation of Lin et al. (2014) an address because of not an optimal (100) under technology-intensive manufacturing environment.

5) $\alpha_i + \beta_j = 1.1$: a combination of two elasticities using the parameters $\alpha_i = 0.23$ *and* $\beta_j = 0.87$, resulting in 98.72 and identified as under normal returns to scale and 1.28 below the optimisation value of 100. More production facilities and workers can help companies achieve optimum productivity. Additionally, the outcome shows that more effort is required to satisfy customer expectations for time to market (see Figure 5.1).

6) $\alpha_i + \beta_j = 1.2$: a combination of two elasticities using the parameters $\alpha_i = 0.21$ and $\beta_j = 0.99$, resulting in 99.46 and identified as normal return to scale and 0.54 below the optimisation value of 100 to satisfy customer expectations. But it is over resources use, minimising profit.

7) $\alpha_i + \beta_j = 1.3$: a combination of two elasticities using the parameters $\alpha_i = 0.21$ and $\beta_j = 1.09$, resulting in 122.4 and identified as above returns to scale and 22.4 higher than optimisation value of 100. Fewer production facilities and workers can help achieve optimum productivity (see Table 5.3). Additionally, the outcome can satisfy customers time-to-market expectations. Bu it is to minimise profit and over resource use.

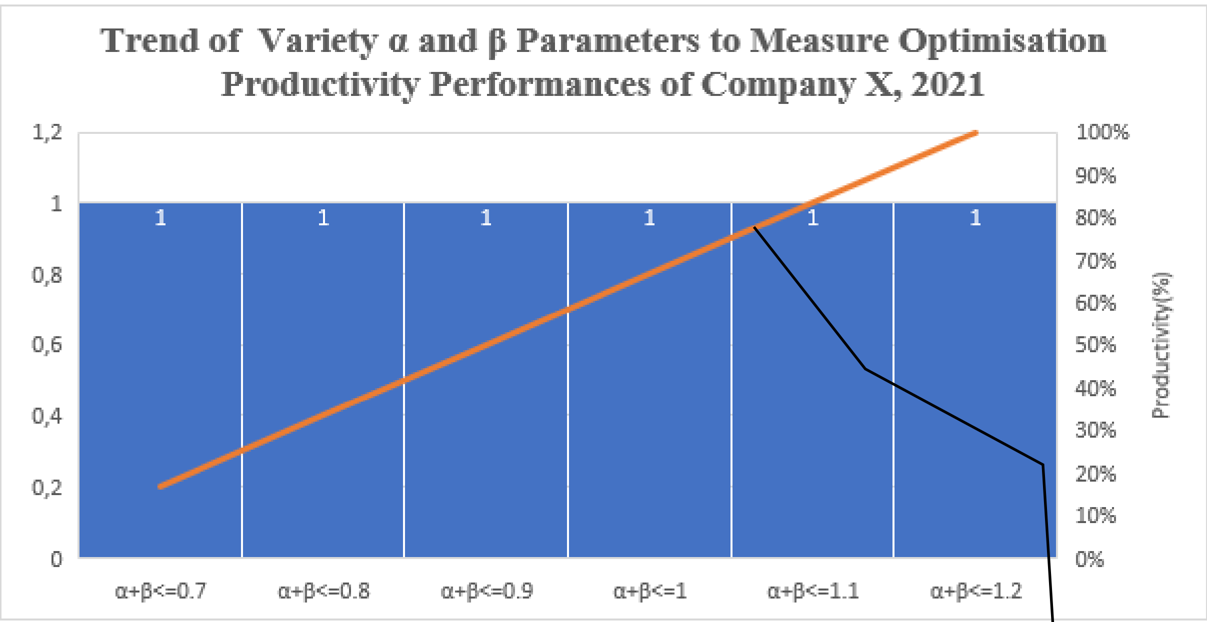


Figure 5.7 Trend of Productivities in Variety α and β Parameters Using XLMiner™—Data Warehouse (Chan, 2018)

Figure 5.7 in orange-line based on Table 5.18 result to plot a chart. It is a straight regression line and provides data for the empirical stochastic frontier analysis for equation development. However, a survey outcome and collection of production methods and machine operation procedures help determine equations for geopolymer-based cement productivity measures.

5.1.5 Productivity measure using empirical stochastic frontier analysis method

5.1.5.1 Applying the Empirical Stochastic Frontier Analysis to Cement Industry

In Section 5.1.4, the Cobb–Douglas Production Function Measures used trial-and-error to optimise the returns to scale for a productivity measure. In machine-intensive manufacturing environments such as those of Company Z (2021), no element in a rigid equation studies production facility performance (Yeon, 1977) because the relevant equations focus on labour, capital and elasticity parameters all at once. The empirical stochastic frontier analysis equation can devise technical efficiency measures. Section 5.1.4 adapted and extended the trial-and-error method to examine hydraulic and pneumatic system circuit working systems for open/close valving systems. This involves high-efficiency material delivery and minimises breakdown events; it is classified as a reliability and safety device in material delivery. The survey outcome identified various diameters for the sliding distance for the inlet/outlet options. The optimisation of valving systems travel only allows 20 seconds (see Appendix A13.1) to finish the open and close motions. Preventing fly ash from running anywhere avoids environmental, occupational and health issues, resulting in considering the linear motion is a solution and defining it as distance equals velocity multiplied by times instead of functional status as follows:

$$\mathrm{Q_i}=\mathrm{f}(\mathrm{x_i}, \beta)\times\mathrm{TE_i}\rightarrow \mathrm{d}=v_i\times d_i\times \mathrm{TE_i}\begin{cases}\text{Case 1, } \mathrm{TE_i}=1\\ \text{Case 2, } \mathrm{TE_i}\leq 1\\ \text{Case 3, } \mathrm{TE_i}\geq 1\end{cases}\qquad(5.18)$$

Here TEi equal to zero is not considered as the result the system down.

Table 5.16 Selection of Optimisation Valving Systems (See Appendix A6, Appendices A13 to A15, Appendix A17 and Companies X, Y and Z, 2021)

	Parameters / **Proposed Equations** $d_k = v_j \times t_i$	**Seeking Pneumatic Valving with Silo Systems (Chan, 2018) Optimisation velocity and diameter (e.g., travel distance) for the Empirical Stochastic Frontier Equations**			
1.	**Linear Pneumatic cylinder Velocity(v_i) - metre/second**	0.045	0.05	0.0626	0.075
2.	**Travel Time(t_j) - second**	20	20	20	20
3.	**Diameter (Linear Distance, d_k) - metre**	0.9	1	1.25	1.5
		Below	Normal	Over	

Legend
below = below return to scale
normal = normal return to scale
over = over return to scale

In order to minimise potential fire hazards caused by frictional forces among fly ash particles to generate sparks during mass falling by gravity from up to down processes, a speedy close/open valving system stopped energy accumulation in the dropping down movement is one of the economical ways to achieve the tasks. Thus, the survey outcome of valving system operation for an optimal velocity in 1-metre travel within 20 seconds can solve the problems. Additionally, Table 5.19 illustrates 5 tonnes per batch raw material straight drop-down from upfront to downstream processes once of the valving system at the velocity 0.05m/s to slide completion 1000mm within the 20s either open or close motion, which fulfils the design criteria and provides a roadmap for conditional maintenance by trimming mechanical type valve control device (see Appendix A12, Figure A12.1 in black box).

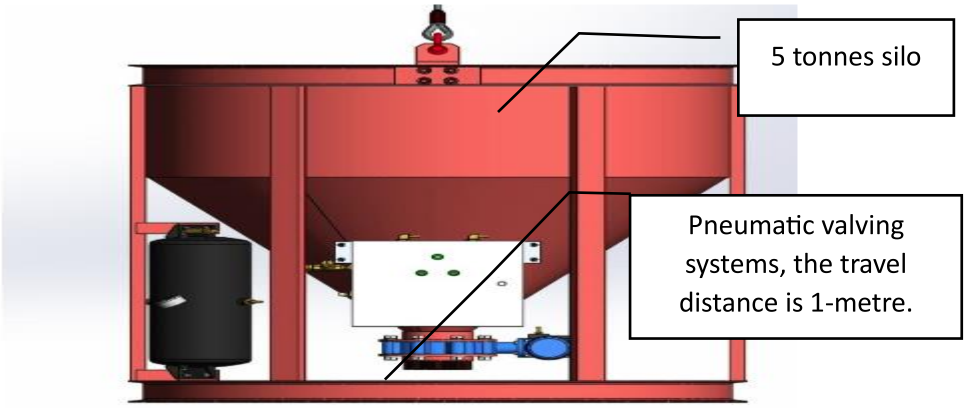


Figure 5.8 Pneumatic Valving with Silo Systems (Alibaba, 2021)

Based on Table 5.16 outcomes, the grading (scale) system is defined as follows:

1). Qi > 100% represents overuse of resources includes
  1.1) large-scale ultra-sonic mill with vibration technology
  1.2) traditional-scale ultra-sonic mill with vibration technology
  1.3) material handling using drop-down methods
  1.4) valving with silo systems
2). Qi = 100% is the normal expectation leading to optimisation
3). Qi =50% is below expectation, classified as an idle production system
4). Qi = zero (not consider because of system down)

see Equation (5.18)

Organised Equation (5.19) based on Equation (5.18) due to examine such as average technical efficiency equals to 100%, 50% and so on, even under conditional maintenance condition equal to 80% seeking an opportunity to an optimal return of scale (see Table 5.20) as obtained:

$$Q_i = f(x_i, \beta) \times TE_i \rightarrow f(v_i, t_i) \times TE_i, = \begin{cases} \text{A. Case 1, } TE_i = 100\% \\ \text{B.Case 2.1 } 5\% \leq TE_i \leq 100\% \\ \quad \text{Case 2.2 } TE_i = 60\% \\ \text{C.Case 3, } TE_i = 110\% \end{cases} \qquad \text{.........................(5.19)}$$

Legend

d = maximising travel distance of linear actuator valving function (e.g., same stroke around); Q_i = d
v = constant speed of the actuator
t = actuator travel time
Qi =di and $f(x_i, \beta) = f(v_i, t_i)$ and technical efficiency, TE_i

- Case 1, TE = 100%

a) Large-scale ultra-sonic mill with vibration technology: grinding GBBFS (slag) into desired particles sizes

Here is adapted ultra-sonic with vibration technologies characteristic and extended for optimisation grinding process (see Appendix A11) using continuous movement forwards, backwards, left and right using the movement occurs at a particular sonic frequency (e.g., below resonant) with oscillation, harmonic motion and vibration to break big pieces of raw material into particles, as a result, it is the linear motion and later developed regression equation.

b) Traditional-scaled ultra-sonic mill with vibration technology into tiny particles sizes

This device's working principles are the same as item A, but smaller in scale for further grinding to produce AS-type high early strength (HE) customised cement.

c) Drop-Down (e.g., Top-Bottom) Method

Once the front process is complete and using their weight to drop the downstream process through the valving system, this results in mass linear motion.

d) Valving System When TEi is Equal to 1 (e.g.,100%)

Table 5.19 shows three different velocities and travel distances in the valving system (Company Z, 2021). As a result, it uses speedy opening or closing at a 100cm (e.g.,1-metre) diameter square shape and seat valve (dark box) that effectively prevents fly ash particles from spreading in the air—this spread presents fire, occupation, and health safety hazards.

Tableaux items a) to d) are in Tables 5.17 to 5.19 using the proposed equation $d = v_i * t_i$, to examine performance and extended consideration when technical efficiency equals one (100%), 0.5(50%), 1.1(110%) and zero scores.

Table 5.17 Productivity Study of Item a) to d) Using the Empirical Stochastic Frontier With Technical Efficiency Equal to 100%

Optimisation of Empirical Stochastic Frontier Analysis to Measure Productivity / **Parameters**	**Case 1: When TE= 100%, Proposed Equation, $\mathbf{d_k = v_j \times t_i}$**			
Items	**Travel Distances(di)**			
Valving Systems				
Pneumatic Device Velocity(v_i) - metre/second	0.045	0.05	0.0626	0.075
Travel Time(t_j) - second	20	20	20	20
Valve Diameter (Travel Distance, d_k) - metre	0.9	1	1.25	1.5
Processes	**Technical Efficiency, TEi = 100%**			
a) Large-scaled ultra sonic mill with vibration	100	100	100	100
b) Small-scaled ultra-sonic mill with vibration	100	100	100	100
c) Drop-down Method	100	100	100	100
d) Pneumatic slide open/close system	100	100	100	100
Average Technical Efficiency (%)	100	100	100	100
Subtotal,$v_i t_i \times TE_i(\%)$	81	100	156.5	225
	Below	Normal	Over	

Legend
under = under return to scale
normal = normal return to scale
over = over return to scale

Table 5.18 Productivity Study of Item a) to d) Using the Empirical Stochastic Frontier With Technical Efficiency Equal To 50%

Productivity Parameters / **Optimisation of Empirical Stochastic Frontier Analysis Measure**	**Case 2: When TE= 50%, Proposed Equations, $d_k = v_j \times t_i$**			
Items	**Travel Distances(di)**			
Valving Systems				
Velocity(v_j) - metre/second	0.045	0.05	0.0626	0.075
Time(t_i) - second	20	20	20	20
Distance(d_k) - metre	0.9	1	1.25	1.5
Processes	**Technical Efficiency, TE_i = 50%**			
a)Large-scaled ultra sonic mill with vibration	50	50	50	50
b)Small-Scaled ultra-sonic mill with vibration	50	50	50	50
c)Drop-Down method	50	50	50	50
d)Pneumatic slide open/close system	50	50	50	50
Average Technical Efficiency	50	50	50	50
Subtotal, $v_i t_i \times TE_i$(%)	45	50	62.6	112.5
	Below			Over

Legend

below = below return to scale
normal = normal return to scale
over = over return to scale
d =linear actuator valving function maximising travel distance
v = speed of an actuator
t = actuator travel time

$B2. Case\ 2: TE_i\ = 50\%$

Table 5.21 illustrates an individual production facility based on expert advice designed to achieve better technical efficiency is equal to 0.5 or 50% resulting in either below or above the return of scale that minimises profit and does not meet the company's interest.

Therefore, Bhattacharyya (2012) used the simulation method to model the chance of machine malfunction, resulting in organising conditional repairs and maintenance frequency, keeping TEi equal to one or 100%. The development of a model is time-consuming in terms of data collecting; Buliono et al. (2021) and Zhang et al. (2017) addressed opportunistic maintenance of facilities by intensively examining each component's functions, seeking alternative methods for optimal productivity (see Sub-heading B2.1, Table 5.20 for further discussion).

$B2.1\ \ 1.1 \leq TE_i\ \ \geq 0.5\ or\ 110\%1 \leq TE_i \geq 50\%$

Table 5.19 Productivity Study of Item a) to d) Using the Empirical Stochastic Frontier With Technical Efficiency Defined Range

Parameters / Optimisation of Empirical Stochastic Frontier Analysis Measure	Case 2: When $50\% \leq TE_i \leq 100\%$, Proposed Equations, $\mathbf{d_k = v_j \times t_i}$			
Items	**Travel Distances(di)**			
Valving Systems				
Velocity(v_j) - metre/second	0.045	0.05	0.0626	0.075
Time(t_i) - second	20	20	20	20
Distance(d_k) - metre	0.9	1	1.25	1.5
Processes	Various Technical Efficiency, TE_i (%)			
a)Large-scaled ultra sonic mill with vibration	50	50	50	50
b)Small-scaled ultra-sonic mill with vibration	50	50	50	50
c)Drop-down Method	100	100	100	100
d)Pneumatic slide open/close system	100	100	100	100
Average Technical Efficiency (%)	75	75	75	75
Subtotal ($v_i t_i \times TE_i$ %)	61	75	117.4	169
	Below		Normal	Over

Legend
below = below return to scale
normal = normal return to scale
over = over return to scale
d = linear actuator valving function maximising travel distance
v = speed of actuator
t = actuator travel time

Table 5.19 illustrates individual production facility performance at 0.5 or 50% technical efficiency, including large- and small-scale ultrasonic mills with vibration devices, a valving system at a velocity of 0.05m/s and 1-metre travel taking time 20 seconds to close and open sliding valve. As a result, it is an under-scaled return concerning productivity.

Further, Farrar and Worden (2013), Tang et al. (2018b) and Zhang et al. (2017) examined operational procedures for production facilities to achieve better machine performances. Their approaches were adapted and extended under specific case situations, such as machine malfunction and conducting routing conditional repair and maintenance. The dark box in Figure 5.22 shows that considered at a speed of 0.0625m/s and travel of 1.25m, the productivity outcome is 1.174 (e.g., 117.4%) by installing a speed controller of the pneumatic/hydraulic systems for productivity improvement. This provides a direction in the machine for optimal results.

Therefore, this study considers the actuator travel speed as 0.0625m/s for 1-metre valve distances, seeking normal returns to scale (e.g., 100) in terms of productivity, as shown in Table 5.20, which maximises resource use and minimises downtime.

Sub-heading B2.2, Table 5.20 illustrates the various speeds of actuator performances, seeking optimal returns to scale. This is an economical way to improve productivity.

$B2.2\ TE_i \geq 60\%$ for large and small-scale ultra-son mill with vibration and the rest production technical efficiency equal to 1 and same travel distance (e.g., 1m)

Table 5.20 Productivity Study of Item a) to d) Using the Empirical Stochastic Frontier With Technical Efficiency Equal to 60% and the Rest Equal to 100% of Same Travel Distance

Parameters / **Optimisation The Empirical Stochastic Frontier Analysis Measure**	**Case 2: When $60\% \leq TE_i \leq 100\%$, Proposed Equation, $d_k = v_j \times t_i$**			
Items	**Travel Distances(di)**			
Valving Systems				
Velocity(v_j) - metre/second	0.045	0.05	0.0626	0.075
Time(t_i) - second	20	20	20	20
Distance(d_k) - metre	0.9	1	1	1.5
Processes	Various Technical Efficiency (%)			
a)Large-scaled ultra sonic mill with vibration	60	60	60	60
b)Small-scaled ultra-sonic mill with vibration	60	60	60	60
c)Drop-down method	100	100	100	100
d)Pneumatic slide open/close system	100	100	100	100
Average Technical Efficiency (%)	80	80	80	80
Subtotal ($v_i t_i \times TE_i\%$)	64.8	80	100.16	180
	Below		Normal	Over

Legend

below	= below return to scale	d	= maximising travel distance
normal	= normal return to scale	v	= speed of actuator
over	= over return to scale	t	= actuator travel time

Based on the survey outcome and summarised in Table 5.23, which illustrates trial-and-error methods for the technical efficiencies of large- and small-scale ultrasonic vibration devices set to 0.6 (60%), the rest of the production facilities are 1(100%) in technical efficiency and take average is 0.8 (80%) at the velocity trims to 0.0626 m/s; travels 1-metre within the 20s. The productivity is 100.16. It is 0.16 above 100 for optimal productivity. As a result, it makes scheduled conditional maintenance such as draining off the condensate water inside the compressed air piping system, filter cleaning and so on work out without affecting the mass customisation production performances (see Appendix A12, Figure A12.1). It also meets the design limit, avoiding machine breakdown and fulfilling Table 5.1 time-to-market.

*B*3. TE_i = *1.1 or 110%*

Table 5.21 Productivity Study of Item a) to d) Using the Empirical Stochastic Frontier With Technical Efficiency Equal to 110%

Parameters / **Optimisation The Empirical Stochastic Frontier Analysis Measure**	**Case 3: When TE=110%, Proposed Equation, $\mathbf{d_k = v_j \times t_i}$**			
Items	**Travel Distances(di)**			
Valving Systems				
Pneumatic slide velocity(v_j) - metre/second	0.045	0.05	0.0626	0.075
Travel time(t_i) - second	20	20	20	20
Travel distance(d_k) - metre	0.9	1	1.25	1.5
Technical Efficiency, TE_i = 110%	**Unit (%)**			
a)Large-scaled ultra sonic mill with vibration	110	110	110	110
b)Small-scaled ultra-sonic mill with vibration	110	110	110	110
c)Drop-down method	110	110	110	110
d)Pneumatic slide open/close system	110	110	110	110
Average Technical Efficiency (%)	110	110	110	110
Subtotal, $v_i t_i \times TE_i$(%)	89	110	172	246
	Below	Over		

This case of TE_i equals 110%, resulting in the system being over return to scale and minimising profit.

Legend

below	= below return to scale	d	= maximising travel distance
normal	= normal return to scale	v	= speed of actuator
over	= over return to scale	t	= actuator travel time

$B2. Case\ 4: TE_i\ = 110\%$

Table 5.21 illustrates that the technical efficiency performance is equal to 110%, resulting in either under or over return to scale that minimises profit and does not meet the company's interests.

The best methods for using the simulation method to model machine malfunction for planning and scheduling conditional repairs and maintenance and keeping all-around production facilities in healthy conditions.

5.1.5.2 Summary of Using the Empirical Stochastic Frontier Analysis Method

Table 5.22 Summary of Using the Empirical Stochastic Frontier Analysis Method

Parameters		Stochastic Fronter Analysis $Q_i=f(x_{i,}\ \beta)\times TE_i$	Technical Efficiency (TEi %)	Results
Velocity	**Travel Distance**	**Sub-total (di)**	**Average 4 Production Facilities Technical Efficiency (%)**	**Subtotal**
0.045	20	0.9	100	81
0.05	20	1		$\boxed{100}$
0.0626	20	1.25		125
0.075	20	1.5		150
TEi = 50%			**Average 4 Production Facilities Technical Efficiency**	**Subtotal**
0.0465	20	0.9	45	45
0.05	20	1	50	50
0.0626	20	1.25	62.5	62.5
0.075	20	1.5	75	75
TEi = 60%			**Average 4 Production Facilities Technical Efficiency (%)**	**Subtotal**
0.045	20	0.9	80	64.8
0.05	20	1		80
0.0626	20	1.5		$\boxed{100.16}$
0.075	20	1		180
TEi = 110%			**Average 4 Production Facilities Technical Efficiency**	**Subtotal**
0.045	20	0.9	110	89
0.05	20	1		110
0.0626	20	1.25		172
0.075	20	1.5		246
TEi = 0			**Average 4 Production Facilities Technical Efficiency (%)**	**Subtotal**
0.045	20	0.9	0	0
0.05	20	1		0
0.0626	20	1.25		0
0.075	20	1.5		0

Table 5.22 summarises the trial-and-error method results; the findings shown in the two black boxes are normal return to scale (e.g., optimisation) that maximise resources use. The main differences between the two are as follows:

- The first black box has technical efficiencies equal to one and scores productivity in 100. It is expected outcome due to all the production facilities are in good condition and in a full load situation.
- The second black box is 0.8 (80%) on average technical efficiency due to routine repair and maintenance tasks. But score is 100.16 (optimal return of scale). To achieve optimisation, engineers based on the design limit (see Appendix A12, Table A12.1), the slide stroke velocity of the pneumatic cylinder can be justified to maximise at the same travel distance of 1-metre, avoiding machine breakdown and maximising resource use. This outcome gives cement entrepreneurs the right times and procedures for conducting maintenance without incurring extra costs.

5.1.6 Comparing the classic Cobb-Douglas production function and empirical frontier analysis equations for productivity measures

Various changes of α, β parameters using the classic Cobb–Douglas production functions are based on keeping constant capital and labour with two shifts. As a result of less capital investment and minimised resources, the result is promising because the productivity optimisation figures are $\{Q_{ij}\} \rightarrow$ 99.29, 97.98 and 99.46, respectively. Three combinations result in $\alpha_i + \beta_j$ as follows:

(a) when $\alpha_i + \beta_j = 0.9 \rightarrow (\alpha_i \quad \beta_j) \rightarrow (0.29 \quad 0.61) \rightarrow \{Q_{ij}\} \rightarrow \{99.29\}$
(b) when $\alpha_i + \beta_j = 1 \rightarrow (\alpha_i \quad \beta_j) \rightarrow (0.25 \quad 0.75) \rightarrow \{Q_{ij}\} \rightarrow \{97.98\}$
(c) when $\alpha_i + \beta_j = 1.2 \rightarrow (\alpha_i \quad \beta_j) \rightarrow (0.21 \quad 0.99) \rightarrow \{Q_{ij}\} \rightarrow \{99.46\}$

In the view of the stochastic frontier analysis method for machine-intensive production with the same Cobb–Douglas production function manufacturing conditions, there are two options for optimisation where $\{1\}$ or $\{100\}$ is equals to optimisation the same as the unit's conversion:

a) When the technical efficiency of all production facilities equals one based on the defined equation, it scores normal return to scale; $\{Q_{ijk}\} = \{v_i \quad t_j \quad d_k\} \rightarrow \{0.05 \quad 20 \quad 1\} \rightarrow \{100\}$ where i, and k are constants
b) When the technical efficiency of all production facilities equals one, it scores normal returns to scale; $\{Q_{ijk}\} = \{v_i \quad t_j \quad d_k\} \rightarrow \{0.0625 \quad 20 \quad 1\} \rightarrow \{100.16\}$

Comparing the outcomes of the two methods above from items (a) to (c) and a) to b), the finding shows that a cement entrepreneur should carefully select their manufacturing strategy based on built-to-last priorities and maximising resources use. The two bullet point items can always ensure that production facilities are in good condition and time-to-market are optimum is that:

- Maximising customised geopolymer-based cement manufacturing for better profit and customer needs
- Maximising labour use for each shift and minimising capital investment

Further, to achieve success, satisfy customer needs and achieve productivity optimisation, new production technology can be deployed in geopolymer-based manufacturing. An example is, using the extra-large correct proportion of sodium hydroxide and potassium solution pool, three to five tonnes of fly ash directly sunk into the pool with the assistance this technology (Tang et al., 2018a; 2018b) to accelerate the chemical reaction. The total productivity of customised geopolymer-based cement production with new technologies involving innovative cement manufacturing and using the empirical stochastic frontier analysis method ranges from 99.5 to 100. The result is shown in Table 5.23 and is obtained as follows:

Table 5.23 Comparison of Total Productivity Measures Between Classic Cobb–Douglas Production Function and Empirical Stochastic Frontier Analysis Methods for Small Lot Customised Cement Productivity Measures

Outcomes / Productivity Tools	Two Methods Results
Classic Cobb–Douglas Production Method	from 97.98 to 99.46 ranges
Empirical Stochastic Frontier Analysis	100 to 100.16%

Table 5.23 illustrates the Cobb–Douglas production function productivity results from 97.98 to 99.46%. The empirical stochastic production analysis outcomes are 100 to 100. 16% are due to the technical efficiency performance and the defined equation (e.g., velocity is multiplied by time equal to distance). Both methods use trial-and-error to seek optimum machine-intensive production environments measures, resulting in variety of outcomes. This is because the set of the two tools' parameters relies on their characteristics. The Cobb–Douglas production function focuses on labour, capital and elasticity. It is classified as a rigid equation. However, the customised stochastic frontier analysis equation is intended to compensate for the Cobb–Douglas production function and does not concern issues of machine performance, such as malfunction or idle time. The cement entrepreneur can formulate manufacturing strategies based on two tools' outcomes.

5.1.7 Compared advantages and disadvantages of two methods

Table 5.24 illustrates both methods and their advantages and disadvantages:

- Long calculation, which can easily lead to mistakes
- Trial-and-error seeks alternatives
- New technologies involve simulation technologies for the optimisation process.

Table 5.24 Compared Advantages and Disadvantage of Classic Cobb–Douglas Production Function and Empirical Stochastic Frontier Analysis Methods in Geopolymer-based Cement Production (Company Y, 2021)

Comparison / Method		Advantages		Disadvantages	
		Classic Cobb–Douglas Production Function	**Empirical Stochastic Frontier Analysis**	**Classic Cobb–Douglas Production Function**	**Empirical Stochastic Frontier Analysis**
$F(K^{\alpha_i}, L^{\beta_j})$	Capital(K) Labour(L) Elasticity, α_i Elasticity, β_j	Rigid equation using trial-and-error seeking optimal	Vary of combination elasticities and suitable for mass customisation seeking optimal	Long calculation and easily get mistakes	
$F(x_i,\beta) \times TE_i$ $F(x_i,\beta) \rightarrow F(v_i, t_j)$	TE_i TEi=0.5(50%) and 0.6(60%) due to scheduling route maintenance TEi=1(100%) TEi=1.1(110%)	Collect data to develop equation and trial-and-error seeking optimisation	Customised equation based on the production facilities and manufacturing methods using the survey seeking optimal		

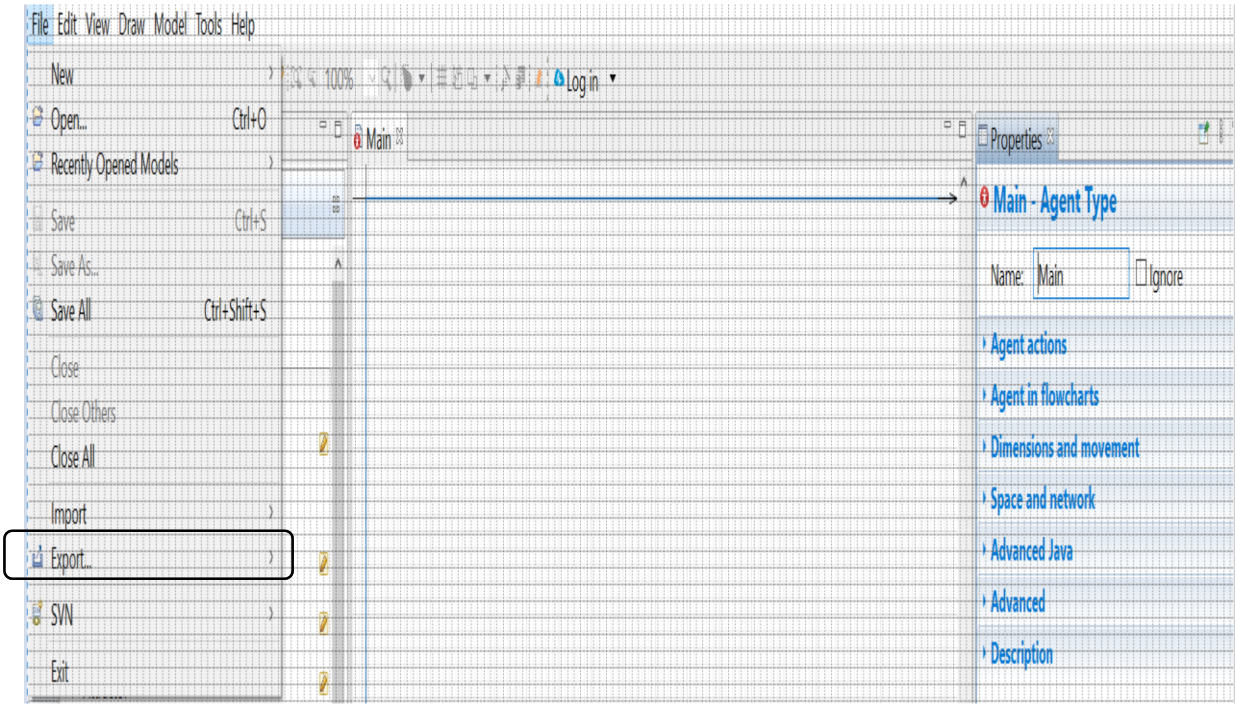


Figure 5.9 AnyLogic™ Export Data to Excel

In Figure 5.9, the black box illustrates AnyLogic™ enabling export of optimisation data to Excel™; it can then be shared for further analysis.

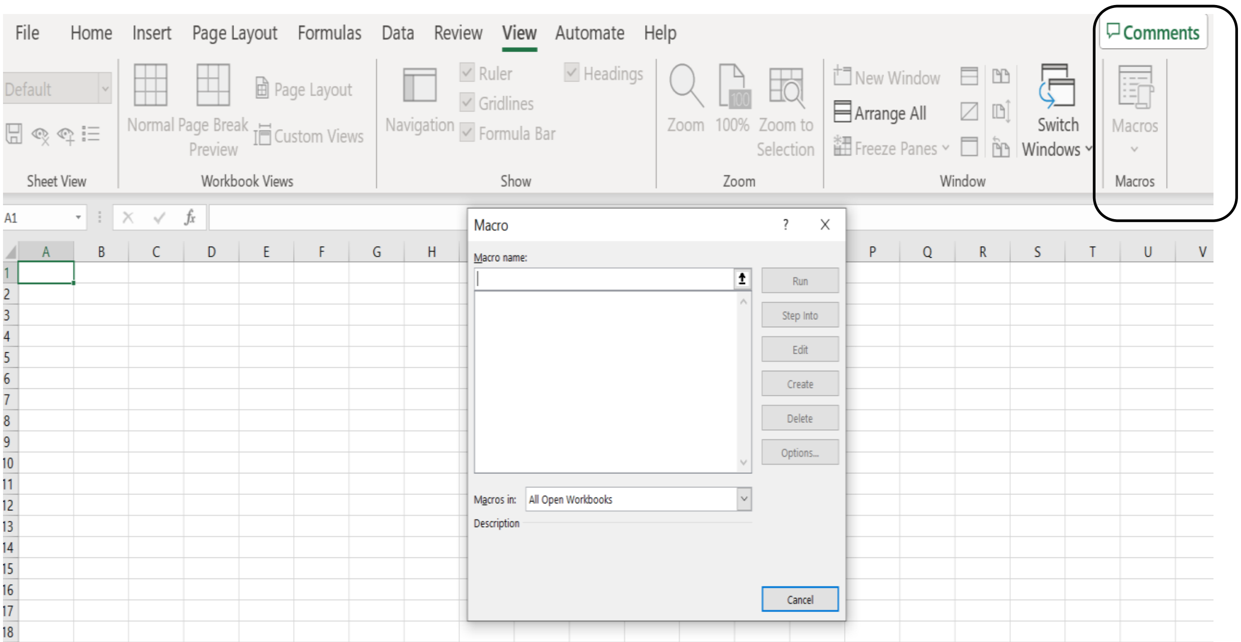


Figure 5.10 Customised Visual Basic Programming for Optimisation Calculation and Trend Data

A quick way to solve Table 5.24's trial-and-error calculation issue is by using visual basic application programming. One of the "Macro" functions of Excel™, as shown in Figure 5.10's black box, can achieve dynamic online data analysis of the production status at time intervals. These data-sharing functions are suitable foe micro/small cement factories, as they have the same function as enterprise resources planning (ERP) but cost less.

The outcome can provide immediate expert advice to cement entrepreneurs who are formulating manufacturing strategies to maximise resource use and time to market.

5.1.8 Compendium

Scenario 1 discussed data collection for geopolymer-based cement fabrication from multiple sources, including literature reviews, associations such as the CCAA, target cement companies' financial reports, simulations, and surveys. Gathering them in Microsoft Office™ and Excel™ used with XLMiner™ (Chan, 2018) can provide better data analysis to examine the three statuses of returns to scale using trial-and-error methods. Here, varying technical efficiency parameters for the empirical stochastic frontier analysis and different combinations of the elasticities in the classic Cobb–Douglas Production Function Measures are used to seek productivity optimisation.

This chapter also discussed using manual methods to organise cement production and to solve bottlenecks for the mass customisation of two common types of geopolymer-based cement up to expected productivity. The main disadvantages of these methods are not efficiently solving the problems of small lot customised cement production because of frequently changing production status, causing time-consuming production data collection. However, a simulation method can tackle statics, dynamics production data and potential problems, resulting in unlimited interaction with systems. To achieve optimisation processes using changes below entities' parameters and process flow to achieve via modelling methods:

- Attributes independent entity includes production facilities (e.g., capital) and raw materials, finished goods (fixed and current assets)
- Process independent entity includes cement production methods such as top-bottom integration manufacturing methods involving new production technologies and so on (see Appendix A7 and Appendix A14).
- Process similar entity includes geopolymer-based and Portland-based cement, homogeneous and heterogeneous materials. This is because of similar structures, but customised cement involves modifying fabricating methods, such as using extra-process to produce Australian Standard (AS) high strength (HE)-grade cement.

Capital and labour with exponential two elasticities for the classic Cobb–Douglas production analysis equation is expressed below in mathematical format:

$$f(\alpha, \beta) = \begin{cases} \alpha+\beta=1 \\ \alpha+\beta\leq 1 \\ \alpha+\beta\geq 1 \end{cases}$$

Further analysis with the two elasticity combinations of when $\alpha + \beta \leq 0.9$ and $\alpha + \beta \leq 1.1$ can optimise normal returns to scale productivity by keeping a constant labour force and using a trial-and-error method, leading to a healthy balance sheet (Griffin, 2011; Coelli et al., 2005; Dirata et al., 2019; Lin et al., 2014).

The alternative productivity measure is the empirical stochastic frontier analysis method.

$$q_i = f(x_i, \beta) \times TE_i \begin{cases} TE_i = 1 \\ TE_i \leq 1 \\ TE_i \geq 1 \end{cases}$$

The $f(x_i, \beta)$ identifies as a linear regression equation because of all new production facilities in linear motions (see Appendices A12 to A14). The findings in the survey for all production facilities have no breakdown in Company's Z records based on over the past several years. The productivity outcomes are 100% and 100.16%, even though routine repair and maintenance of the large- and small-scale ultrasonic mills. One case is when at an average of 80% overall technical efficiency (see Table 5.20). An engineer takes an opportunity to trim flow control of the mechanical type pneumatic valving system (see Appendix A6, Figure A6.4 in black box) to a design limit speed instead of replacing new parts, preventing downtime, resulting in finishing a 1-metre travel distance within 20 seconds (see Appendix A12, Figures A12.1 and A12.3), The outcome is the optimal return of scale. It is one of the reasons Company's Z production facilities are always in good condition. Both tools have advantages and disadvantages. If they are used in the cement industry for productivity measures, the empirical stochastic frontier analysis is suitable for technology- intensive because it considers technical efficiency.

CHAPTER 6: SCENARIO 2

Scenario 2 uses the same approaches as Scenario 1 based on Chapter 4 results. This chapter concerns customised Portland-based cement production with similar processes for on-time delivery to market, based on the Australian rather than international standards for general Portland (GP), blend Portland (GB), high early strength (HE) and so on—this suits the Australian cement market and identifies homogenous materials (e.g., GP, HE) and similarity processes. This section discusses a variety of customised small lot Portland-based cement processes that do not affect the regular mass production of GP cement, using a traditional manual method to predict the workflow, simulation both for dynamics and statics work processes to optimise production. The classic Cobb–Douglas production function is used for the trial-and-error method based on the ranges of α_i = 0.21 to 0.29 at the increasing intervals of 0.01 and decreasing at intervals 0.01 for β_j under the three statuses of the returns to scale, seeking productivity optimisation (see Chapter 3, Section 3.5.1.1 in Section 3.5.1). Another tool using XLMiner™ identifies data to develop linear regression, which are being developed to achieve technical efficiency in production.

6. SCENARIO 2

Company Y (2021) is a cement and concrete firm located in Brisbane, Australia. It supplies ordinary Portland cement (GP) and fly-ash-based geopolymer cement to domestic and international markets. Its infrastructure projects decreased by 13% because of COVID-19 in 2020 (Rozhkov et al., 2022; Australian Bureau of Statistic, 2022). However, Company Y (2021) as shown in Tables 6.1 and 6.2, experienced a 15% increase in producing small lot customised Portland-based cement, such as general Portland (GP), blend Portland (GB) and high early strength (HE)-grade cement because of time to market issues. Facing this challenge, Company Y (2021) cannot use the traditional mass production built-in-stock method to fabricate a variety of ordinary Portland cement, which results in a business gap (Chan, 2018). Company Y (2021) also considered using the Japanese manufacturing method. The method used by Toyota just-in-time (JIT) to drive growth. Rather, subcontracting to small cement factory is another tactic for achieving more efficient time to market. Introducing state-of-the-art production technologies and keeping Australian-made brand-name products are part of easily time-controlled short- and long-term strategies.

The first element to review is the current manufacturing capability of Company Y (2021). The company has a lot of oversized silos (e.g., 20 tonnes capacity per each) that are less flexible manufacturing for fast-moving customised cement production because of frequently loading a small number of raw material items for changing lines. As a result, it does not have enough space to store a small number of various types of raw materials, spending extra time in loading from traditional silos and limited resource uses. Other findings are that ball roller grinding, vertical grinding and so on have only single supply and outlet tubing (see Appendices A1 to A4), resulting in time-consuming delivery using conveyor belt material handling between processes. Based on the survey outcome, Company Y (2021) takes 30 minutes to one hour to change one batch to another for different types of Portland cement production. It is because the raw material handling system is for mass production of the cement for which there is market demand and subcontracted overseas customised cement, resulting in Company Y not considering a multi-channel inlet and outlets to solve frequently changing production. Company Y (2021) must find a way to improve business challenges, particularly in the COVID-19 epidemic worldwide situation and time-to-market delivery tactics as below:

- How do resources minimise consumption but increase profit to achieve customised small lot Portland-based cement production and satisfy customer expectations without affecting the regular mass production of other cement types?
- Do mass customisation technologies provide optimum process flow, and the following of two tools offer alternatives that can provide optimised productivity?

    - classic Cobb–Douglas production function
    - empirical stochastic frontier analysis

Table 6.1 Small Lot Portland-based Cements Production Order in Year 2021 (Company Y, 2021)

Types of Cement	Quantities (Tonnes)	Delivery Time Status
GP	1,300	Quarters 1 and 4
GB	350	Quarters 1 and 3
HE	150	Quarters 2 and 4
Subtotal (Tonnes)	1,800	

6.1 Analysis in forecast small lot cement orders distribution

Table 6.1 illustrates the forecast for customised small lot Portland-based cement based on the outcome of the survey questions (see Appendix A11), which show that the busiest quarters are 2 to 3. Facing these challenges, reorganising the manufacturing strategy improves productivity by using new production methods (see Appendix A7, Appendix A10 and Appendices A12 to A14). Despite Australian standard (AS) high early (HE) cement characteristics, the general lime (GL) type is only lime cement that does not need further processes (Ramesh, 2019).

Table 6.2 Organising the Production Schedules of Cement Plant (Company Y, 2021)

Schedules / Cement	Quarter 1	Quarter 2	Quarter 3	Quarter 4
GP	72%			
GB	19%			
HE		8%		

Further, Quarters 2 to 4 are in over capabilities based on current production facilities performances, particularly in general Portland (GP) and blend Portland (GB) types of cement scheduled for delivery in quarters 3 and 4. As a result, Company Y (2021) seeks a method to solve to satisfy customers' need market. Therefore, the main and sub-tools can offer ways of measuring productivity and resolving bottlenecks, solving fast-moving customised cement challenges facing Australian-owned companies that:

- Sub-tools use the modelling method of data collection and analysis of production problems, providing essential expert opinions for the optimisation process.
- Main tools include the classic Cobb–Douglas production function and the empirical stochastic frontier analysis and trial-and-error methods to seek optimisation of the returns to scale.

6.2. Sub and main tools

The modelling includes the manual method and voice of the house of deployment in the mass customisation matrix, which are discussed in this section.

6.2.1 Two sub-Tools

Two sub-tools discussed as below:

6.2.1.1 Simulation modelling includes manual methods to seek dynamic and static data.

6.2.1.2 Voice of the house of deployment in mass customisation is for modularity preference.

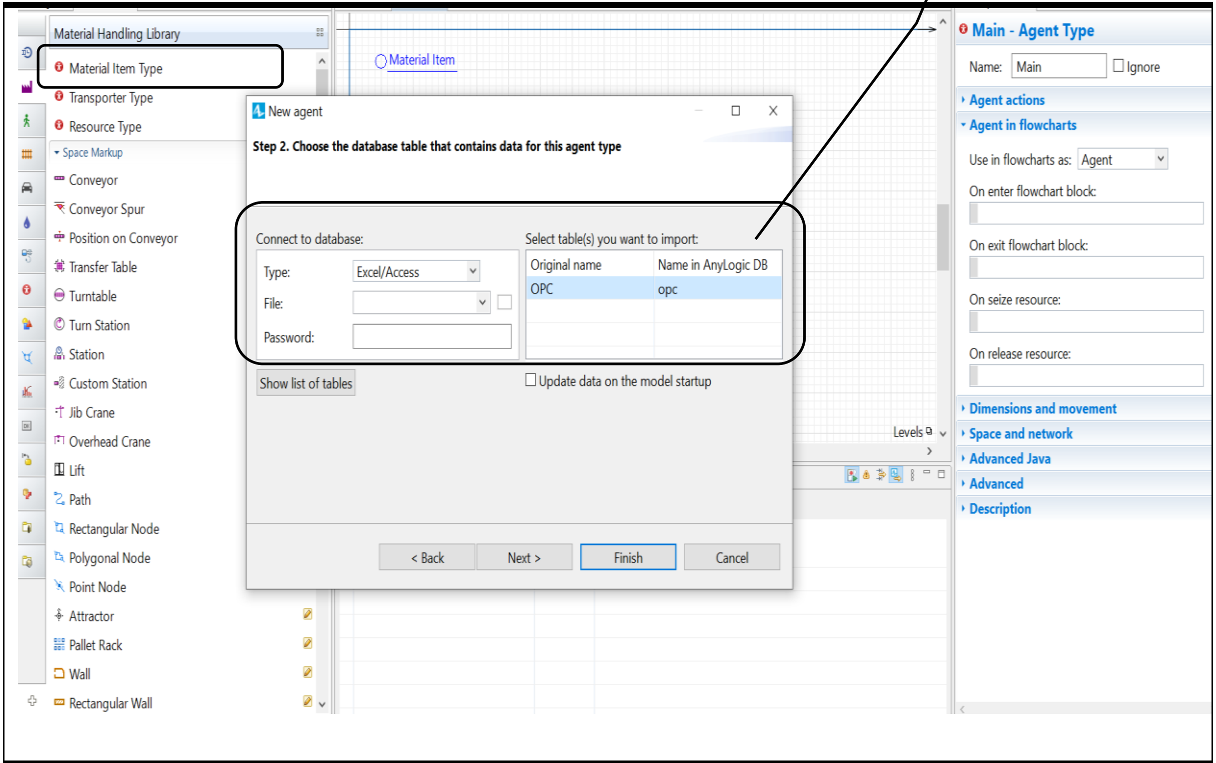
6.2.1.1. Modelling Method

This section further discusses general Portland (GP), blend Portland and high early strength (HE) or Portland cement with supplementary cementitious materials, which share the same structures and similar process, which means the sub-tool simulation agent can achieve modelling to produce this cement in Table 6.2 and seeks alternative ways of manufacturing more customised cement based on the current method. Therefore, modelling methods can achieve collaborative virtual manufacturing for productivity improvement, fulfilling company interests.

Further, the modelling system is designed around the fact these cement types of similar processes and characteristic concerns general (GP) and high early strength (HE) Portland cement because they have similar composition structures and close compressive strength performances in the temperature variation range are 20 to 24 hours within 18º to 28ºC. However, high early strength (HE) cement has fine particles, resulting in extra grinding after or before gypsum raw materials are added to improve corrosion resistance.

Thus, simulation models can provide service in batch control quality using the separation valves or linear actuator valving system between the source tank and mix tank in production processes.

Linked Microsoft Office™ to develop more than one input data



Independence Attributes	Process Independence: providing space for data justification until optimisation

Figure 6.1 AnyLogic™ Link with Excel™

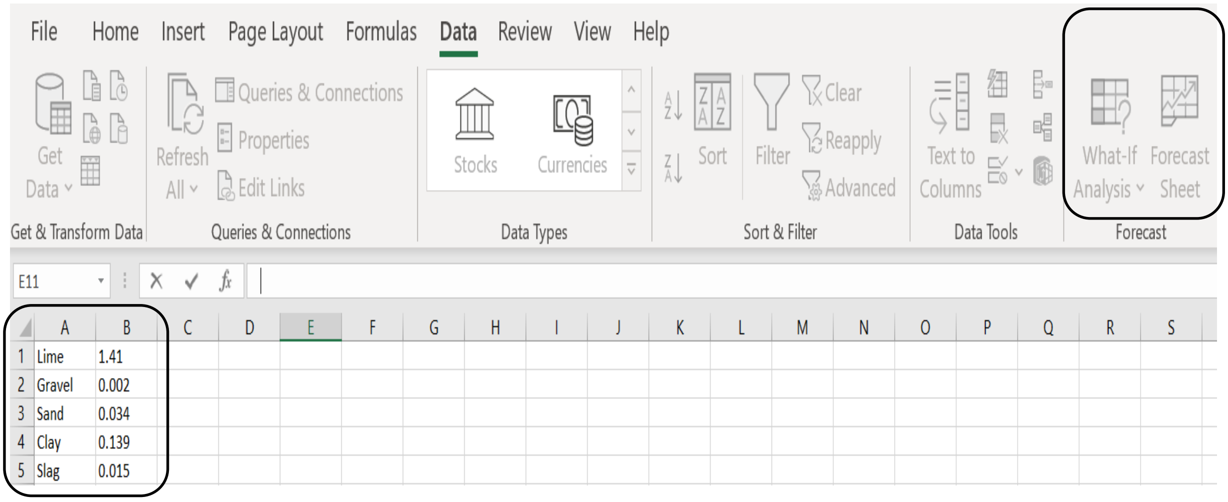


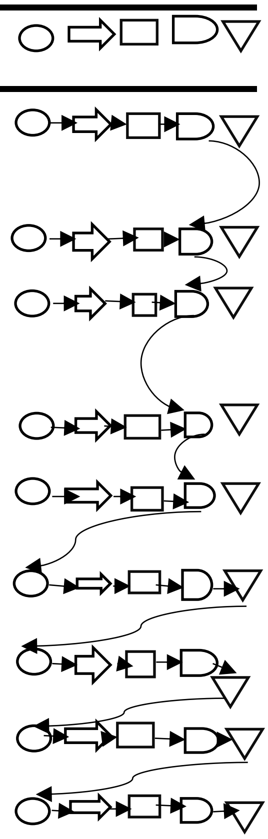
Figure 6.2 Updated and Linked AnyLogic™ with Excel™

Figure 6.1 uses the embedded function in the AnyLogic™ linked to Excel™ for further analysis using the ‘What if analysis’ icon in the top right corner, as shown in Figure 6.2.

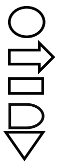
Table 6.3 illustrates the traditional manual process flow for Portland cement, resulting in time-consuming online data production and is suitable for a single cement product fabrication. Compared with the modelling method, it cannot immediately tackle dynamic manufacturing production systems using visual data management. Kim et al. (2015) also addressed that visual data management is a form of communication that provides a snapshot of manufacturing operations like a manufacturing scoreboard that is easy to trick performances.

Table 6.3 Traditional Portland-based Cement Flow Process Chart

Item \ Labours		Capitals		Flow Processes
Item	Labours	Raw Materials	Production Facilities	Process
1	3	lime	silos, pipeline, valves, blower	material handling unit(MHU)
2	2	gravel	vessels, pipeline	grinding MHU
		slag	vessel, material handling unit	grinding and MHU
3	2	clay	vessels, material handling unit	MHU
4	3	sand	silos, material handing unit	MHU
5	3	mixed items 1 to 5		clinker
6	4	gypsum	added and mix	Mixer
7	3			pack
8	2			Delivery
Subtotal	22			



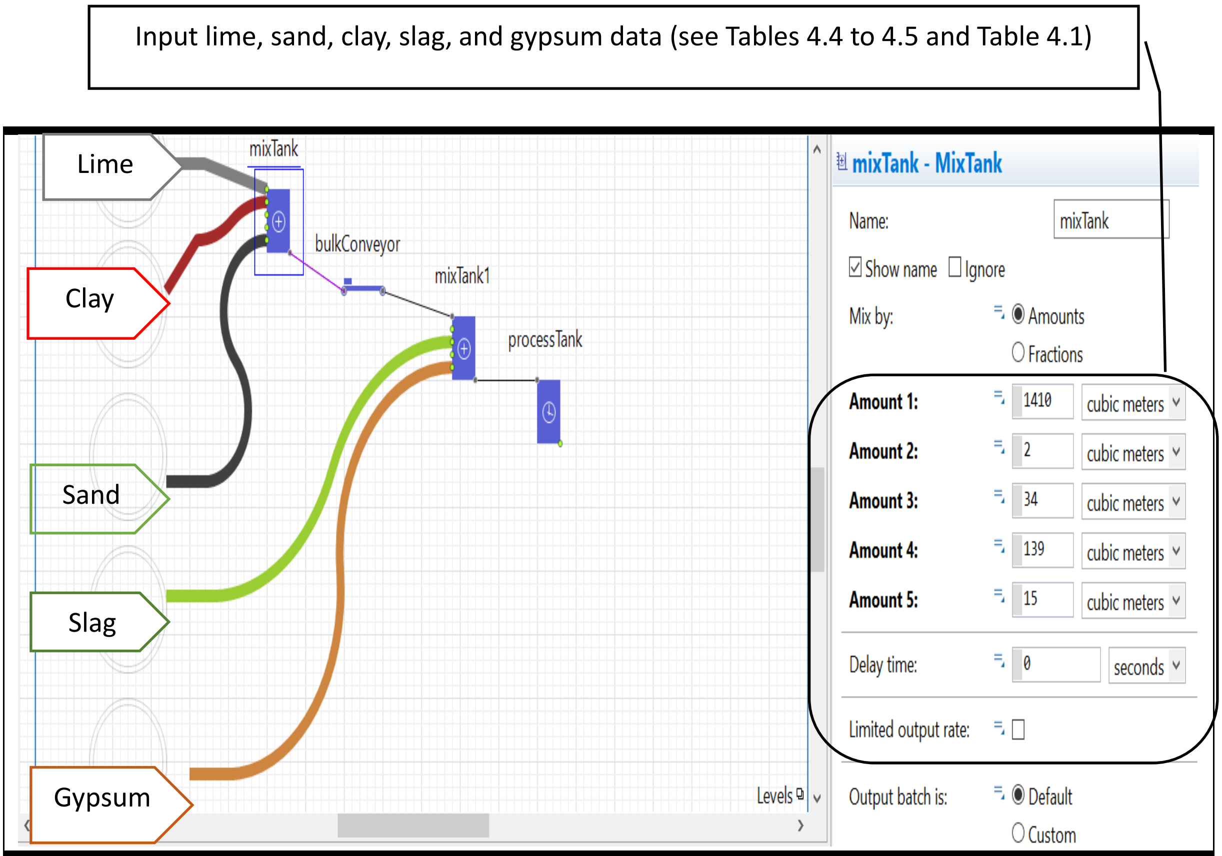
Legend



Assembles
Process
Inspection
Flow forward
Stop

6.2.1.1.1 Simulation Model for Fabrication of Portland-based Cement

6.2.1.1.1.1 Classic Portland Cement Manufacturing Simulation Model



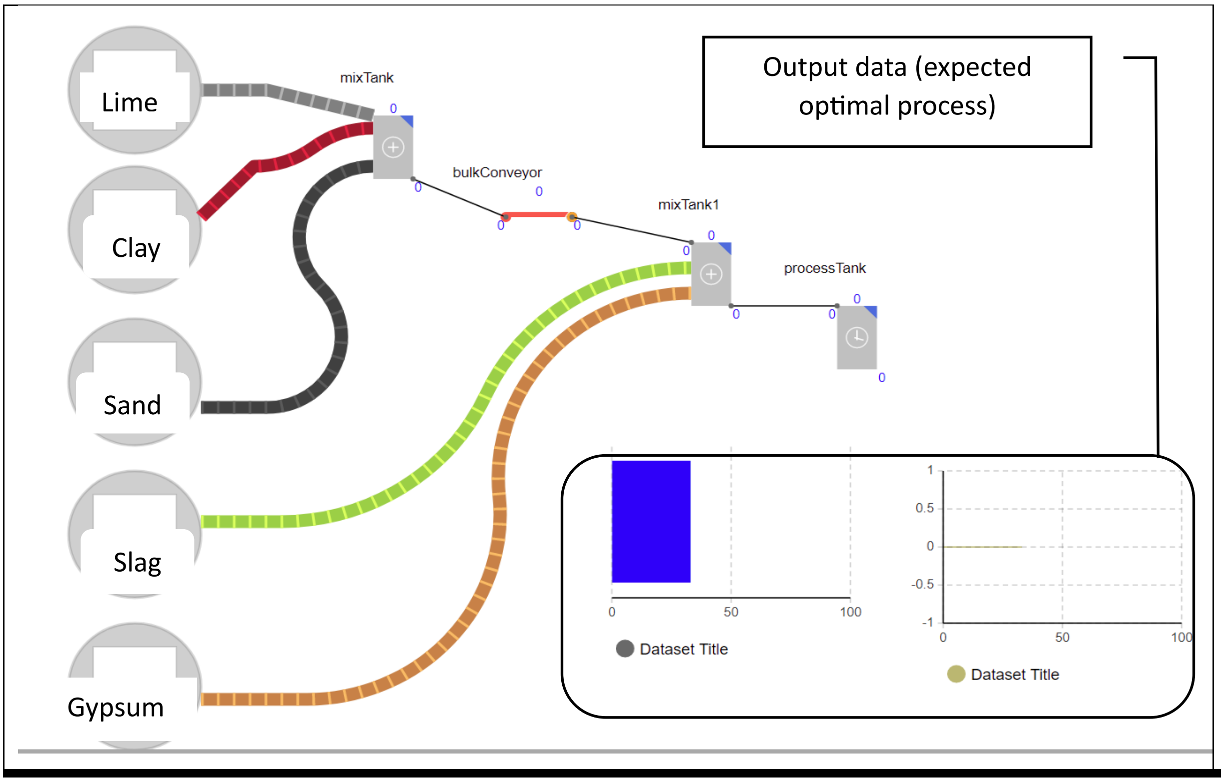
Independence Attributes	Process Independence: providing space for data justification until optimisation

Figure 6.3 The Classic Result of Portland-Based Cement Production (Not to Scale)

Figure 6.3 illustrates the use of independence attributes and process independence to construct the traditional Portland cement fabrication simulation model, including lime, clay, sand, slag and gypsum and a conveyer belt to deliver raw materials for further processes. In the top right corner (the black box), the user can adjust the attributes of the parameter flow in/out based on batch-by-batch production status for optimisation. All data can be transferred to Excel™ for further analysis and to XLMiner™ to develop the empirical stochastic frontier analysis equation.

Further, Figure 6.3 shows an agent-based modelling method. This method is used because each attribute can be assigned an individual goal and can perform according to set parameters (see the top right corner). The modelling methods operate as follows:

- Each silo contains enough raw materials (lime, clay, sand, gravel, and gypsum), minimising downtime.
- All sources are delivered to mixed tanks via a bulk conveyor belt that moves on a timer (see the left column). The middle tank is a mix tank (process independence), which mixes the first raw materials; they are then moved via a bulk conveyor belt to another process for further mixing with gypsum in the correct ratio and finally becoming general Portland (GP) cement through a kiln process. Figure 6.4 in the red right corner illustrates the outcome of this process is steady cement production. After packing, the batch is ready for delivery to customers.



Independence Attributes | Process Independence and Process Similarity

Figure 6.4 Parts of Normal Operation for GP Cement Production (Not to Scale)

Figure 6.4 illustrates the outcome data with time intervals, as shown at the bottom right corner (black box), for the mass production of ordinary Portland cement based on the mix tank performance. The mix is then moved via a conveyor belt to another tank for mixing with slag and gypsum before being subject to further processing. As a result, this is not an optimal operation due to not considering changing line frequency. So, there is space to improve productivity by reorganising manufacturing methods and less investment in production facilities.

One finding is a parallel production method for three types of cement that have the same structures and can require similar production processes, meeting the production schedules shown in Table 6.2. This arrangement can satisfy customer needs and manufacturer expectations for optimisation.

6.2.1.1.1.2 Proposed Optimisation to Produce GP, GB and HE Portland-based Simulation Models

Figure 6.6 shows modelling for GP, GB and HE cement that involves running simultaneous paralleling production, thus fulfilling business interests.

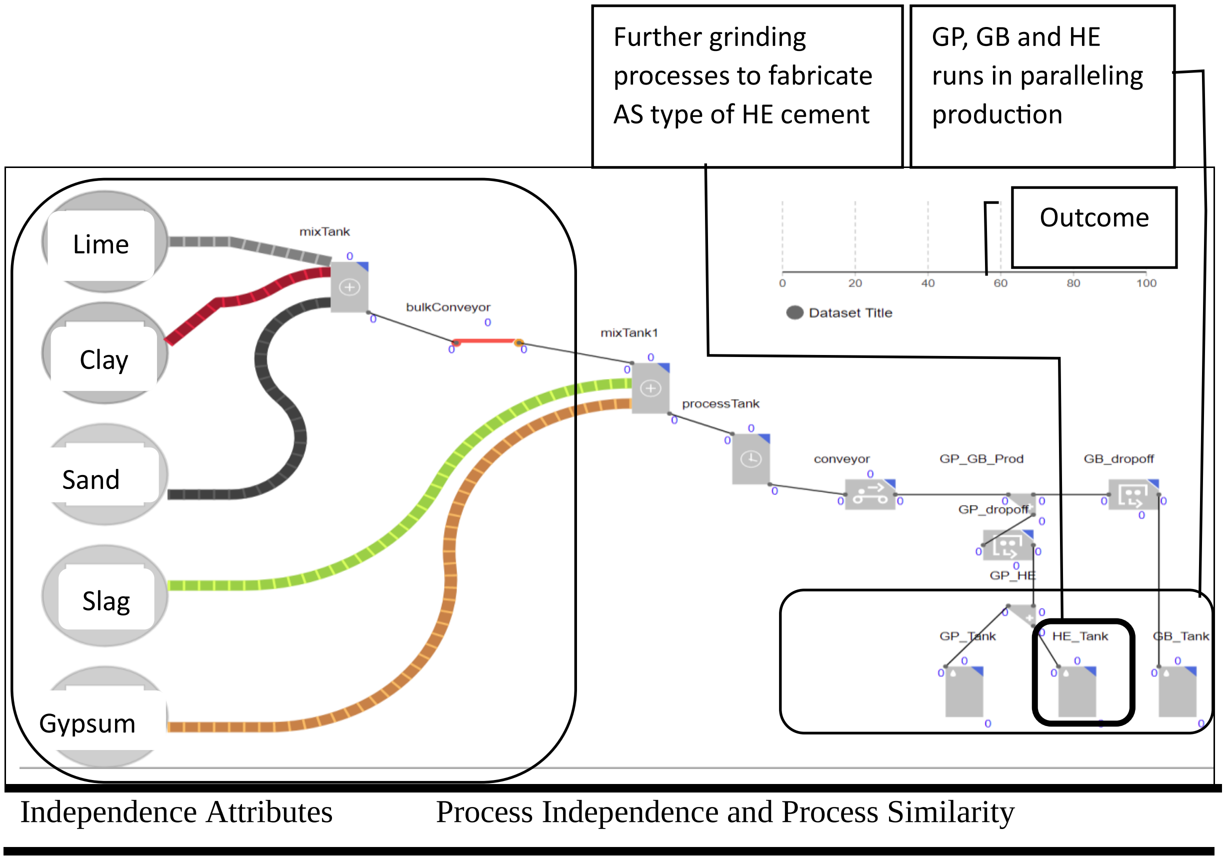


Figure 6.5 Parts of Normal Operation for GP/GB/HE Cement Production Using Separate Devices and Extra Material Handling Units (Not to Scale)

Five individual sources are on the far left; this visual presents the top-bottom integration manufacturing method. Silos and the specially designed vessel have a linear actuator valving system. This contains enough raw materials (lime, clay, sand and so on) to achieve the following:

- Controlling the flow sequence because of Australian Standard (AS) types of high early strength (HE) of cement precious grind after mixing with gypsum process to ensure expected cement as shown in Figure 6.6 the blue box
- Controlling the cement quality, avoiding unnecessary mix proportion, minimising resources, and meeting clients’ time-to-market expectations
- Minimising technical efficiency using conditional maintenance methods

Further, the process shown in the right corner uses commercial-scaled ultrasonic and vibration devices for mixing instead of the methods shown in Figures 6.4 to 6.5; these devices are 38% faster than conventional mixers with an acceptance working capital ratio (Company Y, 2021). The kiln uses hydrogen fuel instead of diesel, maximising resource use and being environmentally friendly. The production performance is shown in Figure 6.5, located in the right-top corner orange box once compiling the model system. After packing, this batch is ready for delivery to customers.

In summary, the advantages of this new production technology are as follows:

- Time-saving and suitable for similar small lot cement products such as general Portland (GP), general blend (GB) and high early strength(HE) cement.
- Easily trickling production performance due to outcome result is shown orange box that is using visualisation management to improve productivity.

One of the success factors of Toyota's business is using the voice of the house of deployment to understand more clients' needs (Cudney et al., 2015; Cunha et al., 2010). Zhang et al. (1990) and Chan et al. (2010d) developed the voice of the house in mass customisation to build a good relationship with clients and manufacturers using enterprise resources planning (ERP) software, resulting in providing customised service to them and meeting company interest-maximising resource use. Adapted and extended this tool, directly collected data through a survey, and then developed a modularity preference matrix in productivity improvement to bridge the gap.

6.2.1.2 Voice of the House of Deployment in the Mass Customisation

This is one of the sub-tools that can assist the main tools in achieving better modularity preference. Two voices are shown on the left-hand side of Figure 6.3, representing manufacturers and customers' needs and resulting in modularity conditions for small lot production.

- The middle box gathers the two voices' established assessment matrices.
- The right-hand box is the outcome of modularity preference.

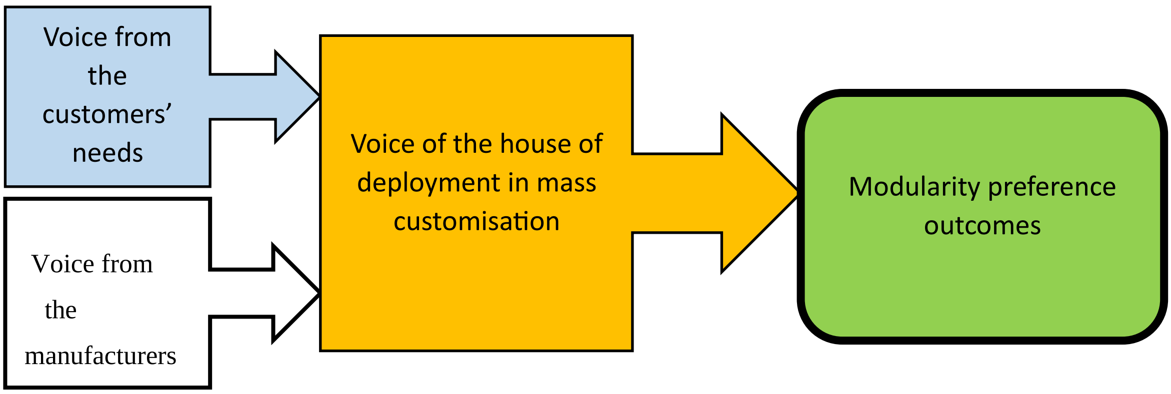


Figure 6.6 Flow Chart of Construction the Voice of the House of Deployment in Mass Customisation

The modelling method—one of the sources providing data to XLMiner™ to develop the empirical stochastic frontier analysis equations—is based on the outcome of developing an agent-based simulation model.

6.3 Two main tools

6.3.1 ***The classic Cobb–Douglas production function is the first main productivity tool***. Its role here is to seek optimal normal returns to scale by changing various combinations of the elastics parameters using the trial-and-error method, which is based on adapting and extending Cobb's earlier research results (see Section 3.4.1 and Section 3.4.2.1).

6.3.2 ***The empirical stochastic frontier analysis is the second productivity tool***. It considers using machine-intensive manufacturing conditions. It is because one element, technical efficiency, leads to a new production method that closely examines the target company's production facilities' performances, determining the equation status of whether TE is equal to one (e.g., 100%) for optimal technical efficiency (see Section 3.5). In addition, the mining tool XLMiner™ (Chan, 2018) gathers multiple sources and analyses data to develop linear regression equations associated with the main tools for the empirical stochastic frontier analysis productivity measure.

Section 6.4 further discusses the application of these two main tools.

6.4 Productivity measure of Portland-based cement using classic Cobb-Douglas production function methods

Table 6.4 Classic Cobb–Douglas Production Function Measures Productivity for Fabrication of Portland-based Cement (Company Y, 2021; Alibaba, 2021)

Parameters / **Cobb–Douglas Production Function**		**Reorganising Variety Workforce in Two Shifts for Agile Small Lot Production**			
Total Productive Factor (A)		1			
Total Input Labours, L (e.g., by Shift)		Number of persons in morning shift		Number of persons in evening shift	Subtotal (persons)
		5		5	10
Capital, K (Measure Individual Production Facilities Capitals including Pipeline)					
Individual Production Facilities / **Process**		**US$'000**			
Qty	**Description**				
4	Tank for in/Out	20	20	20	20
2	Small scale ultrasonic and vibration type instead of horizontal ball mill	110	110	110	110
2	Large scale ultrasonic and vibration types instead of vertical mill	150	150	150	150
1	Kiln using hydrogen fuel (Referred to Appendix A4)	200	200	200	200
4	Mixers (vibration and artificial wave types)	40	40	40	40
5	Piping	20	20	20	20
6	Linear actuator valving system (drop-down by gravity	50	50	50	50
Capital Subtotal		590	590	590	590
Cobb–Douglas Production Function		$f(L^{\beta}, K^{\alpha})$ is variety combination of elasticity			

Table 6.4 illustrates Company Y's (2021) production facilities data. Company Y uses new cement technologies to fabricate three types of Portland-based cement simultaneously to satisfy demand markets. The new technologies are listed below:

A. Small-scale ultrasonic and vibration grinder
B. Large-scale ultrasonic and vibration grinder
C. Clinker
D. Vibration and artificial wave-type mixer
E. Linear actuator valving system
F. Extra tank.

A. Small-scale ultrasonic and vibration grinder: this device replaces the vertical roller grinding machine (see Appendix A3). It can provide precious particles up to nano grade with fewer repairs and maintenance. The traditional grinder needs its rollers replaced periodically, which is costly. Therefore, this machine is suitable for high early strength (HE) cement fabrication.
B. Large-scale ultrasonic and vibration grinder: this device replaces the horizontal ball mill machine (see Appendices A2 and A3) and this ultrasonic grinder works in the same way as a grinding mill. Therefore, this grinder has its settings changed so that I can grind all kinds of raw materials using changing frequency domain.
C. Kiln: this device uses hydrogen fuel (see Appendix A4) instead of diesel fuel. Therefore, it saves energy costs because the cement plant (Chan, 2018) can produce hydrogen gases and sodium hydroxide solution using the electrolysis method of seawater.
D. Mixers: this device replaces the traditional mixers. It uses commercial-scale and smaller-scale ultra-sonic vibration methods for efficient mixing with semi-products, which needs further processing.
E. Linear actuator valving system: this device is one of the efficient methods for material delivery. It uses drop-down by gravity instead of conveying, which is faster and saves energy.
F. Extra tank: this device has a capability that is suitable for small lots of customised cement production quantities.

This section presents new production technologies and multiple data for fabricating three types of Portland cement simultaneously using the classic Cobb–Douglas production function for productivity.

Further, this study adapts Li and Park's (2017) earlier work on the Cobb–Douglas function, extending Equation (5.2) concerning α, β range data from which α keeping a particular value within the range 0.21 to 0.29 instead of equal to 0.3, resulting in corresponding β values also change under three statuses of the combination of α and β such as $\alpha_i + \beta_j \leq 1$, $\alpha_i + \beta_j = 1$, and $\alpha_i + \beta_j \geq 1$. The purpose of this is to keep α_i within the range of 0.21 to 0.29 through Equations (6.2) to (6.8). All production facilities (assets) are either amortised from the financial institutions or need to be able to create wealth for a company facing small lot customised cement production challenges, as illustrated in Tables 6.1 and 6.2. The manufacturing strategy considers flexible working hours for time to market. By contrast, β_j has various parameters related to α_i under three statuses of a combination of α_i and β_j with the intervals increasing/decreasing by these amounts using the trial-and-error method, seeking normal returns to scale (e.g., 100% and optimal). Meanwhile, a productivity score less than 100% is below the return of scale, and greater than 100% is above the return of scale. Examined below are three cases as obtained:

1) Case A when $\alpha_i + \beta_j = 1$
2) Case B when $\alpha_i + \beta_j \leq 1$ as obtained
    - $\alpha_i + \beta_j \leq 0.7$
    - $\alpha_i + \beta_j \leq 0.8$
    - $\alpha_i + \beta_j \leq 0.9$
3) Case C when $\alpha_i + \beta_j \geq 1$ as obtained
    - $\alpha_i + \beta_j \geq 1.1$
    - $\alpha_i + \beta_j \geq 1.2$
    - $\alpha_i + \beta_j \geq 1.3$

The adapted equations above are discussed in Scenario 1 and extended in Equations (6.1) to (6.8) for Scenario 2.

Additionally, Table 6.4 shows machine-intensive rather than labour-intensive work. This is because Company Y (2021) is interested in a variety of customised cement to procure more business for government infrastructures plans. This provides an opportunity explore optimising the three statuses of the returns to scale study. This research considers two decimal points of the elasticity values involving exponential calculation for the classic Cobb–Douglas production function. Expression in mathematic format, $(K, L) = AK^{\alpha}L^{\beta}$ is obtained as follows:

$$f(K, L) = AK^{\alpha}L^{\beta} = \begin{cases} \text{Case A} \\ \text{Cases B1 to B3} \\ \text{Cases C1 and C2} \end{cases} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(6.1)$$

Probing further, Equation (4.9) for cases A to C is obtained as follows:

A. Case A = $\alpha + ß = 1$, $\begin{cases} \alpha = 0.21 \text{ to } 0.29 \\ \beta = 0.79 \text{ to } 0.71 \end{cases}$ ……………………(6.2)

B. Case B

B1. Case B1 $\alpha + ß = 0.7$, $\begin{cases} \alpha = 0.21 \text{ to } 0.29 \\ \alpha = 0.21 \text{ to } 0.29 \end{cases}$ ……………………(6.3)

B2. Case B2 $\alpha + ß = 0.8$, $\begin{cases} \alpha = 0.21 \text{ to } 0.29 \\ \beta = 0.59 \text{ to } 0.51 \end{cases}$ ……………………(6.4)

B3. Case B3 $\alpha + ß = 0.9$, $\begin{cases} \alpha = 0.21 \text{ to } 0.29 \\ \beta = 0.69 \text{ to } 0.9 \end{cases}$ ……………………(6.5)

C. Case C

C1. Case C1 $\alpha + ß = 1.1$, $\begin{cases} \alpha = 0.21 \text{ to } 0.29 \\ \beta = 0.89 \text{ to } 0.81 \end{cases}$ ……………………(6.6)

C2. Case C1 $\alpha + ß = 1.2$, $\begin{cases} \alpha = 0.21 \text{ to } 0.29 \\ \beta = 0.99 \text{ to } 0.91 \end{cases}$ ……………………(6.7)

C3. Case C2 $\alpha + ß = 1.3$, $\begin{cases} \alpha = 0.21 \text{ to } 0.29 \\ \beta = 1.09 \text{ to } 1.01 \end{cases}$ ……………………(6.8)

Legend

- Productivity factor, A = 1 (Shen et al., 2016; Dzeng and Wu, 2013)
- Capital, K = 180,000 (Company Y, 2021; Hasan et al., 2012)
- Labour, L = 8 in two shifts due to workmanship issues (Company Y, 2021; Nadi, 2019)
- α is from the ranges of 0.21 to 0.29 and changes corresponding β, $f(\alpha, \beta)$, with 0.01 increasing/decreasing corresponding values under the three statuses, examining returns to scale and productivity optimisation.

Adapted equations (6.1) to (6.8) were applied in Scenario 1 and extended to Scenario 2 for Portland-based cement productivity measure, seeking expert advice. Here, using a comprehensive calculation trial-and-error method with an injection of new production technologies, such as commercial and traditional-scale ultrasonic and vibration grinding methods, is one of the key factors in seeking an optimisation alternative.

A. Case A: Equation (4.10) - Case A $\alpha + \beta = 1$ when $\begin{cases} \alpha = 0.21 \text{ to } 0.29 \\ \beta = 0.79 \text{ to } 0.71 \end{cases}$

This examines the range α = increasing interval from 0.21 to 0.29 and justifies the corresponding β values from increasing/decreasing 0.01interval from the range 0.79 to 0.71 when the status α + β = 1. Table 6.5 illustrates all production facilities, productivity factors, workforces and so on (Company Y, 2021).

Table 6.5 Considering Close to 100% Total Productivity When α + β = 1 Using Classic Cobb-Douglas Production Function Measures

Classic Cobb- Douglas Production Function Method ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 1$ α_i=0.21 to 0.29 and β_j=0.79 to 0.71									
A	1	1	1	1	1	1	1	1	1
K	590000	590000	590000	590000	590000	590000	590000	590000	590000
L	10	10	10	10	10	10	10	10	10
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.79	0.78	0.77	0.76	0.75	0.74	0.73	0.72	0.71
Q_i	100.4	98.15	125.11	139.64	136.45	173.94	194.15	217.69	241.85

Normal Below Over

Legend

normal = normal return of scale
below = below return of scale
over = over return of scale
i = variables increasing from 0.21 to 0.29
j = variables decreasing from 0.79 to 0.71

Table 6.5 using the trial-and-error method via the classic Cobb–Douglas production function equation. The calculation method (see Section 3.5.1) is used here to seek the returns to scale status and productivity optimisation based on the combination of $\alpha_i + \beta_j = 1$ and Q_i by changing the corresponding two elastic α, β values, obtained as follows:

The solution of when $\alpha + \beta = 1 \rightarrow \{\alpha, \beta\} \rightarrow \{0.21, 0.79\}$, obtained as follows:

$f(K, L) = (1) * (590{,}000)^{0.21} 10^{0.79} = 100.4$……………..…………………………..(6.9)

Further, three black brackets at the bottom of Table 6.5 are as follows:

- The most left dark bold bracket is normal return to scale (optimisation)
- The middle bracket is below of scale
- The most right bracket is over return to scale.

Additionally, Table 6.5 provides a series of results using Equation (6.9). As a result, the most left (yellow bracket) is the optimum normal returns to scale operation for the target company's capital and labour use. This is an economical method of small lot customised cement production because:

- It provides maximin productivity and normal return of scale.
- It provides an opportunity to minimise direct labour and maximise profit.

The trial-and-error method for the classic Douglas production function analysis will continue to be used to measure the three statuses of scale until productivity optimisation is achieved.

B. Three cases, B1 to B3, are derived from case B of combinations of α and β when $\alpha + \beta \leq 1$, is obtained as follows:

B1) Case B1 when $\alpha + \beta = 0.9$

B2) Case B2 when $\alpha + \beta = 0.8$

B3) Case B3 when $\alpha + \beta = 0.7$

B1) Case B when $\alpha + \beta = 0.9$

There are several studies in setting α_i, β_j

- α_i = from 0.21 to 0.29
- β_j = from 0.69 to 0.61

Tableaux results use the trial-and-error method, as shown in Table 6.6.

Table 6.6 Considering Close to 100% Total Productivity When $\alpha + \beta \leq 0.9$ Using Classic Cobb–Douglas Production Function Measures

Classic Cobb- Douglas Production Function Method ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 0.9$ α_i=0.21 to 0.29 and β_j=0.69 to 0.61									
A	1	1	1	1	1	1	1	1	1
K	590000	590000	590000	590000	590000	590000	590000	590000	590000
L	10	10	10	10	10	10	10	10	10
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.69	0.68	0.67	0.66	0.65	0.64	0.63	0.62	0.61
Q_i	79.78	89.04	99.37	110.91	123.8	136.17	154.21	172.13	192.11
	Under		Normal	Over					

Legend
below = below return of scale
normal = normal return of scale
over = over return of scale

In Table 6.6, using the trial-and-error for the classic Cobb–Douglas production function calculation results in the figure inside the dark bold box, 99.39, which is close to maximum productivity and is obtained as follows:

The solution for when $\alpha + \beta \leq 0.9 \rightarrow \{\alpha, \beta\} \rightarrow \{0.23, 0.67\}$ is obtained as follows:

$f(K, L) = (1) * (590{,}000)^{0.23} 10^{0.67} = 99.37$…………………………………………..(6.10)

Additionally, Equation (6.10) provides close maximum productivity. This is because:

- It can provide to close to maximum productivity with three cases of the returns to scale:
  - the left at the bottom of Table 6.6 is under return to scale
  - the middle at the bottom of Table 6.6 is normal return to scale (dark bold colour) that is optimisation.
  - The right at the bottom of Table 6.6 is over return to scale.
- It is not necessary when $\alpha + \beta = 1$; the resulting combination of $\alpha + \beta = 0.9$ is an alternative. This is the advantage of machine-intensive work and represents lean manufacturing strategy.

The trial-and-error method for the classic Douglas production function analysis will continue to be used to measure the three statuses of scale until productivity optimisation is achieved.

B2) Case B2 when $\alpha + \beta \leq 0.8$

Equation (6.10) only provides close to optimal/maximum productivity. Here, continuous calculation using the trial-and-error for the classic Cobb–Douglas Production Function Measures is obtained as follows:

Table 6.7 Considering Close to 100% Total Productivity When $\alpha + \beta \leq 0.8$ Using Classic Cobb–Douglas Production Function Measures

Classic Cobb- Douglas Production Function Method ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 0.8$

α_i=0.21 to 0.29 and β_j=0.59 to 0.51

A	1	1	1	1	1	1	1	1	1
K	590000	590000	590000	590000	590000	590000	590000	590000	590000
L	10	10	10	10	10	10	10	10	10
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.59	0.58	0.57	0.56	0.55	0.54	0.53	0.52	0.51
Q_i	63.37	70.73	78.94	88.11	98.34	109.76	122.5	136.72	152.6

Below Normal Over

Legend
below = below return of scale
normal = normal return of scale
over = over return of scale

In the trial-and-error calculation method, the 98.34 figure in Table 4.46 in bold black inside middle box is close to total productivity using the classic Cobb–Douglas production function equation for agile small lot customised cement production, obtained as follows:

The solution for $\alpha + \beta \leq 0.8 \rightarrow \{\alpha, \beta\} \rightarrow \{0.25, 0.55\}$ is obtained as follows:

$f(K, L) = (1) * (590{,}000)^{0.25}10^{0.55} = 98.34$……………………………………………..(6.11)

Additionally, the result of Equation (6.11) provides close to maximum productivity optimisation. This is because:

- It can provide close to maximum productivity with the three cases of the returns to scale and can satisfy customer needs. It proposes to reorganise the manufacturing system to make it optimal.

    - the left at the bottom of Table 6.7 is under return to scale
    - the middle at the bottom of Table 6.7 is normal return to scale. But it is 1.66 below the 100 (e.g., optimisation).
    - the right at the bottom of Table 6.7 is over return to scale

- It is to reorganise manufacturing methods, including machine performances to make them optimal.

The trial-and-error method for the classic Douglas production function analysis will continue to be used to measure the three statuses of scale until productivity optimisation is achieved.

B3) Case B3 when $\alpha + \beta \leq 0.7$

Equation (6.11) only provides close to optimal optimal/maximum productivity. Here, a continuous calculation using trial-and-error for the classic Cobb–Douglas Production Function Measures is obtained as follows:

Table 6.8 Considering Close to 100% Total Productivity When $\alpha + \beta \leq 0.7$ Using Classic Cobb–Douglas Production Function Measures

Classic Cobb- Douglas Production Function Method ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 0.7$ α_i=0.21 to 0.29 and β_j=0.49 to 0.41									
A	1	1	1	1	1	1	1	1	1
K	590000	590000	590000	590000	590000	590000	590000	590000	590000
L	10	10	10	10	10	10	10	10	10
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.49	0.48	0.47	0.46	0.45	0.44	0.43	0.42	0.41
Q_i	31.03	56.18	62.7	69.99	78.11	87.19	97.3	108.6	121.21
	Below						Normal	Over	

Legend
below = below return of scale
normal = normal return of scale
over = over return of scale

In Table 6.8, the 97.3 figure inside the middle black box is close to optimum productivity using the trial-and-error calculation method, obtained as follows:

The solution of $\alpha + \beta \leq 0.8 \rightarrow \{\alpha, \beta\} \rightarrow \{0.27, 0.43\}$ is obtained as follows:

$$f(K, L) = (1) * (590{,}000)^{0.27} 10^{0.43} = 97.3 \quad \text{(6.12)}$$

Additionally, Equation (6.12) provides close to optimal/maximum productivity. This is because:

- It can provide close to maximum productivity with the three cases of returns to scale and can satisfy customer needs. The proposed tactic is to reorganise the manufacturing system to make it optimal.

    - the left at the bottom of Table 6.8 is under return to scale
    - the middle at the bottom of Table 6.8 is normal return to scale. But it is 2.7 below the 100 (e.g., optimisation).
    - the right at the bottom of Table 6.8 is over return to scale.

The trial-and-error method for the classic Douglas production function analysis will continue to be used to measure the three statuses of scale until productivity optimisation is achieved.

C. Three cases C1 to C3 are derived from case C of combinations of α and β obtained as follows:

C1) Case C1 when $\alpha + \beta = 1.1$

C2) Case C2 when $\alpha + \beta = 1.2$

C3) Case C3 when $\alpha + \beta = 1.3$

C1) Case C1 when $\alpha + \beta \leq 1.1$

Table 6.9 Considering Close to 100% Total Productivity When $\alpha + \beta \leq 1.1$ Using Cobb-Douglas Production Function Measures

Classic Cobb- Douglas Production Function Method ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 1.1$ α_i=0.21 to 0.29 and β_j=0.89 to 0.81									
A	1	1	1	1	1	1	1	1	1
K	590000	590000	590000	590000	590000	590000	590000	590000	590000
L	10	10	10	10	10	10	10	10	10
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.89	0.88	0.87	0.86	0.85	0.84	0.83	0.82	0.81
Q_i	126.4	141.12	157.51	175.79	196.2	218.99	214.01	272.8	304.48
	Normal	Over							

Legend
normal = normal return of scale
over = over return of scale

In Table 6.9, the 126.4 figure in the dark bold box is obtained using the trial-and-error calculation method as follows:

The solution of $\alpha + \beta \leq 1.1 \rightarrow \{\alpha, \beta\} \rightarrow \{0.21, 0.89\}$ is obtained as follows:

$f(K, L) = (1) * (590,000)^{0.21} 10^{0.89} = 126.4$ ……………………………………..(6.13)

Equation (6.13) outcome is over-scaled of return and far away to optimal/maximum productivity. So, the lean manufacturing (Anderosn, 2004) is assumed to eliminate waste.

- the most left at the bottom of Table 6.9 is normal return to scale but 26.4 above 100 of the optimal.
- the right at the bottom of Table 6.9 is over return to scale and expected lean manufacturing (Anderson, 2004).

The trial-and-error method for the classic Douglas production function analysis will continue to be used to measure the three statuses of scale until productivity optimisation is achieved.

C2) Case C2 when $\alpha + \beta \leq 1.2$

Table 6.10 Considering Close to 100% Total Productivity When $\alpha + \beta \leq 1.2$ Using Cobb-Douglas Production Function Measures

Classic Cobb- Douglas Production Function Method ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 1.2$ α_i=0.21 to 0.29 and β_j=0.99 to 0.91									
A	1	1	1	1	1	1	1	1	1
K	590000	590000	590000	590000	590000	590000	590000	590000	590000
L	10	10	10	10	10	10	10	10	10
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	0.99	0.98	0.97	0.96	0.95	0.94	0.93	0.92	0.91
Q_i	159.2	177.66	198.29	221.31	247.01	275.69	307.7	343.43	383.31
	Normal	Over							

Legend
normal = normal return of scale
over = over return of scale

In Table 6.10, the 159.2 figure in the most left box is close to optimal and is obtained using the trial-and-error calculation method as follows:

The solution of $\alpha + \beta \leq 1.2 \rightarrow \{\alpha, \beta\} \rightarrow \{0.21, 0.99\}$

$f(K, L) = (1) * (590{,}000)^{0.21}10^{0.99} = 159.2$……………………………………..(6.14)

Additionally, Equation (6.14) outcome is over-scaled of return and far away to optimal/maximum productivity causing by:

- This minimises profits and overuse resources and proposed a lean manufacturing is focused on cutting ‘fat’ from production activities (Jacka and Keller, 2010; Aartsengei and Kurtoglu, 2015).

    - the left at the bottom of Table 6.10 is normal return to scale but 59.2 above 100 of optimal figure that over resources use.
    - the right at the bottom of Table 6.10 is over return to scale and over resource use.

The trial-and-error method for the classic Douglas production function analysis will continue to be used to measure the three statuses of scale until productivity optimisation is achieved.

C3) Case 3 when $\alpha + \beta \leq 1.3$

Table 6.11 Considering Close to 100% Total Productivity When $\alpha + \beta \leq 1.3$ Using Classic Cobb–Douglas Production Function Measures

Classic Cobb- Douglas Production Function Method ($AK^{\alpha_i}L^{\beta_j}$) When $\alpha_i + \beta_j = 1.3$ α_i=0.21 to 0.29 and β_j=1.09 to 1.01									
A	1	1	1	1	1	1	1	1	1
K	590000	590000	590000	590000	590000	590000	590000	590000	590000
L	10	10	10	10	10	10	10	10	10
α_i	0.21	0.22	0.23	0.24	0.25	0.26	0.27	0.28	0.29
β_i	1.09	1.08	1.07	1.06	1.05	1.04	1.03	1.02	1.01
Q_i	200.39	223.66	249.63	278.62	310.97	347.07	387.37	432.35	482.56
	Over								

Legend
over = over return of scale

In Table 6.11, the figure 200.39 in the black box is close to optimal and is obtained using the trial-and-error calculation method.

The solution of $\alpha + \beta \leq 1.3 \rightarrow \{\alpha, \beta\} \rightarrow \{0.21, 1.09\}$ is obtained as follows:

$f(K, L) = (1) * (590{,}000)^{0.21} 10^{1.09} = 200.39$……………………………………..(6.15)

The outcome result of Equation (6.15) is over-scaled of return and far away from optimal productivity (e.g., 200.29). This is because:

- This minimises profits and overuse of resources and proposes lean manufacturing concerning cutting ‘fat’ from production activities (Jacka and Keller, 2010; Aartsengei and Kurtoglu, 2015) to eliminate waste and unnecessary processes and re-organise workforces per shift from 5 to 4 workers (see Table 6.4 second line of input labour row).

    - the middle at the bottom of Table 6.11 is over return to scale that is over resource use.

The trial-and-error method for the classic Douglas production function analysis will continue to be used to measure the three statuses of scale until productivity optimisation is achieved.

A summary of the trend across various combinations of $\alpha_i + \beta_j$ in seeking productivity optimisation for Q_{ij} is as shown in Table 6.12 dark bold box (e.g., normal).

Table 6.12 Summary of Productivity Findings for Portland-based Cement Production

CBPF / α_i,β_j,Q_{ij}		Optimisation Parameters and Results based on A=1, K=180000, L=8			Statuses of Return to Scale
		α_i	β_j	Q_{ij}	
$\alpha + \beta \leq 1$	$\alpha + \beta = 0.7$	0.27	0.43	97.3	below
	$\alpha + \beta = 0.8$	0.25	0.55	98.34	below
	$\alpha + \beta = 0.9$	**0.23**	**0.67**	**99.37**	**normal**
$\alpha + \beta = 1$		**0.21**	**0.79**	**100.4**	**normal**
$\alpha + \beta \leq 1.3$	$\alpha + \beta = 1.1$	0.21	0.89	126.4	above
	$\alpha + \beta = 1.2$	0.21	0.99	159.2	above
	$\alpha + \beta = 1.3$	0.21	1.09	200.39	above

Legend
A = productivity factor
K = capital
L = labour
below = below return of scale
normal = normal return of scale
above = above return of scale
Q_{ij} = total productivity, q is available
α_i, β_j = elasticities parameters, i and j are available

Need to somewhere else lean manufacturing system (Anderson,2004), which is waste elimination and needs productivity improvement that improves profit and re-organise workforce (see Table 6.13 and Table 6.4)

Further, Tale 6.12 summarised various outcomes using changing elasticities, seeking optimal return of scale for productivity. The slight black box is over-scaled of return and needs lean manufacturing to minimise waste and maximise resource use (Andrson, 2004). The dark bold box represents close to optimal/maximum productivity. The rest are below return of scale, resulting in minimising profit. Further discussion of changing elasticity performance is in Section 6.6.

Table 6.12 black box shows one of the optimal return scales are 99.37 as $\alpha_i + \beta_j = 0.9$ and 0.65 less than the optimal 100 with a pair $\alpha_i = 0.23$ and another $\beta_j = 0.67$. This finding is a variation with the traditional maximum as α + β = 1 when $\alpha_i = 0.21$ and another $\beta_j = 0.79$. The outcome result here is 100.4 and 0.4 that is traditional optimal but needs extra resources.

6.5 Performance of change $\boldsymbol{\alpha}, \boldsymbol{\beta}$ parameters

The individual result of different combinations two elasticities based on the classic Cobb–Douglas production function, $AK^{\alpha_i}L^{\beta_j}$, equation study as listed below:

1) $\alpha_i + \beta_j = 0.7$: the pair is $\alpha_i = 0.27$ and as $\beta_j = 0.43,$ is equal to 97.3. This is 2.7 below the optimum figure (e.g., 100). This does not meet clients' time-to-market expectations. Therefore, Company Y's (2021) strategy justifies increasing the working hours from 8 to 10 hours per day or putting on additional per shift, resulting in labour-intensive work rather than increasing machine usage but causing downtimes.
2) $\alpha_i + \beta_j = 0.8$: the pair is $\alpha_i = 0.25$ and as $\beta_j = 0.55,$ is equal to 98.34. This is 1.63 below the optimum figure (e.g., 100). This does not meet clients' time-to-market expectations. Therefore, Company Y's (2021) strategy justifies increasing the working hours from 8 to 10 hours per day or putting on additional staff per shift, resulting in labour-intensive work rather than increasing machine usage but causing downtimes.
3) $\alpha_i + \beta_j = 0.9$: the pair is $\alpha_i = 0.23$ and as $\beta_j = 0.67$ is equal 99.37. This is 0.03 below the optimum result (e.g., 100). It closely meets clients' time-to-market expectations. Therefore, Company Y's (2021) strategy is to keep the current situation to maximise profit but reduce extra expenditure. This is one of the examples of a balance machine and labour-intensive tactics, as the result is a variation of the normal return to scale that represents optimal use of the manufacturing system.

(d) $\alpha_i + \beta_j = 1$: the pair is $\alpha_i = 0.21$ and as $\beta_j = 0.79,$ is equal to 100.37. This is 0.37 above the optimum result (e.g., 100). It closely meets clients' time-to-market expectations. Therefore, Company Y's (2021) strategy is to keep the current situation to maximise profit. This is one of the examples of a balance machine and labour-intensive tactics, as the result being a variation of the normal return to scale that represents optimal use of the manufacturing system.

(e) $\alpha_i + \beta_j = 1.1$: the pair is $\alpha_i = 0.21$ and as $\beta_j = 0.89$, is equal to 126.4. This is 26.5 above the optimum result (e.g., 100). It does not meet the company's interest but fulfils clients' time-to-market expectations. It is over return of scale.

(f) $\alpha_i + \beta_j = 1.2$: the pair is $\alpha_i = 0.21$ and as $\beta_j = 0.99$, is equal to 159.2. So, it is 59.2 above the optimum result (e.g., 100). It does not meet the company's interest but fulfils clients' time-to-market expectations. It is over return to scale.

(g) $\alpha_i + \beta_j = 1.3$: the pair is $\alpha_i = 0.21$ and as $\beta_j = 1.09$, is equal to 200.39. So, it is 100.39 above the optimum result (e.g., 100). It does not meet the company's interest but fulfils clients' time-to-market expectations. It is over return of scale.

6.6 Development of empirical stochastic frontier analysis regression equations for each production facilities

This section adapts Scenario 1 and extends it to Scenario 2 for a Portland-based cement productivity study under the same conditions as the classic Cobb–Douglas production function. The new technologies and methods involved in the production are as follows:

1) Working hours arrangement
2) Commercial-scale ultrasonic and vibration with screening grinder
3) Linear actuator valving system: moving the semi or raw material from upstream to downstream process to quicken material handling
4) Hydrogen-fuel instead of diesel fuel.

The black boxes in Table 6.12 illustrate the working hours for traditional cement production, which are due to fine grinding to produce HE-type cement. This is a labour-intensive process. The table shows/explains this process tactic to satisfy client needs by moving working hours and processes into shift-based instead of hour-based operation. To minimise production breakdown (Company Y, 2021), morning and evening shift teams 10 persons each.

Table 6.13 The Fundamental Various Processes of Working Hours and Man-Hours for Portland-based Cement (Chan, 2018, p. 100)

Using mass production method all year round

Introducing new mass customisation production method to maximise resource

Process / Item	Unit Capability (ton/ hr)							Various Work hour per day(hr/d)			
	GP	**GB**	**GL**	**HE**	**LH**	**SL**	**SR**	**8**	**12**	**16**	**24**
Vertical Mill	3	3.3		3.34				2400	3600	4800	7200
Horizonal Ball Mill	3.1	3.1		3.1							
Mixer	3.3	3.3		3.37				2400	3600	4800	7200
Material Handling	3	3		3.3				2400	3600	4800	7200

The other items are discussed in the next section.

6.6.1 Productivity measures using empirical stochastic frontier analysis method

This section further discusses items 2) to 4), using new production technologies for optimal productivity (Hajifathalian et al., 2012; Layek et al., 2000; Li et al., 2017; Lin et al., 2014; Chan, 2018; Jufri and Siswanto, 2020) instead of the traditional method (see Appendix A5) via the empirical stochastic frontier analysis method. This is because what is the relationship between the three statuses and on machine efficiency and machine capacity (see Section 3.4.2). All the new production technologies rely on distance, velocity, and times, as detailed below:

- Linear actuator valving system (see Appendices A6 to A7 and Appendix A13): this opens and closes the position to drop raw material from upstream to downstream. It is a linear regression equation and a reliable device.
- Linear vibration type screen (see Appendix A11): this can effectively handle massive grinding tasks (Woywadt, 2017; Tang et al., 2018b). It also identifies linear regression equations and is a reliable production facility.
- Hydrogen fuel instead of diesel gas in a kiln (clinker) operation (Hewlett & Lista, 2019): this is environmentally friendly and identifies the flame propagation as linear regression equation. It is also a reliable source and device.

Table 6.14 Identified Independence Attributes, Process Independence, Process Similarity and ™Modularity for Development of Geopolymer-based Cement Simulation Model AnyLogic™

Replaced commercial-scaled ultrasonic and vibration with screen grinders

Name / Item		Mass Customisation Technologies		
	Independence Attributes	**Process Independence**	**Process Similarity**	**Modularity**
1	GP GB HE	Grinding Mixing Clinker (Kiln)	Grinding Mixing Clinker (Kiln)	Mix-&add-in modularity

Scenario 1 has been adapted so it can be applied and extended to study of productivity for Portland-based cement production. Compared with the two tools, it seeks merits and alternatives.

6.6.1.1 The Three Statuses of TE_i

Hou et al. (2015) and King (2011) use a linear actuator (slide mode) of the valving system in the process plant for effective batch-by-batch production methods. Scenario 2 adapted their approaches in batch separation concerning dynamic quality assurance and minimising idle time because of open and closed dropping amount control to downstream processes as classified as simple, essential, and reliable production facility. As a result, it seldom needs repairs but does require routine maintenance, ensuring good production conditions. Company Y (2021) used top-bottom integration manufacturing methods with new technology involvement for quicker material handling, resulting in the formula $q_i = v_i * t_i$ instead of $q_i = f(x_i; \beta)$ the equation. Here is Scenario 1's grading scale adapted for use in Scenario 2:

$$Q_i = f(x_{i,}\ \beta) \times TE_i \rightarrow v_i t_i \times TE_i, \begin{cases} A.\ Case\ 1, TE_i = 100\% \\ B.\ Case\ 2.1\ 50\% \le TE_i \le 100\% \\ \quad Case\ 2.2\ TE_i = 60\% \\ C.\ Case\ 3, TE_i = 110\% \end{cases} \quad \ldots\ldots\ldots\ldots\ldots(6.16)$$

where i=available

Legend

d = maximising travel distance of linear actuator valving function (e.g., same stroke around); Q_i = d
v = constant speed of actuator
t = actuator travel time

To minimise particles in the air, speedy hydraulic and pneumatic devices facilitated by a square-sized valve sit set ensure quicker close and open positions for better control of leaks and material flow (Swanepoel et al., 2014). Further, the fly ash contains a five-tonne enclosure for heavy goods, ensuring that it works properly, a heavy-duty hydraulic and pneumatic device considers performing this task. Otherwise, the production system is in idle time or stops.

Figure 6.7 Pneumatic and Hydraulic Valving with Silo Systems (Alibaba, 2021)

To organise technical efficiency in the grading (scale) systems (see Equation 6.16) for the three statuses measure is obtained as follows:

1). Qi > above 100% represents overuse of resources including:
   1.1) Large-scale ultra-sonic mill with vibration technology
   1.2) Traditional-scale ultra-sonic mill with vibration technology
   1.3) Material handling using drop-down methods
   1.4) Pneumatic and hydraulic valving with silos system
2). Qi = 100% is the normal expectation leading to optimisation
3). Qi = 50% to 90% is below expectation, classified as an idle production system
4). Qi = zero (not considered because of system down).

see Equation (6.16)

Legend

d = maximising travel distance of linear actuator valving function (e.g., same stroke around); Q_i = d
v = constant speed of the actuator
t = actuator travel time
Qi = di and $f(x_{i,}\,\beta)= f(v_i,t_i)$ and technical efficiency, TE

6.6.1.1.1 Application of the Three Statuses of TE_i

A Case 1 When $TE_i = 100\%$ obtained as follows

Table 6.15 Productivity Study Using the Empirical Stochastic Frontier With Technical Efficiency Equal to 100%

100% / Parameters	**Proposed Equations $d_k = v_j \times t_i$ when TEi =**	**Seeking Optimisation Using the Empirical Stochastic Frontier Analysis Measure Productivity When Technical Efficiency Equal to 100%**			
Items		**Travel Distances(d_i)**			
Velocity(v_j) - metre/second		0.045	$\boxed{0.05}$	0.0626	0.075
Time(t_i) - second		20	$\boxed{20}$	20	20
Distance(d_k) - metre		0.9	$\boxed{1}$	1.25	1.5
Processes		**Technical Efficiency = 100%**			
a)Large-scaled ultra sonic mill with vibration		100	100	100	100
b)Small-Scaled ultra-sonic mill with vibration		100	100	100	100
c)Drop-Down Method		100	100	100	100
d)Valving System		100	100	100	100
e) Kiln using hydrogen fuel		100	100	100	100
f) Wave technology		100	100	100	100
Average (%)		100	100	100	100
Subtotal, $Qi=f(x_{i,} \beta)\times TE_i$		$\boxed{90}$	$\boxed{100}$	$\boxed{100}$	$\boxed{150}$
		Below	Normal	Normal	Over

Legend

t = actuator travel time
v = speed of actuator
d = maximising travel distance

below = below return to scale
normal = normal return of scale(optimisation)
over = over return to scale

Table 6.15 illustrates when the TE_i equals 100%, including large/medium-scale ultrasonic mill, valving system, etc., at a velocity of 0.05m/s, taking 20 seconds finished 1-meter travel based on $Q_i = \sum_{i=1} v_i \, t_i$ the linear actuator. As a result, the drop-down vertical integration manufacturing method is more efficient than the traditional conveyer-belt material delivery method, minimising idle time. It also meets the time-to-client strategy in Tables 6.1 to 6.2 without incurring extra cost.

Budiono et al. (2021) and Deniz and Umunc (2013) addressed a flexible range of component functions, which can be more margin to adjust to find optimal system performance. Buliono et al. (2021) and Zhang et al. (2017) also used opportunistically for conditional maintenance of the facilities by intensively examining each component's functions and seeking alternative methods for optimal productivity. Bhattacharyya (2012) used the simulation method to model the chance of machine malfunction, resulting in organising conditional repairs and maintenance frequency, keeping TEi equal to one or 100%. Additionally, the survey outcome and machine product specifications provide data understanding more individual component functions capability of the pneumatic system, particularly in trimming the speed controller to a maximum speed of quickly opening and closing the valving system (see Appendix A12, Table A12.1 and Appendix A6, Tables 6.16 and 6.17 for further discussion).

Table 6.16 Productivity Study Using the Empirical Stochastic Frontier With Technical Efficiency Equal to 50%

Parameters / Proposed Equations $d_k = v_j \times t_i$ when TEi = 50%	Seeking Optimisation Using The Empirical Stochastic Frontier Analysis Measure Productivity When Technical Efficiency Equal to 50%			
Items	**Travel Distances(d_i)**			
Pneumatic and Hydraulic Valving System				
Velocity(v_j) - metre/second	0.045	0.05	0.0626	0.075
Time(t_i) - second	20	20	20	20
Distance(d_k) - metre	0.9	1	1.25	1.5
Processes	**Technical Efficiency, TE_i = 50%**			
a)Large-scaled ultra sonic mill with vibration	50	50	50	50
b)Small-Scaled ultra-sonic mill with vibration	50	50	50	50
c)Drop-down method	50	50	50	50
d)Valving system	50	50	50	50
e) Kiln using hydrogen fuel	50	50	50	50
f) Wave technology	50	50	50	50
Average (%)	50	50	50	50
Subtotal $Qi = f(x_{i,}\beta) \times TE_i(\%)$	45	50	62.5	75
	Below	Normal	Over	

Legend
d = linear actuator valving system maximising travel distance
v = speed of actuator
t = actuator travel time
below = below return to scale
normal =normal return of scale (optimisation)
over = over return to scale

B. Case 2.1 when technical efficiency is an average of 80%, obtained as follows:

Table 6.17 illustrates the average of 80% technical efficiency but consider trimming the speed of the speed controller, seeking optimal results, obtained as follows:

Table 6.17 Average 85% Technical Efficiency Distribution of the Proposed Production Facilities

Parameters / **Optimisation The Empirical Stochastic Frontier Analysis Measure**	**Case 2.2: When Various Technical Efficiency Due to Route Maintenance Using Proposed Equations, $d_k = v_j \times t_i$**			
Items	**Travel Distances(di)**			
Valving Systems				
Velocity(v_j) - metre/second	0.045	0.05	0.0626	0.075
Time(t_i) - second	20	20	20	20
Distance(d_k) - metre	0.9	1	1	1.5
Processes	**Various Technical Efficiency (%)**			
a) Large-scaled ultra sonic mill with vibration	60	60	60	60
b) Small-scaled ultra-sonic mill with vibration	60	60	60	60
c) Drop-down method	100	100	100	100
d)Pneumatic slide open/close system	100	100	100	100
e) Kiln using hydrogen fuel	100	100	100	100
f)Wave technology	90	90	90	90
Average Technical Efficiency (%)	85	85	85	85
Subtotal ($v_i t_i \times TE_i$%)	68.85	86.67	107.5	194.5
Legend	Below	Below	Normal	Over

below = below return to scale
normal = normal return to scale
over = over return to scale

d = maximising travel distance
v = speed of actuator
t = actuator travel time

Table 6.17 illustrates various technical efficiency performances at an overall average of 80%, including 60% loading of the large- and small-scale ultrasonic mill with a vibration device, 100% drop-down integrated process, kiln, and pneumatic and hydraulic valving at 100% performance and 90% of the wave technology working efficiently because of conducting routine maintenance to prevent breakdown.

In such a working environment, to continue plant operations, the hydraulic and pneumatic valving systems are calibrated at 0.0626 m/s with one-meter travel, resulting in an outcome of 107.5%. This is close to optimisation, resulting in the pneumatic and hydraulic actuator velocity reaching the design limits (see Appendix A12); otherwise, malfunction will occur because specifications are incorrect.

Additionally, the black box in Table 6.18 illustrates various technical efficiency performances at an overall average of 80% and a score of 100.16. It is an optimal result, providing a roadmap for cement entrepreneurs because it encourages them to undertake routine repair and maintenance tasks for these systems and large/medium ultra-sonic devices without affecting the mass customisation production performance, using trimming mechanical types of speed controller (see Appendix A6).

B. Case 2.2

Table 6.18 illustrates the average of 80% technical efficiency for large/medium-scale ultrasonic devices, with the actuator speed at 0.0625m/s in the open/close valving system.

Table 6.18 Average 80% Technical Efficiency Distribution of the Proposed Production Facilities

Parameters / **Optimisation The Empirical Stochastic Frontier Analysis Measure**	**Case 2.2: When Various Technical Efficiency Due to Route Maintenance Proposed Equation, $d_k = v_j \times t_i$**			
Items	**Travel Distances(di)**			
Valving Systems				
Velocity(v_j) - meter/second	0.045	0.05	0.0626	0.075
Time(t_i) - second	20	20	20	20
Distance(d_k) - meter	0.9	1	1	1.5
Processes	**Various Technical Efficiency (%)**			
a) Large-scaled ultra sonic mill with vibration	60	60	60	60
b) Small-scaled ultra-sonic mill with vibration	60	60	60	60
c) Drop-down method	100	100	100	100
d)Pneumatic slide open/close system	100	100	60	100
e) Kiln using hydrogen fuel	100	100	100	100
f)Wave technology	90	90	100	90
Average Technical Efficiency (%)	85	85	80	85
Subtotal ($v_i t_i \times TE_i$%)	68.85	86.67	100.16	194.5
Legend	Below		Normal	Over

below = below return of scale
normal = normal return of scale
over = over return of scale
d =linear actuator valving function maximising travel distance
v = speed of actuator and t = actuator travel time

Table 6.18 shows the average technical efficiency in 80%, maximising resource use.

C. Case 3 TEi = 110%

All large- and small-scale ultra-sonic mill with vibration and production technical efficiency equal to 110% travel at 0.05m/s and as obtained:

Table 6.19 Productivity Study of Items a) to f) Using the Empirical Stochastic Frontier With Technical Efficiency Equal to 110%

Parameters / **Optimisation The Empirical Stochastic Frontier Analysis Measure**	**Case 3: When TE=110%, Proposed Equation, $d_k = v_j \times t_i$**			
Items	**Travel Distances(di)**			
Pneumatic and Hydraulic Valving Systems				
Pneumatic slide velocity(v_j) - metre/second	0.045	0.05	0.0626	0.075
Travel time(t_i) - second	20	20	20	20
Travel distance(d_k) - metre	0.9	1	1.25	1.5
Technical Efficiency, TE_i = 110%				
a)Large-scaled ultra sonic mill with vibration	110	110	110	110
b)Small-scaled ultra-sonic mill with vibration	110	110	110	110
c)Drop-down method	110	110	110	110
d)Pneumatic slide open/close system	110	110	110	110
e)Kiln Using Hydrogen Fuel	110	110	110	110
f)Wave Technology	110	110	110	110
Average Technical Efficiency (%)	110	110	110	110
Subtotal, $v_i t_i \times TE_i$(%)	89	110	172	246
	Below	Over		

Legend
below = below return to scale
normal = normal return to scale
over = over return to scale
d = linear actuator valving function maximising travel distance
v = speed of actuator t = actuator travel time

The result is either under or over return to scale that minimise profit.

Case when $TE_i = 0$

Table 6.20 Productivity Study Using the Empirical Stochastic Frontier with Technical Efficiency Equal to Zero

Parameters / **Proposed Equations** $d_k = v_j \times t_i$ **when TEi = zero**	**Seeking Optimisation Using the Empirical Stochastic Frontier Analysis Measure Productivity When Technical Efficiency Equal to Zero**			
Items	**Travel Distances(d_i)**			
Pneumatic and Hydraulic Valving System				
Velocity(v_j) - metre/second	0.045	$\boxed{0.05}$	0.0626	0.075
Time(t_i) - second	20	$\boxed{20}$	20	20
Distance(d_k) - metre	0.9	$\boxed{1}$	1.25	1.5
Processes	**Technical Efficiency, TE_i = zero**			
a)Large-scaled ultra sonic mill with vibration	0	$\boxed{0}$	0	0
b)Small-Scaled ultra-sonic mill with vibration	0	$\boxed{0}$	0	0
c)Drop-Down Method	0	$\boxed{0}$	0	0
d)Valving System	0	$\boxed{0}$	0	0
e)Kiln Using Hydrogen Fuel	0	$\boxed{0}$	0	0
Average (%)	0	0	0	0
Subtotal, $Q_i = f(x_{i,}\beta) \times TE_i(\%)$	0	$\boxed{0}$	0	0

In this case, TE_i equals zero, and consequently the total productivity becomes zero. The company needs to rethink their manufacturing strategy.

6.6.1.1.2 Summary of Findings Using Empirical Stochastic Frontier Analysis Methods

Table 6.21 is a summary all trial-and-error results as below:

Table 6.21 Summary of Using the Empirical Stochastic Frontier Analysis Methods

Parameters	**Stochastic Fronter Analysis** $Q_i=f(x_{i,}\ \beta)\times TE_i$		**Six Technical Efficiency (TEi), Including Large and Small-scaled Ultrasonic Mill with Vibration Device, Drop-Down Method, Valving System, Kiln Using Hydrogen Fuel and Wave Technology**	**Results**
Velocity	**Travel Distance**	**Sub-total (di)**	**Average 6 Production Facilities Technical Efficiency at 100%**	**Subtotal**
Unit(m/s)	Unit(s)	Unit(m)	100	Unit (%)
0.045	20	0.9		81
0.05	20	1		$\boxed{100}$
0.0626	20	1.25		125
0.075	20	1.5		150
TEi = 50%			**Average 6 Production Facilities Technical Efficiency at 50%**	**Subtotal**
Unit(m/s)	Unit(s)	Unit(m)	50	Unit (%)
0.0465	20	0.9		45
0.05	20	1		50
0.0626	20	1.25		62.5
0.075	20	1.5		75
Various Technical Efficiency for Individual Production Facilities but Average TEi = 85%			**Average 6 Production Facilities Technical Efficiency (%)**	
Unit(m/s)	Unit(s)	Unit(m)	Unit (%)	Subtotal
0.045	20	0.9m	85	68.85
0.05	20	1m		86.67
0.0626	20	1m		$\boxed{107.5}$
0.075	20	1.5m		194.5
Various Technical Efficiency for Individual Production Facilities but Average TEi = 80%			**Average 6 Production Facilities Technical Efficiency (%)**	
Unit(m/s)	Unit(s)	Unit(m)	Unit (%)	Subtotal
0.045	20	0.9m	80	68.85
0.05	20	1m		86.67
0.0626	20	1m		$\boxed{100.16}$
0.075	20	1.5m		194.5

Table 6.21 (Continued) Summary of Using the Stochastic Frontier Analysis Methods

TEi = 110%			**Average 6 Production Facilities Technical Efficiency (%)**	Subtotal
Unit(m/s)	Unit(s)	Unit(m)	Unit (%)	Unit (%)
0.045	20	0.9	110	89
0.05	20	1		$\boxed{110}$
0.0626	20	1.25		172
0.075	20	1.5		246
TEi = 0%			**Average 6 Production Facilities Technical Efficiency (%)**	
Unit(m)	Unit(s)	Unit(m)	0	Unit (%)
0.045	20	0.045		0
0.05	20	1		0
0.0626	20	1.25		0
0.075	20	1.5		0

Table 6.20 summarises the trial-and-error results, which use the change of the technical efficiency parameters at the setting actuator speed at 0.05m/s and 20 seconds finished one-meter distance (valve diameter), meeting the design criteria shown in Table 6.21 black boxes, show the optimal result. This is the most economical way to achieve company goals with less investment and to execute the time-to-market strategy shown in Tables 6.1–6.2.

Further, the pneumatic/hydraulic systems facilitate variable speed controllers for speed adjustment. Therefore, three options identify near optimisation under different combinations of the known equations (e.g., velocity multiplied time) and a variety of technical efficiencies, resulting in conducting routine repair and maintenance tasks. This pneumatic/hydraulic system is suitable for temporary part substitution to achieve continuous system operation by trimming the hydraulic and pneumatic valving systems' velocity within the system design limit, avoiding downtime. Therefore, the functional format of technical efficiency using input divided by output equal to 100% into the equation also keeping full load conditions, resulting in an optimal productivity result.

A cement entrepreneur determines the manufacturing strategies to maximise profit and resources used in small lot businesses.

6.7 Compare between classic Cobb-Douglas production function and empirical analysis for productivity measures

New production technology instead of traditional methods is involved in manufacturing Portland-based cement. Therefore, the total productivity for the empirical stochastic frontier analysis method is close to 100% due to machine-intensive work that minimises profit. The result is shown in Table 6.22 as below:

Table 6.22 Comparison of Productivity Measures Between Classic Cobb–Douglas Production Function and Empirical Stochastic Frontier Analysis Method for Small Lot Cement Production

Productivity Tools	**Comparison Two Methods**
Classic Cobb–Douglas Production Method	from 97.3% to 100.4% ranges
Empirical Stochastic Frontier Analysis	100%, 100.16%, 107.5% and 110%

The Cobb–Douglas production function productivity results are from 97.98 to 100.4%. The empirical stochastic production analysis outcomes are 100 to 110% due to technical efficiency performance and the defined equation (e.g., velocity is multiple by a time equal to distance). Both approaches use trial-and-error methods to seek optimum measures for machine-intensive production environments, resulting in variety. This is because the parameters of the two tools rely on their characteristics. The Cobb–Douglas production function focuses on labour, capital and elasticity and is classified as a rigid equation. However, the customised stochastic frontier analysis equation is intended to compensate for the Cobb–Douglas production function and does not concern issues of machine performance, such as malfunction or idle time. The cement entrepreneur can formulate manufacturing strategies based on the two tools' outcomes.

Further, both tools have their advantages, disadvantages, and limitations. This study uses new production methods, including simulation, putting the ideal processes in a virtual environment to seek an optimisation process, and then collecting data. However, there is a limitation. Developing a simulation model needs mega-data, identification of process independence, similar production methods and other factors.

In addition, traditional cement manufacturing is suitable for mass production because there is less market demand (CIF, 2023). As a result of the government's infrastructure stimulus plan (2019) and small- and medium-scale projects, the market segments are more complex and price competitive. Therefore, mass customisation is a mainstream approach in the market.

Furthermore, Cement Industry Federation (2023) addressed customised cement production subcontracts to overseas or small Australian-owned companies as a general practice of international cement company in the past decades. However, this method suffers from quality and time-to-market issues, particularly in COVID-19 pandemic worldwide. As a result, this minimises profits and will be business competitors' small lots of cement in the foreseeable future (Ghosh and Kalagnanam, 2006; Gosling, 2011).

6.8 Compared advantages and disadvantages of two methods

Table 6.22 illustrates both tools' advantages and disadvantages. The problem is long calculation, which can lead to mistakes. The following can resolve this issue:

- Customised Excel™ using an embedded visual basic application program is user friendly, and the function 'What if analysis' it allows the user to set target cell and thus void data trap
- Tailor-made Python™ enables online manipulation of data and calculation to minimise calculation mistakes.

Table 6.23 Compared Advantages and Disadvantages of Classic Cobb–Douglas Production Function and Empirical Stochastic Frontier Analysis Methods for Portland-based Cement Production

Method	Advantages		Disadvantages	
	Classic Cobb–Douglas Production Function	**Empirical Stochastic Frontier Analysis**	**Classic Cobb–Douglas Production Function**	**Empirical Stochastic Frontier Analysis**
$F(X_i, \beta)$	Trial-and-error enabling keep factor, capital labour constant	Collect data to develop equation	Calculation mistakes	Suitable for small lot but calculation mistakes
TE_i	Trial-and-error enabling keep factor, capital labour constant	Collect data to develop equation	Calculation mistakes	Suitable for small lot but calculation mistakes
$F(K^{\alpha}, L^{\beta})$	Trial-and-error enabling keep factor, capital labour constant	Collect data to develop equation	Calculation mistakes	Suitable for small lot but calculation mistakes
$f(\alpha, \beta)$	Expert advice with wide range of data	Expert advice with wide range of design specifications	Calculation mistakes	Suitable for small lot but calculation mistakes

6.9 Compared classic Cobb-Douglas production function and empirical stochastic frontier analysis for productivity measures

Various changes to α, β parameters using the classic Cobb–Douglas production functions are based on keeping capital and labour constant, with two shifts because of workmanship issues, less capital investment, and minimising resources; the result is promising. The classic Cobb–Douglas production function is suitable for a mass production manufacturing environment because of capital and labour parameters,

However, the empirical stochastic frontier analysis method is for technology and machine-intensive fabrication because the technology efficiency concerns production facilities' performance.

Both tools need significant quantities of data for further equation study.

6.10 Compendium

This section discusses the development of Scenario 2: simultaneous fabrication of three Portland-based cement types. The data collection was achieved via the following:

- Survey (see Appendix A11)
- Agent-based simulation models
- Related articles, including financial reports (Company X, 2021)
- Related associations and institutions like CCAA.

The mining tool XLMiner™ (Chan, 2018) can integrate multiple sources into a single source for further development:

- The linear regression equation is for empirical stochastic frontier analysis with the three statuses for technical efficiency and machine-intensive performance study.
- It also closely examines the three statuses of elasticity for the classic empirical Cobb–Douglas production function of the productivity measure in an environment of new technologies.

Scenario 2 uses the voice of house of deployment in mass customisation for the modularity preference outcome and mix-and-add-in. This is associated with Anderson's (2005) approach to developing a simulation model for the optimisation processes of data collection under new production involving (see Appendices A6 to A8 and Appendix A11). The roles of these new technologies are to replace traditional methods (see Appendices A1 to A5) for optimal results. Anderson's approach is also used to identify the following:

A. Attribute Independence, such as raw materials
B. Process Independence: the processes flow of traditional cement production and new technologies' fabrication methods
C. Similar Process: the same process is used to produce cement types that have the same structure

A. Attribute Independence: raw materials and production facilities belong to his group. The materials include sand, clay limestone(lime), slag and gypsum. The production facilities are traditional cement production machines and methods (see Appendices A1 to 5) and new techniques involved in production (see Appendices A6 to A7, Appendix A10, Appendices A12 and A14).
B. Process Independence: Appendix A5 represents traditional cement production, but Appendix A14 is a new production method for productivity improvement.
C. Similar Process: due to simultaneous parallel production to improve productivity, this study identifies ordinary Portland (GP), blend Portland (GB), and high early strength (HE) type cement as having the same structure but different processes for fabrication and quality. Therefore, adding or eliminating manufacturing process via the simulation model method solves this issue, ensuring that clients' cement needs are met. This method can solve a variety of small lot customised cement production problems due to frequently changing production status.

Combining with the other outcomes, this result provides an opportunity for further study based on the change in the three statutes of elasticities for the classic Cobb–Douglas production function of productivity measures:

$$f(\alpha,\beta)=\begin{cases}\alpha+\beta=1\\ \alpha+\beta\leq 1\\ \alpha+\beta\geq 1\end{cases}$$

Various case studies are illustrated in Equations (4.9) to (4.14) and Tables 4.24 to 4.32. The result is promising. This study' main finding of $\alpha+\beta\leq 0.9$ and $\alpha+\beta\leq 1.1$ status can be achieved optimal productivity for returns to scale instead of most researchers addressed that $\alpha+\beta=1$ (Griffin, 2011; Coelli et al., 2005; Dirata et al., 2019; Lin et al., 2014).

The alternative productivity measure is the empirical stochastic frontier analysis method shown below:

$$q_i = f(x_i, \beta) \times TE_i \begin{cases} TE_i = 1 \\ TE_i \leq 1 \\ TE_i \geq 1 \end{cases}$$

As a result of the linear motions of all new production facilities, the analysis method was identified as $f(x_i, \beta)$, a linear regression equation, and conjugated with three statutes of technical efficiency, TEi. But the findings show that the production facilities have experience no breakdowns in the past decades (e.g.,$TE_i = 1$).

Additionally, both tools are for productivity measures and have advantages and disadvantages. Their limitations must be carefully considered before being applied to cement industry performance measures.

6.11 Summary

This section summarises the approaches of Chapters 4 and 6:

- Data collection methods in Chapter 4
- Applications using scenarios and results in Chapter 5 and 6 based on Chapter 3's proposed framework

Chapter 4 discusses the different data collection and analysis methods to develop various simulation models, formulate the classic Cobb–Douglas production function, and formulate the empirical stochastic frontier analysis based on mini-advanced integrated cement factories (Chan, 2018) with assistance of the voice of house of deployment in the mass customisation matrix modular preference.

The two scenario studies of major cement manufacturers are detailed in chapters 5 and 6. These are based on one of the mining tools, XLMiner™, to derive multiple sources for the development of a linear regression equation for the empirical stochastic frontier analysis and provides further in-depth data to study the classic Cobb–Douglas production function by changing the combination of two elasticities, resulting in measuring optimal productivity. The role of one sub-tool, the voice of the house of deployment of the mass customisation matrix, is for the modularity preference. Therefore, the mix-and-add-in modularity is the best of the class, meeting the voice of both manufacturers and customers. Another tool is from Anderson (2005) and is used to identify attribute independence, process independence and process similarity for simulation model development. These are:

- Attribute Independence: production facilities, raw materials and finished goods
- Process Independence: cement production methods such as mass customisation
- Process Similarity: geopolymer-based and Portland-based cement are homogeneous and heterogeneous materials. FA-based geopolymer, MK-based geopolymer and GBBFS-based geopolymer are from the same product series. They have the same material behaviour and structures and similar production methods, classified as homogeneous materials and have similar processes. Therefore, simulation based on these characteristics develops a series of optimisation models.

The two scenarios in chapters 5 and 6 study a variety of customised cement types:

A. Scenario 1 illustrates a variety of geopolymer-based cement production methods at the same time.
B. Scenario 2 illustrates a variety of Portland-based cement production methods at the same time.

A. Scenario 1: discussed data and analysis collected from multiple sources. XLMiner™ used their outcomes to develop the linear regression equation for the empirical stochastic frontier for productivity measures and to further study the classic Cobb–Douglas production analysis equation. This chapter discussed two sub-tools to assist the main tools and closely examine:
   - Modularity preference using the voice of the house of deployment in mass customisation, ensuring the voice of customer and manufacturer needs
   - Modelling methods for the optimisation process, putting actual practice into virtual manufacturing and capturing dynamic data for visual management instead of the manual flow chart method because this can quickly solve frequently changing customised cement production statuses.

It also used the trial-and-error method, seeking an essential combination of two elasticities for optimum normal returns to scale for the classic Cobb–Douglas production function equation. Here, many new production methods and technologies are involved in geopolymer-based production. Therefore, carefully studying the machine performances and developing a related equation for the empirical stochastic frontier analysis equations involves:

- Commercial-scale ultrasonic and vibration device for precious grinding
- Commercial-scale ultrasonic and vibration and wave technologies device for mixing and grinding
- Vertical integrating manufacturing method
- Special enclosure facilitated with valving system for fly ash collection and directly involving or interacting with sodium hydroxide solution for fabrication FA-based geopolymer cement. All such technologies are identified linear motion and equation as well.

$$f(\alpha,\beta) = \boxed{\begin{cases} \alpha_i + \beta_j = 1 \\ \alpha_i \ + \beta_j \leq 1 \\ \alpha_i \ + \beta_j \geq 1 \end{cases}}$$

where $\alpha_i$and β_j are dependent and independent variables i and j are variables

Probing further and considering various combinations in the black box, one of the typical outcomes meets the optimal productivity as follows:

- $\alpha_i + \beta_j \leq 0.9$
- $\alpha_i + \beta_j \leq 1.1$

This finding is a challenge for current researchers, who have addressed $\alpha_i + \beta_j = 1$ as the normal returns to scale. However, the Scenario 1 result is when $\alpha_i + \beta_j \leq 0.9$, it is the optimal return, maximining resource uses and satisfying customer needs. Another finding is $\alpha_i + \beta_j \leq 1.1$, which is also optimum, but the status is over returns to scale, resulting in unnecessary resource use that minimises profit.

The alternative productivity measure is the empirical stochastic frontier analysis method below:

$$q_i = f(x_i,\beta) \times TE_i \begin{cases} TE_i = 1 \\ \boxed{TE_i \leq 1} \\ TE_i \geq 1 \end{cases}$$

The $f(x_i,\beta)$ identifies as a linear regression equation because of linear motions. Based on a survey finding of the production facility, the outcome is $\mathrm{TE_i} = 1$ (in the black box) due to malfunction, breakdown records and other factors. Using the simulation-modelled impacts in case of technical efficiency is less than one. All is in the idle time and increasing of non-conformity products. Therefore, the performance is promising and always in full-put condition.

B. Scenario 2: discussed data and analysis collection from multiple sources. XLMiner™ used their outcome to develop the linear regression equation for the empirical stochastic frontier for productivity measures and to further study the classic Cobb–Douglas production analysis equation. This chapter discussed two sub-tools to assist the main tools closely examine:

- Using the manual process flow to develop traditional cement manufacturing, and later undertaking the modelling method to organise cement production to collect dynamic production data and solve bottleneck problems. Therefore, this involves comparison advantages and disadvantages of data manipulation.
- The role of developing the voice of the house of the deployment in the mass customisation matrix is for the modularity preference instead of the popular methods used by the current researchers. Thus, it is a scientific measure of precious selection.
- It also implemented mass customisation technologies to assist the agent-based simulation model in finding optimal processes.
- It collected and analysed multiple sources using the XLMiner™ tool, developing various linear regression equations for the empirical stochastic frontier analysis and formulating the classic Cobb–Douglas production function.
- It also scrutinised various elasticities of the classic Cobb–Douglas production function, seeking under which conditions total productivity is achieved. The outcome is promising because many researchers addressed $\alpha_i + \beta_j = 1$ as the normal return to scale. But $\alpha_i + \beta_j \leq 0.9$ also have a close score, resulting in an alternative to optimal productivity. Therefore, several factors affect the return to scale performance:

    - production priorities
    - resource capabilities
    - customer satisfaction.

The alternative productivity measure is the empirical stochastic frontier analysis method shown below:

$$q_i = f(x_i, \beta) \times TE_i \begin{cases} TE_i = 1 \\ TE_i \leq 0.5 \\ TE_i \geq 1 \end{cases}$$

The setting for technical efficiency is 1, 0.5 and greater than one for assessment based on survey findings regarding machine performance. It donated normal, under and over returns to scale. Under or above is represented in the idle time, frequent breakdown and increasing non-conformity products. The technical efficiency is always in full-put condition (e.g., 100%).

Both methods have their advantages, disadvantages, and limitations.

Advantages and Disadvantages

- Two tools are used to measure productivity, but in different orientations:
    - The classic Cobb–Douglas production methods essentially apply to the labour-intensive industries using mass production methods. This is because all production methods rely on labour skills and standard manufacturing methods. The equation is rigid. Therefore, trial-in-error can obtain the answer.
    - The empirical stochastic frontier analysis is a flexible equation because of two elements in the function $f(x_i, \beta)$ format, and another technical efficiency, TEi, concerns machine performance. So, it takes them to collect data for equation management.

Limitations

- Both tools need long calculations and easily make mistakes in the computing process. Free statistic software like RStudio™ and Python can effectively help, but customised coding is required. Zhu (2003) addressed that the spreadsheet is the economical way to gather and analyse data, enabling data sharing. So, Excel™ is an alternative.
- As a result of new technologies' involvement with innovative production, taking time for the data collection on machine performances for equation development means that agent-based simulation modelling methods can quickly achieve visual management.

CHAPTER 7: RESULTS

Chapter 4 discussed detailed data collection (undertaken using methods such as surveys and simulation) and analysis of geopolymer-based and Portland-based cement production processes. Chapters 5 to 6 explored scenarios 1 and 2 using trial-and-error and varying two elasticities α, β while keeping labour, capital, and total productivity constant to further investigate mass customisation production, seeking to maximise productivity methods in technology-intensive manufacturing environment and aligning with the methodology discussed in Chapter 4 results. To better understand multiple data sources, this research used a data mining tool, XLMiner™ (Chan, 2018), to develop the empirical stochastic frontier analysis aligned with technical efficiency seeking optimal productivity, including return of scale. This study summarises their advantages and disadvantages based on the results for the two productivity tools.

7. INTRODUCTION

The results found in chapters 4 to 6 are based on the classic Cobb–Douglas production function (see Section 3.5; Section 3.5.1), the empirical stochastic frontier analysis (see Section 3.4.2) and a variety of simulation methods focused on the optimisation process using the agent-based modelling method associated with superior modularity preference in mass customisation to measure customised small lot geopolymer-based and Portland-based cement at the same time (Wacker, 1975). Each method's purpose is detailed below:

A. *Classic Cobb–Douglas Production Function Measures*. This is one of the methods for measuring cement plant productivity using advanced production technologies. This research used both change elastics α_i and β_j within the three combinations of α_i and β_j as obtained:

$$f(\alpha, \beta) = \begin{cases} \alpha_i + \beta_j = 1 \\ \alpha_i + \beta_j \leq 1 \\ \alpha_i + \beta_j \geq 1 \end{cases}$$

where $\alpha_i$and β_j are dependent and independent variables i and j are variables

Two scenario studies for geopolymer-based and Portland-based cement production using the classic Cobb-Douglas production function the intervals α_i, increasing 0.1 intervals and the corresponding β_j decreasing 0.1 by this amount and vice versa, keeping productivity factor, capital and labour constant within the defined limits. This resulted in optimum combinations, minimising downtimes, and ensuring optimum size and minimum the results create opportunities to achieve long-and-short terms savings. The expected outcome is as follows:

- Minimise labour force but improve productivity (see chapters 5 to 6)
- Mechanise simplified processes (simulation) (see Figure 4.15, Appendices A13 to A14)
- Minimise risk but lower cost of capital, including production facilities (see Chapters 5 to 6)

A. the significant outcomes of optimal productivity are as follows:

- $\alpha + \beta = 0.9$ when $\alpha = 0.23$ and $\beta = 0.67$, and the result is 99.27. The outcome is 99.37 (see Table 4.30 and Section 4.4.1.7.1).
- $\alpha + \beta = 1$ is the traditional expectation solution (Long et al., 2015; Lin and Du, 2014). This finding shows that machine-intensive labour instead of number of workers can achieve small lot production (see Section 3.5.1, Section 3.51.1, Equations 3.8 to 3.9).

B. *Empirical Stochastic Frontier Analysis Method.* This identifies all processes in the proposed manufacturing method as linear regression equations using modern production technologies such as wave-by-wave technologies and vibration types (see Appendix A8) instead of conventional mixers methods (see Appendices A1 to A5) and so on for optimal productivity measures.

C. *Simulation Method*. This method examines the optimisation of manufacturing process flow. It provides fly ash, metakaolin-based geopolymer and Portland-based (GP, GB, HE and GL) alternative cement production process flow to improve agile customisation for small lot production, minimising downtimes and resource use and maximising production facilities use, including via a vibration-type mill (Gao and Yan, 2017), wave-by-wave (Tang et al., 2018a; 2018b) equipment and a linear actuator valving system (Hou et al., 2015) instead of traditional cement production methods (CIF, 2023) until optimal productivity is achieved. Further, a modelling method associated with mass customisation technology is to develop a simulation model. This includes:

- Attributes independence (raw materials)
- Process independence (production facilities)
- Similarity processes (homogenous and heterogenous structures).

Chapter 4 discussed the simulation model for optimisation process flow; Chapter 5 discussed a simulation model for the fabrication of geopolymer-based cement using the agent-based modelling method for optimisation processes; Chapter 6 discussed a simulation model for the fabrication of Portland-based cement using the agent-based modelling method for optimal productivity.

Chapters 5 to 6 detailed the process of exporting data to Excel™ to customise the empirical stochastic frontier analysis and to formulate the classic Cobb–Douglas production function equation to examine productivity outcomes.

All these methods provide optimisation of cement plant operations at an economically efficient scale, thus helping entrepreneurs maximise profit, minimise resources, and maintain core values and competitive advantage in customised small lot cement manufacturing.

7.1 Method of evaluation for small lot production productivity based on outcomes from chapters 4 to 6

Section 7.1.1 details the selection criteria and Section 7.1.2 explains the evaluation based on the selection criteria.

7.1.1 Selection criteria

There are two parts to the selection criteria:

a) Productivity measures. These examine any impact on productivity using a variety of parameter changes. The goal is to maximise the use of production facilities for agile small lot production.

b) Mass customisation. This examines modularity capability to identify an attribute of independence, independence process and process similarity. The goal is to maximise the development simulation model one step further to achieve realistic production methods. It also provides guidelines to capture relevant data to develop an agent-based, export data database system using Excel™.

7.1.2 Evaluation based on selection criteria

Table 7.1 Score Board

Case Study	Aims	Productivity Measures Related to Two Tools	Mass Customisation Associated with Simulation
Scenario	Seeking Optimum	1 2 3	1 2 3

Table 7.1 illustrates the method of evaluating the two scenario performances across two areas with respect to productivity measures and mass customisation.

A three-point scoring scale was developed, from 1 to 3 (1 being the lowest score and 3 being the highest), as shown in Table 7.1. The scores are detailed below:

a) The scenario outcome scale scored 1; as a result, *does not meet* the requirement because of the two methods' non-optimal productivity.
b) The scenario outcome scale scored 2; It *does not fully meet* the requirement because of the two methods' non-optimal productivity.
c) The scenario outcome scale scored 3; The outcome *fully meets* the requirement and achieves optimal productivity.

7.1.3 Score results of the evaluation

Table 7.2 Score Results

Item / Chapter	Aims	Productivity Measure Score	Mass Customisation Score
Chapter 5: Scenario 1	Change of elasticity to measure production status for *geopolymer-based* cement (e.g., fly ash, metakaolin-based) using the classic Cobb–Douglas production function and the empirical stochastic frontier analysis methods based on Chan's (2018) mini advanced cement factory.	3	3
Chapter 6: Scenario 2	Change of elasticity to measure production status for *Portland-based* cement (e.g., GP, GL, HE) using the classic Cobb–Douglas production function and the empirical stochastic frontier analysis methods based on Companies X, Y and Z (2021) and Chan's (2018) mini advanced cement factory.	3	3

Table 7.2 summarises the scores of two productivity measure tools and mass customisation technologies for scenarios 1 and 2 in Chapters 4 to 6. All of them fulfil requirements and attain full marks.

Additionally, the classic Cobb–Douglas production function and the empirical stochastic frontier analysis methods work collectively as the voice of the house of deployment in mass customisation to develop a series of simulation models to optimise production processes for a variety of customised small lot Australian-owned factories; this approach is based on Chan's (2018) cement plant layout and the new involvement of new technologies in production and methods for productivity measures. The result is promising for both tools' outcomes, which can provide expert advice to decision-makers that will allow them to reorganise their strategies.

It also significantly improves customers' relationships with manufacturers because of involving the voice of the house of deployment in the mass customisation matrix to develop mutual understanding of working procedures. Therefore, it shortens the product production life cycle, avoiding over-subcontracting to overseas cement factories. This is a business tactics that can keep core business sustainable and enhance competitive advantages to achieve a healthy balance sheet (Companies X and Y, 2021).

7.2 **Compendium**

This section discusses scenarios 5 and 6 performances and has a promising result in productivity measures and applications of mass customisation.

7.3 comparison of productivity tools

This section summarises and compares various methods associated with assistance tools to measure the mass fabrication of products for which there is market demand and to enhance productivity for the mass customisation of customised cement.

Additionally, this satisfies customer expectations and maximise profit and resource use. Enriching the two productivity measures involves:

- Mass customisation technologies, including modularity and deployment of the voice of mass customisation: the purpose is to develop a simulation model to captures related attributes, etc. Thus, the simulation model generated the expected data for further assessment and provided a databased system similar to Access™. This is a Microsoft Office software product and can interact with simulation for data exchange. This pack is suitable for small- and micro-scale cement factories because of its many users worldwide.
- Manual process chart: the purpose is to give an idea of the traditional process flow for FA-based and Portland-based cement production. A simulation model based on its approach develops optimisation flow.
- Simulation modelling: the purpose is to provide optimisation process flow.
- Customised spreadsheet using the visual basic application functional tool: the purpose is to give a lengthy systematic calculation.
- Customised Python™ minimising calculation mistakes: the purpose is to improve calculation efficiency and minimise computing errors.
- Customised database system: the purpose is to provide alternative storage of data like the data-based system, Excel™, which is data transferred from AnyLogic™.

All these tools can work collaboratively and without time restrictions to monitor mass production and customised cement production performance. They are suitable for small- and micro-scale cement plants. Further, each can work individually and has several advantages based on the proposed framework flow processes. The above tools can also validate the proposed framework functionality, availability, and flexibility to measure cement industry productivity in the Australian business environment.

Table 7.3 Comparison of Productivity Tools

Associated Tools \ Method		Classic Cobb–Douglas Production Function	Empirical Stochastic Frontier Analysis
Mass Customisation Technologies	Modularity	Provided modularity alternatives to assist simulation model development.	Provided modularity alternatives to assist simulation model development, generating expected data.
	Voice of House of Deployment of Quality (Mass Customisation) Matrix	Measured the suitability of modularity based on the voice of customers (e.g., cement requirement) and manufacturers matric	Measured the suitability of modularity based on voice of customers (e.g., cement requirement) and manufacturers matrix
Manual Process Chart		Provided traditional flow of geopolymer-based and Portland-based process flow, but it cannot solve the dynamic production data. Simulation is one of the solutions.	Provided traditional flow of geopolymer-based and Portland-based process flow, but it cannot solve the dynamic production data. Simulation is one of the solutions.
Excel™ or Access™ (Customised Database System) Conjugated with XLMiner™ and Excel™		Integrated all related sources data to formulate the classic Cobb–Douglas production function for productivity small lot production measures.	Integrated all related sources data for development the empirical stochastic frontier analysis for productivity small lot production. The expected data enrich the data warehouse (Excel™) capability.

Table 7.3 Comparison of Productivity Tools (Continued)

Simulation Modelling	Simulated geopolymer-based and Portland-based cement production process in a virtual environment. The input data, such as machines capabilities, manpower and costs, are part of the development of modelling	Simulated geopolymer-based and Portland-based cement production process in virtual environment. The input data, such as machines capabilities, manpower and costs, are part of the development of modelling. The expected data enrich the data warehouse (Excel™) capability. The development linear regression equation for empirical stochastic frontier analysis derived is derived from the data warehouse
Customised Spreadsheet Using what-if function which is embedded in Excel™	Used to be efficient and effective to calculate the classic Cobb–Douglas production equations	Used to be efficient and effective to calculate the empirical stochastic frontier analysis equations, avoiding calculation mistakes
Customised Python™	Minimised calculation mistakes	
Customised RStudio™		Ensure optimisation process
Customised Database System (Excel™) Conjugated with AnyLogic™ and XLMiner™		Provided alternative sources to develop linear regression equations using the empirical stochastic frontier analysis method

7.4 Summary

This chapter has reviewed the achievements of Chapters 2 to 6. It compared the two tools and sub-tools for small lot productivity measures based on suitability and capabilities; they have advantages, disadvantages, and limitations, but as they are tailor-made, they can be realistically applied to Australian-owned businesses (see Chapter 5, Section 5.3). The discussion below uses to measure by main and sub-tools methods as follows:

Two main tools:

- Classic Cobb–Douglas production function
- Empirical stochastic frontier analysis.

Several sub-tools:

- Mass customisation technologies
- Voice of the house of the deployment in mass customisation
- Manual process chart
- Simulation modelling
- Customised spreadsheet.

This chapter also evaluated the performances of the two tools based on a scale system. All meet the requirements.

7.5 Conclusion

The studies detailed in the previous chapters have yielded several findings:

- The traditional $\alpha_i + \beta_j = 1$ is normal return to scale, resulting in optimal productivity. But $\alpha_i + \beta_j \leq 0.91$ and $\alpha_i + \beta_j \leq 1.1$ can also have close results: they are 99.37 and 100.4 respectively because of the involvement of new technology and methods in the parallel production geopolymer-based cement.

Although satisfying customers' needs is a priority based on the voice of the house of deployment in the mass customisation matrix outcome, carefully collecting numerous data and undertaking analyses before formulating a less risky manufacturing strategy, such as a productivity measure tool, is one of the keys to success for a sustainable business. Additionally, risk management is a process of finding, assessing, and controlling threats to a company's healthy balance sheet (Kumbhakar et al., 2015).

Each cement factory in Australia has core values and competencies in its manufacturing and returns to scale strategy. However, this research considers maximising profit without incurring extra costs. Further, related methods used in this research involve significant quantities of data for different purposes. Therefore, a database system such as Access™, Excel™ and so on for future analysis is both:

- A reliable source to provide data to develop linear regression equations for the empirical stochastic frontier analysis of productivity measures.
- A reliable storage system that can retrieve static and dynamics data from multiple-dimension data.

Further, manual calculation processes can lead to computing mistakes in online monitoring of cement plant performances. Customisation of Python™ and RStudio™ can speedily solve calculation mistakes, as shown in Appendices 17, Figures A17.1 to A17.3. They are free software programs that are compatible with Microsoft Excel™ and AnyLogic™, resulting in visual management for quicker trickling dynamic production performance. This can lead to speedy reorganisation of manufacturing and business strategies.

In the survey, the company Z (2021) uses RStudio™ in R Editor to perform this task to minimise calculation mistakes and online monitor plant performances, maximising the individual strengths of these types of software as shown in Appendix A17 show how to work with. Additionally, it maximises the use of public free of charge-based software. This software can work on laptops and tablets to trick production performances. One of the examples is that they also allow users to click inside variables using the proposed short programming trickling single process or manipulating data as below:

```
>capability<=read.csv("capability_opc.csv")
```

Name of Spreadsheet

Customised codes for productivity

Simple RStudio™ program

```
>fix(capability)
```

Manipulating

Optimal capability (100) data upon optimal using spreadsheet

Additionally, the filename 'capability' in a spreadsheet like the one shown in the red and green boxes is one of the alternative methods of examining data parameters for speedy productivity analysis using the 'fix ()' function based on Behr's (2015) approach.

This method is less investment and online monitors plant performance using integrated RStudio™ software with Arduino™ hardware. This system can replace expensive supervisory control and data acquisition (SCADA) systems. SCADA is a control systems architecture comprising computers, network data communications and graphical user interfaces supervisorial of machines and processes. It also covers sensors and programmable logic controllers (PLC), which interface with process plants or machinery (Radvanovsky and Brosky, 2010). Arduino™ is manufactures single-board microcontroller kits for building digital devices. Company Z (2021) used multiple purposes sensors to collect technical efficiency data.

CHAPTER 8: CONCLUSIONS

This chapter concludes the overall study of the research topic and research questions. It also discusses the findings and limitations and proposes avenues for future research.

8.1 Two parts to answering the research questions

8.1.1 Question A1 research question: working collaboratively and approaches to answer research questions

- How does mass customisation technology (mix-&-add-in modularity) work collaboratively with simulation models to provide information for optimising the production manufacturing process?

8.1.1.1 Work Collaboratively

This section discusses customisation technologies that work collaboratively with the simulation model to provide optimistic process data.

First, the literature review in Chapter 2 examined the relevant articles on what current researchers have achieved and their application methods. As a result, six modularities were identified, each with its own advantages, disadvantages, and limitations. To solve this problem, Anderson (2004) addressed the essential elements of development modularity (see Chapter 2 Literature, Section 2.2):

a) Attributes independence
b) Process independence
c) Similarity processes

Second, items a) to c) provide fundamental approaches and data for the simulation model development method, leading to expert opinions for optimum modularity process selection (Vianna et al., 2017) through the data exchange icon due to unlimited use.

The next section further discusses concept identification for data collection that effectively further studies the productivity measures of the two main tools.

8.1.1.2 Approaches to Answering Research Questions

Below are distribution step-by-step approaches in each chapter for various modularities, modelling methods and implementation studies. As a result, the two sub-tools work collaboratively for optimum outcome process data to assist two main productivity measures.

a) Chapter 2 Literature Review, Section 2.3.1 Simulation, Chapter 3, Section 3.3.1: Simulation Model; chapters 4 to 6 Simulation Method
b) Chapter 2 Literature Review, Section 2.4, Layout for Cement Production Facilities; Section 2.4.1, Layout for Cement Production Facilities; Section 2.4.2 Survey
c) Chapter 3, Section 3.1.1, Measure Variety of Mass Customisation Technologies Based on Modularity
d) Chapters 5 to 6, Simulation Model for Fabrication of Geopolymer-based Cement
e) Chapter 5 Scenario 1, Compare Classic Cobb–Douglas Production Function and Empirical Frontier Analysis for Productivity in Geopolymer-based Cement (measures and compares advantages and disadvantages of two methods)
f) Chapter 6, Scenario 2, Compare Classic Cobb–Douglas Production Function and Empirical Frontier Analysis for Productivity in Geopolymer-based Cement (measures and compares advantages and disadvantages of two methods; proposes optimisation to produce GP, GB, and HE cement via a simulation model).

Items a) to c) are prerequisites for e) and f), resulting in the use of trial-and-error to seek optimisation of returns to scale. One finding of the empirical stochastic equation is the linear regression equation. Its approach is one of the scientific ways of determining quantitative measures to validate parts of the proposed framework.

8.1.2 A2 Research question: derived data and change the classic Cobb-Douglas production function parameters

- How does the function $f(x_i, \beta)$ from the empirical stochastic frontier analysis equation derive from first and second sets of data sources, such as simulation, survey, and cement, and aggregation associations? How do changing parameters in the Cobb–Douglas production function affect productivity measures?

8.1.2.1 Derived Data

This research adapted Chan's (2018) approach using data mining methods, XLMiner™ and extended skill based on Table 4.7's equations development method. The results were derived from the simulation models outcome, survey, and trial-and-error for the classic Cobb–Douglas production function measure and the empirical stochastic frontier analysis equation development. One finding for all production facility operations is the linear regression equation due to new and state-of-the-art production involving optimistic process study.

8.1.2.2 Change the Classic Cobb–Douglas Production Function

Changing the classic Cobb–Douglas production function is discussed in Chapter 3, Section 3.4.2. Further study can be found in chapters 5 to 6, scenarios 1 and 2. This is based on Cobb's early research, the outcome of which was due to varying two elasticities based on three combinations of two parameters, seeking an optimistic return to scale study to maximise profit.

8.1.2.3. Approaches to Answering A2 Research Questions

Below are the step-by-step approaches in each chapter for studying multiple data using XLMiner™ methods to develop the empirical stochastic frontier analysis equations. As a result, the two sub-tools work collaboratively with two main productivity measures.

a) Chapter 2 Literature Review: Section 2.3 Simulation and Section 2.4.2 Survey
b) Chapter 3 Methodology: Section 3.1.2 Measure Productivity with the Assistance of Simulation and Panel Data; Section 3.1.3 Measure Different Productivity Methods with a Variety of Modularities; Chapter 4 Data Collection and Analysis, figures 4.19 to 4.20
c) Chapter 3 Methodology: Sections 3.3.1 and 3.3.3
d) Chapter 3 Methodology: Section 3.4.2 Empirical Stochastic Frontier Analysis
e) Chapter 3 Methodology: Section 3.5 Change and Compare the classic Cobb-Douglas production function (CBPF) and the empirical stochastic frontier analysis (SFA) [level 5]
f) Chapter 3 Methodology; Section 3.5.1 Change Elasticity Parameters in the Classic Cobb–Douglas Production Function; Section 3.5.1.1 Change Elasticities α and β; Examine stochastic frontier analysis (SFA) in Regression Equation with Data Status
g) Chapter 3 Methodology: Table 3.6. Chapter 4 Data Collection and Analysis, Figures 4.5 to 4.10; Tables 4.1 to 4.6; Tables 4.9 to 4.12; Tables 4.17 to 4.18; Chapter 5 Scenario 1.
h) Chapter 6 Scenario 2.

Items a) to f) are prerequisites for g) and h), resulting from using the trial-in-error method to reorganise process flow and continuously provide optimistic process data to related sub-tools seeking optimisation. This approach is one of the effective ways to validate parts of the proposed framework.

8.1.3 B1 research questions: application areas of the classic cobb-Douglas production function and empirical stochastic frontier analysis methods

- *Productivity Measures for Small Lot JIT Production Orders and Delivery:*
  What are the application areas and limitations of the Cobb–Douglas production function and the stochastic frontier analysis in the cement industry? What sorts of input data are needed to develop these two models and expect output data for small lot productivity measures?

8.1.3.1 Application Areas

Cheng et al. (2014) address the classic Cobb–Douglas Production Function Measures used to measure car maker productivity. Many researchers later applied this in the construction industry because of the equation concerning capital, labour, and productivity factor, which is straight forward labour-intensive rather than involving state-of-the-art technologies for mass production assigned product environments.

Customised cement fabrication has represented 40% of business for the past few decades in Australian cement industry (CIF, 2023; Company Z, 2021). Numerous small- and micro-scale cement factories intended to obtain more business after the infrastructure stimulus plan announcement in 2019. As a result, they suffered heavy investment in production facilities to improve below-expectation productivity compared with Companies X, Y and Z cement factories (CIF, 2023) because they have state-of-the-art technologies and enough resources and money to produce customised cement in optimal productivity.

In order to better understand the technology-intensive manufacturing of customised cement, the empirical stochastic frontier analysis method is one of the tools due to its ability to measure machine efficiency performance, ensuring maximising resource use. It also validates the proposed framework, ensuring optimal productivity. But it needs to solve the function format in the equation. Further discussion is in Section 8.1.3.2.

8.1.3.2 Input and Output Data

Chapter 4 described several methods of data collection data (input), which are for simulation and trial-and-error models. The output data are for developing regression equations instead of function format in the empirical stochastic frontier for productivity measures. The sources of data are:

- Related articles
- Survey
- Simulation, to collect optimal process data etc.

XLMiner™ and mining tools were used to aggregate data and equation development. The outputs are used to further study productivity measures.

8.1.3.3 Approaches to Answering B2 Research Questions

Below are the step-by-step approaches in each chapter to identify multiple input and expected output data using XLMiner™ methods as well as the application areas:

a) Chapter 2 Literature Review, Section 2.5 Total Productivity for Optimisation Measure; Section 2.6 Small-Lots-based Production; Section 3.1.3 Measure Different Productivity Method with Various Modularities; Section 3.1.4 Measure Different Small Lot Productivity with Various Modularities
b) Chapter 3 Methodology Section 3.3.1 Simulation Model; Chapter Methodology 3.4 Classic Cobb–Douglas Production Function and Empirical Stochastic Frontier Analysis (Level 4); Section 3.4.1 Classic Cobb–Douglas Production Function; Section 3.4.2 Empirical Stochastic Frontier Analysis
c) Chapter 4 Data Collection and Analysis; Section 4.2.3 Data Design and Survey Method; Section 4.2.5 Data from Literature Review, Related Associations and Financial Reports from Target Cement Company Methods; Section 4.2.5.1 Data from Literature Review; Sections 4.2.5.2 Data from Related Association; Section 4.2.5.3 Data from Financial Reports from Target Cement Companies.

d) Chapter 4 Data Collection and Analysis, Tables 4.1 to 4.3; Section 4.2.5.4 Classic Plant Operational Data

e) Chapter 4 Data Collection and Analysis; Chapter 5 Scenarios 1 and 2 related tables.

f) Chapter 4 Data Collection and Analysis; Chapter 4 Data Collection and Analysis; Chapters 5 and 6 Scenarios 1 and 2 related tables.

The items above represent the distribution of data collection and analysis for the equation development to validate the proposed framework for mass production and customisation fabrication productivity measures.

8.2 Findings and limitations

8.2.1 Findings

This section discusses the two findings listed below:

A. Repair and maintenance of production facilities
B. Identify a suitable regression equation to develop the imperial stochastic frontier analysis methods.

A. Repair and maintenance of the production facilities:

The first finding is the involvement of new technologies instead of traditional methods to achieve optimum productivity for customised cement. Small lot production involves frequently changing production statuses using valving systems for batch separation avoiding mixing batch and good quality. Therefore, Company X (2021) selected simple and workable devices mechanical valves that required less investment (see Appendix A6), ensuring that all valves easily to repair and maintenance. Further, all ultra-sonic grindings and screen equipment is operated by skilful workers because of different frequency generation an impact of quality of each of single processes.

B. Identify a suitable regression equation to develop the empirical stochastic frontier analysis:

The second finding is that companies X to Z (2021) intended to get more customised cement business; but need to introduce new production methods. This creates the opportunity to re-examine each operations procedure of technology-intensive manufacturing factory instead of traditional labour-intensive cement production for customised cement. The classic Cobb-Douglas production function method is not suitable because of the concerning capital and labour. The empirical stochastic frontier analysis method is an alternative. So, a cement entrepreneur needs to fully understand each production facility's performances, including each process flow and efficiency data, and re-think which regression equation is suitable for replacing the function statuses (see Chapter 3, Equation 3.6) for productivity measures.

8.2.2 Limitations

The main and sub-tools used in the research have been designed for the cement and concrete production industries in Australia and the small and micro cement businesses within it. However, there are limitations to applying the two main methods and sub-tools:

- Two productivity tools are used in different areas because of the elements of the equations:

  - the classic Cobb–Douglas production function comprises three elements. It includes capital and labour associated with two corresponding explicit elasticities and productivity-factor parameters. This research assumed constant values throughout the study and only changed elasticity to seek optimisation under various returns to scale the parameter combinations based on adapting and extending Cobb's early work. Therefore, it is suitable for mass production productivity measures due to its labour-intensive nature. Various researchers announced several versions of the Cobb–Douglas production equations that are suitable for different industries. Thus, it is a limitation that the parameter must be set carefully.

  - the empirical stochastic frontier analysis method is more flexible than the classic Cobb–Douglas production function because of the overall equation function statuses, taking time to develop the equations. Therefore, it is suitable for mass customisation production methods due to frequently changing production lines. However, this is one of the disadvantages of time-consuming collecting a lot of data for an equation development study. Omni™ (2021) is a website-based digital calculator enabling online computing production performance using manual data manipulation methods at time intervals but occupying resources. So, RStudio™ is an alternative (see Figure 7.2) because it can automatically capture dynamic data via sensors, resulting in customised codes to work out. It is one of the limitations.

- Two sub-tools:
  - the simulation method is one way of to providing optimum process data for the two main-tool that is a different way of attaining a productivity measure without affecting real cement production. One limitation is that the input of every single parameter must be carefully set, and it takes time to learn this software during model development.

  - voice of house of the deployment of mass customisation is the second sub-tool and assists with modularity selection. This method is suitable for collecting the voice of customer needs and manufacturer capabilities, bridging the relationship between these factors while spending time marketing events.

Further, the proposed framework is promising for cement productivity improvement within the Australian and New Zealand business environment. However, the target companies X, Y and Z do not consider subcontracting to other countries like Cambodia for cost down. Because the coal-fired power stations are not close to the sea, seawater supplies are only for condenser cooling and a limited amount of it to electrolysis processes, generating sodium hydroxide solutions and hydrogen gases, etc. Company Y (2022) also addressed the risk of a shortage of sodium hydroxide solution due to fly ash being more costly than made in Australia. Although the labour cost is cheaper than in Australia, the geographical location, logistics and supply chain issues are the preference factors. So, Industry 4 or 5 asset management methods cannot work well. The method of Industry 4, smart manufacturing, is a realisation of the digital transformation of the field, delivery of real-time decision-making, enhanced productivity, flexibility, and agility to distribute their products (Chan et al., 2010b).

8.3 Future research

This section discusses future research possibilities using affordable state-of-the-art technologies in target companies X, Y and Z for further productivity improvements like customised Python and RStudio™ for better control process flow and get more in modular integration construction businesses. However, they do not consider extending their overseas business due to the complexity of cultural variation and time zones with other countries' spending effects and resources. Although the ISO 55000 family can provide a guideline, micro/medium companies are not suitable because the cycle of cash return rate is not in proportion, causing a risk in financing difficulty and workforce problems in the foreseeable future (CIF, 2022).

Rather, the best way considers less investment to ensure a healthy balance and a reliable manufacturing network in the COVID-19 epidemic worldwide. S0, company X (2022) focuses on better control of customised traditional cement production using the supervisory control and acquisition system (SCADA) can optimise process controls. However, it is very costly, resulting in a small- and micro-scale cement business having to take on extra investment and diluting profit. Future research can use customised Python™ for simple process control alongside a series of sensors for Portland-based and geopolymer-based cement for autonomous production control. The R-Studies™ pack can undertake online data collection and analysis; the action taken in response to that collection and analysis is according to the process performance outcomes. Further, using a portal or app technologies effectively integrates their advantages and manages the manufacturing systems, helping more cement businesses and achieving optimal productivity (Company Z, 2021).

These merged modular integrated construction methods have been used to successfully solve housing problems in Hong Kong and a smaller carbon footprint:

- The water-proof vessel, containing geopolymer-based cement pastes, can provide raw material for a three-dimensional printer to slab a precast mobile container that shortens the product completion life cycle and delivery time (see Appendix A15).
- The concrete modular construction can be performed under the same conditions, avoiding unnecessary downtime that minimises resource use (see Appendices A15 and A16).

8.4 Summary

Chapters 5 to 6 investigated research questions based on Chapter 4. The results of the two scenarios are essential to validate the proposed framework using the two main tools and two sub-tools to measure productivity under mass customisation production conditions using new production technologies in an Australian-owned cement factory. The results also identify process independence, attributes, and similar flow for modelling cement in paralleling fabrication and virtual manufacturing for optimum productivity to satisfies company business interests. They build a closer relationship between customers and manufacturers due to the voice of the house of deployment in the mass customisation matrix measures. The tools with the new production methods are:

- The results from the classic Cobb–Douglas production function and frontier stochastic analysis are compromising because of achieving optimum normal return to scale.
- The new production technologies to be integrated into the system for optimal productivity are as follows:

    - wave-by-wave and vibration methods (Matson, 2018; Chakraverty and Biswas, 2020; Shibli and Marques, 2019; Ganiev et al., 2015; Guo et al., 2014)
    - drop-down, gravity mixers with vibration activity (Kuzmichev and Verstov, 2017) via linear actuator valving system (Tomeczek and Palugniok, 1996).
    - top-bottom integration production methods (Calix, 2021; Hajihassanisal et al., 2016; Companies X and Y, 2021).
    - reorganising the production processes under simulation models (Hasan et al., 2012; Company X, 2021).

The above technologies offer significant ways of achieving optimal Portland and geopolymer-based cement productivity instead of using conventional methods (Companies X and Y, 2021). They have the following characteristics:

- Saving time and maximising resources for a healthy balance sheet (Esteban, 2018)
- Avoiding breakdown, malfunction, or idle time record for three years (Company X, 2021) due to all production facilities in always good conditions (Gao et al., 2017A) and in good condition, resulting in technical efficiency being equal to one.

Further, the study has discussed the limitations of the two main methods and two sub-tools and proposed future research work that can give general guidance to small- and micro-scale cement factories in relation to customised cement production and affordable investment.

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APPENDICES

APPENDIX A1 VERTICAL MILL FOR CEMENT PLANT

A classic cement production factory has high efficiency, effective and reliable vertical roller mills that grind many raw materials, as shown in Figure A1.1. Particles size is affected by roller status. Structural health care (Tang et al., 2018A and 2018B) is one solution. There are two types of mills:

(a) mill including vertical roller (Baek et al., 2009)
(b) horizontal ball mills (Woywadt, 2017; Bye, 2010)

Vertical roller and horizontal ball milling machines

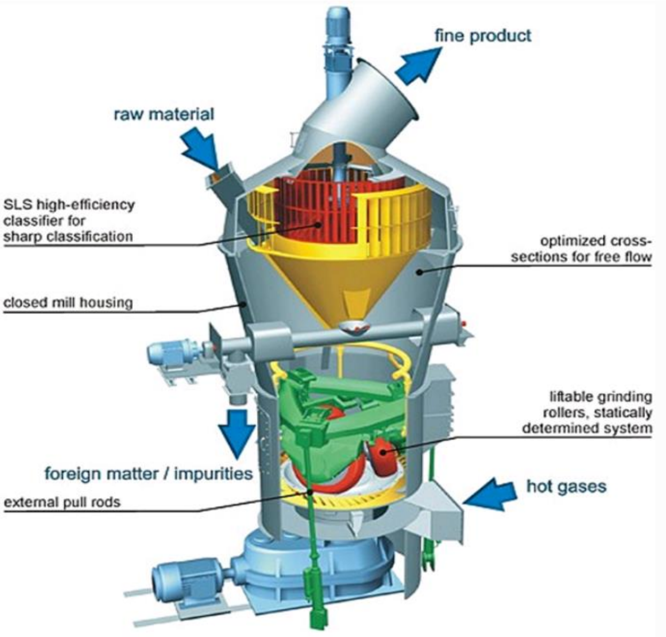


Figure A1.1 Vertical Roller Mill (Courtesy Image Alibaba, 2019)

Further, Figure A1.1 is a material grinding process motor through reducer rotating drive disc, the material falls from the mill under the central entrance and exit, under the action of centrifugal force to the disc edge by the roller to move and the crushing, grinding out lap after the material speed up the flow to and vertical mill with one of the separator, after the meal by the separator back to the mill, the re-grinding; powder while grinding out with air, dust collection equipment in the system to collect down at expected cement size products (Vertical Roller Mill, 2018).

APPENDIX A2 HORIZONTAL BALL MILL

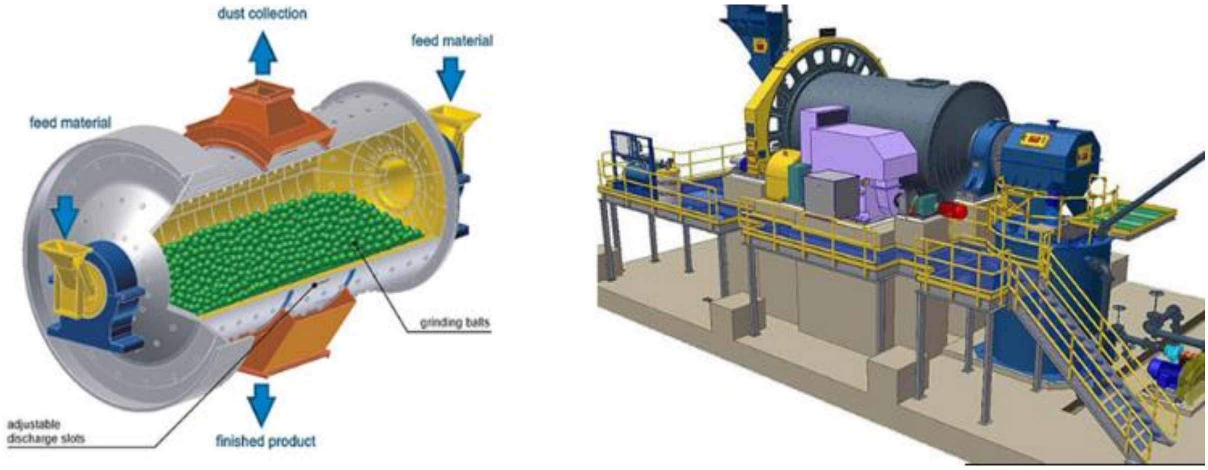


Figure A2.1 Horizontal Ball Mill (Ball Mill, 2018)

A traditional horizontal ball mill (Ball mill, 2018) is shown in Figure A2.1. Doum et al. (2011) described the general operation: a ball mill is a horizontal cylinder partly filled with steel balls (or occasionally other shapes) and that rotates on its axis, causing the balls to tumble and cascade. Material fed through the mill is crushed by impact and ground by attrition between the balls. The grinding media are usually made of high-chromium steel. The smaller grades are occasionally cylindrical (‘pebs’) rather than spherical. There exists a speed of rotation (the ‘critical speed’) at which the contents of the mill would simply ride over the roof of the mill due to centrifugal action. The critical speed (rpm) is given by: $= \frac{42.29}{\sqrt{d}}$, where d is the internal diameter in metres. Ball mills normally operate at around 75% of critical speed, so a mill with a diameter of five metres will turn at around 14 rpm. The mill is usually divided into at least two chambers (although this depends upon feed input size—mills, including a roller press, are mostly single-chambered), but Figure 1.2 shows a mill with only one chamber for ease of illustration, allowing the use of different sizes of grinding media. Large balls are used at the inlet to crush clinker nodules (which can be over 25 mm in diameter). Ball diameter here is in the range of 60–80 mm. Media size must match the size of the material being ground—large media cannot produce the ultra-fine particles required in the finished cement, but small media cannot break large clinker particles.

In a two-chamber mill, the media in the second chamber are typically in the range of 15–40 mm, although media down to five mm are sometimes encountered. As a rule, mills with as many as four chambers, allowing a tight segregation of media sizes, were once used, but this is now becoming rare. Alternatives to multi-chamber mills are as follows:

- pairs of mills, run in tandem, charged with different-sized media
- alternative technology to crush the clinker prior to fine grinding in a ball mill.

A current of air is passed through the mill. This helps keep the mill cool and sweeps out evaporated moisture that would otherwise cause hydration and disrupt material flow. The dusty exhaust air is cleaned, usually with bag filters (Ball mill, 2018); this is a routine repair and maintenance issue, ensuring that the mill maintains normal operations and minimising breakdown. The conditional maintenance in structural health care (Tang et al., 2018a; 2018b) can minimise a breakdown rate. As a result, it also improves the technical efficiency, TE_i , performance. Rather, a new modern grinding technology using ultrasonic vibration mill can solve grinding and mixing efficient and efficiency (see Appendix A8 for further discussion).

APPENDIX A3 COMPARISON OF VERTICAL ROLLER AND HORIZONTAL BALL MILL

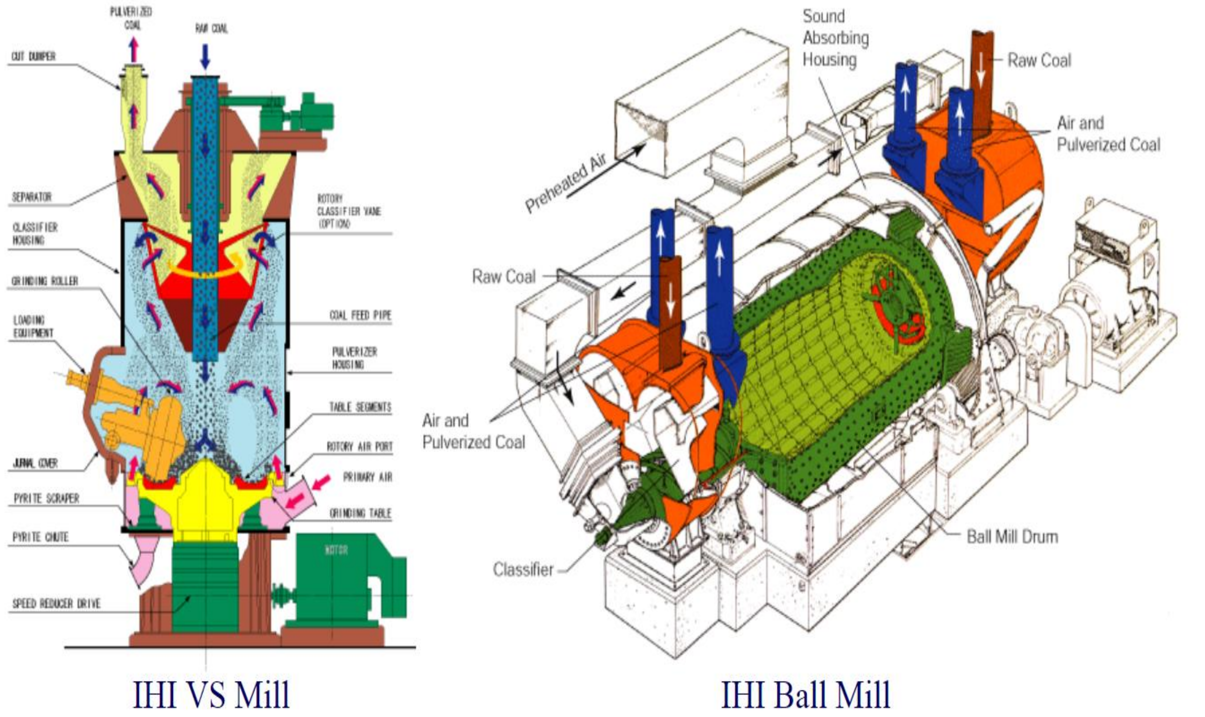


Figure A3.1 Vertical Roller and Horizontal Ball Mills Commonly Used in Coal-fired Power Stations and Cement Factories (Boiler Accessory, 2018)

The aim of further comparison between the vertical roller and horizontal ball internal mills structures, as shown in Figure A3.1, is to develop a good understanding of mill capability, characteristics, and limitations to help cement entrepreneurs improve productivity (Wang et al., 2008; Yan et al., 2017; Tang et al., 2018a, 2018b; Zhang et al., 2017).

Table A3.1 Comparison of Vertical Roller and Horizontal Ball Mill

	Vertical roller mill	Horizontal ball mill
Operational cost (A$)	▲	
Capability (e.g., >2 tonnes)		▲
Noise and vibration (dB)		▲
Efficiency (e.g., 90%)	▲	

APPENDIX A4.1 INTERNAL FEATURES OF VERTICAL ROLLER MILL AND KILN

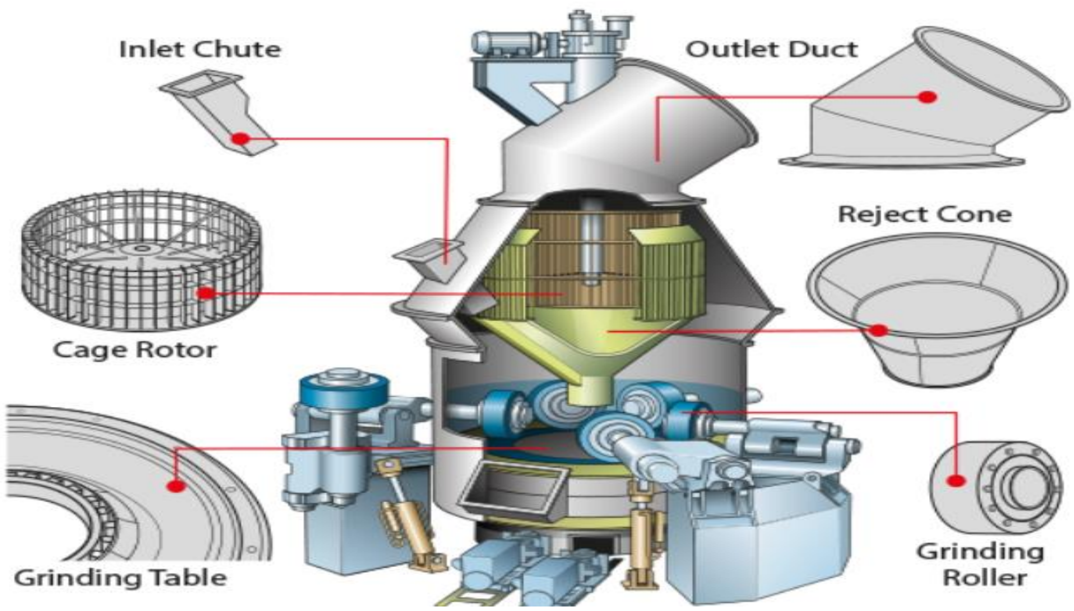


Figure A4.1 The Internal Features of a Traditional Vertical Roller Mill Used in Cement Production (Alibaba, 2019)

Figures A4.1 and A4.2 give insight into the classic internal mechanical structures of horizontal and vertical roller mills. Based on these features and characteristics, cement entrepreneurs arrange production facilities to manufacture types of cement in either small lots or big volumes cement require grinding cement plants (Das et al. 2011). But here, in this kind of production facility, it is very hard to improve productivity and undertake intensive repair and maintenance planning to ensure that equipment is in good condition because moving parts suffer wear that affects grinding performance. To avoid unexpected breakdown events, one company used 300 working days and the other time they available too for major and minor repair and maintenance work (Chan, 2018, Table 4.28). This manufacturing strategy is suitable for mass production of popular cement lines, such as GP or GB cement, but this means customer satisfaction does not meet expectations, particularly a variety of small lot production processes and time-to-market delivery. Therefore, this research uses ultrasonic grinding (Appendix 8) and hydrogen energy (Figure A4.2) to minimise carbon print, improve productivity and undertake less repair and maintenance work instead of the methods shown in Figures A4.1. and A4.2, based on Chan's (2018) and Company Z's (2021) plant layout.

APPENDIX A4.2 INTERNAL FEASTURES OF KILN USING HYDROGEN FEUL INSTEAD OF DIESEL

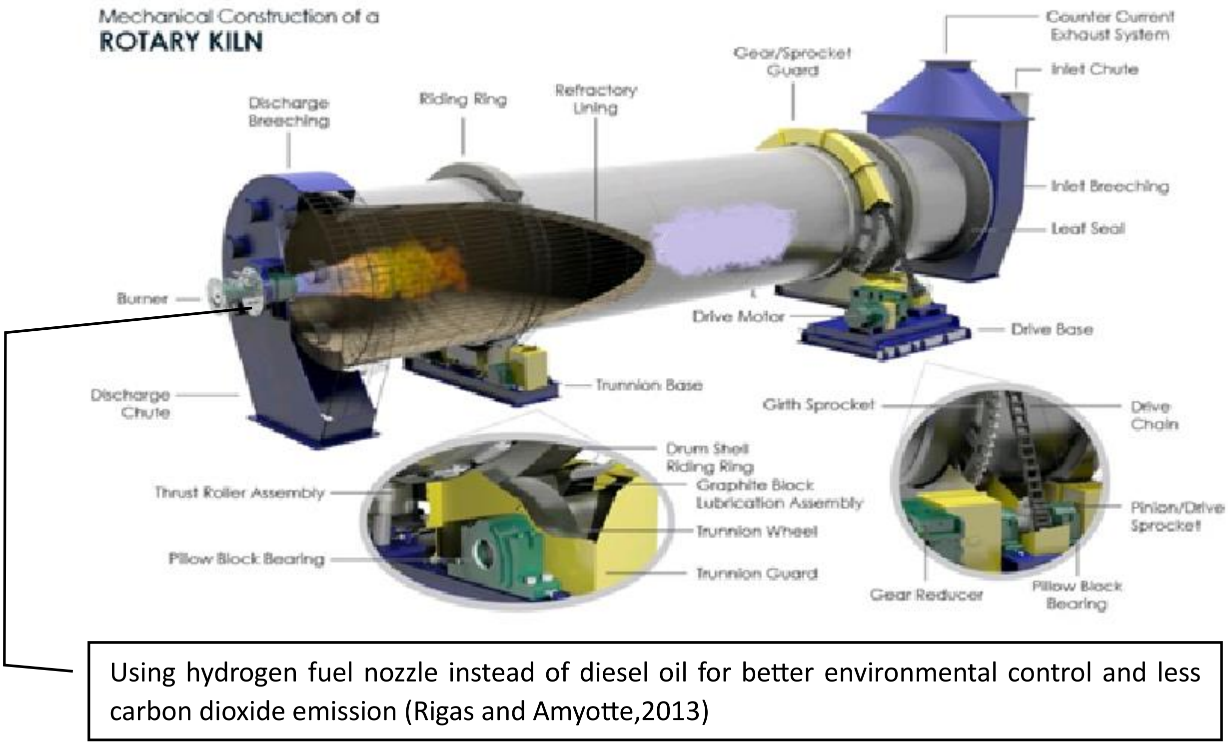


Figure A4.2 Rotary Wet Type Kiln Using Hydrogen Fuel (Alibaba, 2022)

The classic rotary wet type of kiln shown in Figure A4.2 uses hydrogen fuel (Appendix A15) instead of liquid petroleum gasses or diesel fuel, minimising carbon dioxide emissions and maximising the use of renewable energy. It effectively utilises both reflected radianet heat and direct contact with exhaust gas (convection) to maximise heat transfer. It also uses an electrolysis process involving seawater to produce use sodium hydroxide solution and hydroxide gas. Further, there is water left after the burning of hydrogen fuel that minimises carbon footprint.

Fellaous et al. (2018) and Rigas and Amyotte (2013) addressed that the burning hydrogen fuel-air mixture velocity is in the 2.65 to 3.46 m/s range compared with diesel fuel only at 1.6 to 1.8m/s intervals of flame propagation. So, handling hydrogen fuel must be careful to avoid burning injury. One characteristic of hydrogen gas is self-burn when mixed with air in the correct ratio. The Government of Western Australia classified hydrogen as a dangerous good and a potential fire hazard.

APPENDIX A5 CEMENT PROCESS FLOW

The mechanical features of the rotary dry type of processes (e.g., drying, pre-heater, pre-calciner, sintering, cooling, etc.) in cement kilns in Australia and China (CIF, 2019), as shown in Figure A5.1, is the rotary wet type of kiln mechanical features. The process flow of cement production involves raw materials being quarried or mined and transferred to the manufacturing facility to be crushed and milled into a fine powder and delivered to the factory for drying, mixing and blending. They then enter pre-heating and go into a large rotary kiln at a temperature greater than 1400ºC to 1500°C (Gani, 1997). The clinker or kiln product is cooled, and excess heat is typically routed back to the pre-heater units. Prior to packing and transport, gypsum is added to the clinker to regulate the setting time. Figure A5.1 gives a better understanding of the classic internal mechanical structures of horizontal, vertical roller mills and rotary kilns. This offers cement entrepreneurs easier ways of collecting operational data and developing simulation models to build total productivity models to reorganise production scheduling and repair and maintenance tasks for less machine breakdown and stronger business performance. Further, it provides many data-to-data warehouses for developing a simulation model.

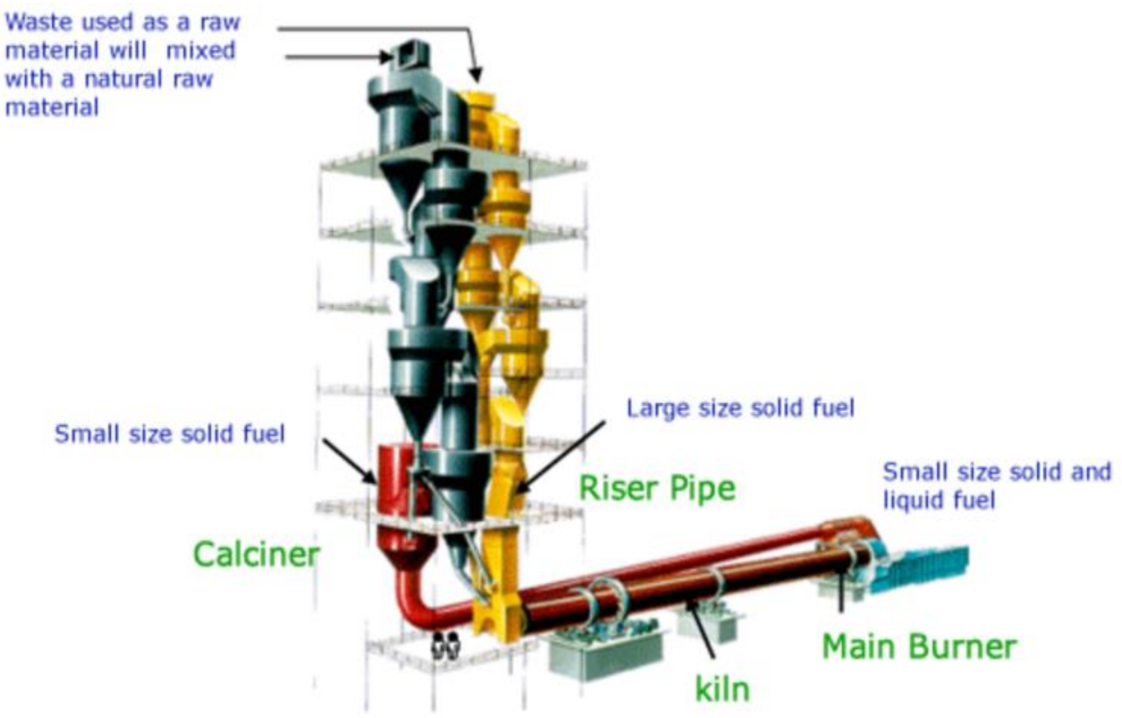


Figure A5.1 Traditional Dry Kiln with Multi-stage Pre-heater/Recalciner Systems Diagram ((Chan, 2018, p. 13)

APPENDIX A6 SEQUENCE CONTROL SHUTTLE VALVE

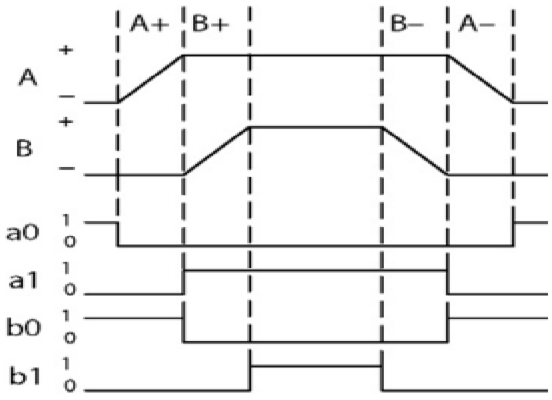


Figure A6.1 Sequence Diagram (Parr, 2000)

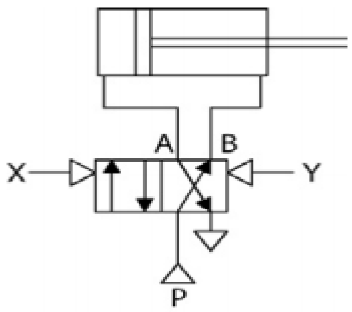


Figure A6.2 A Shuttle Valve with No Spring Return (Parr, 2000)

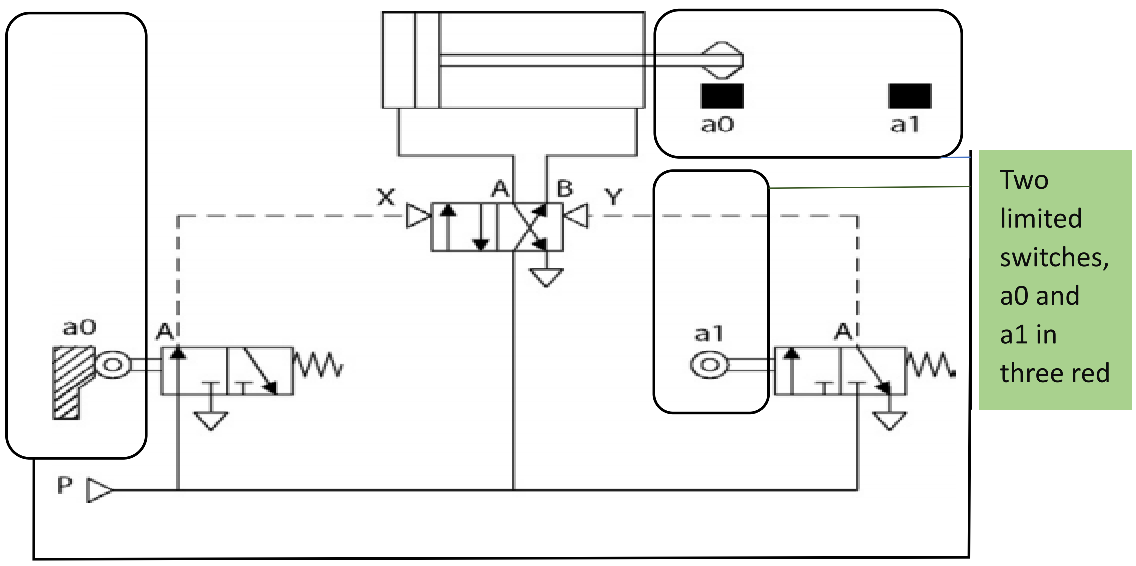
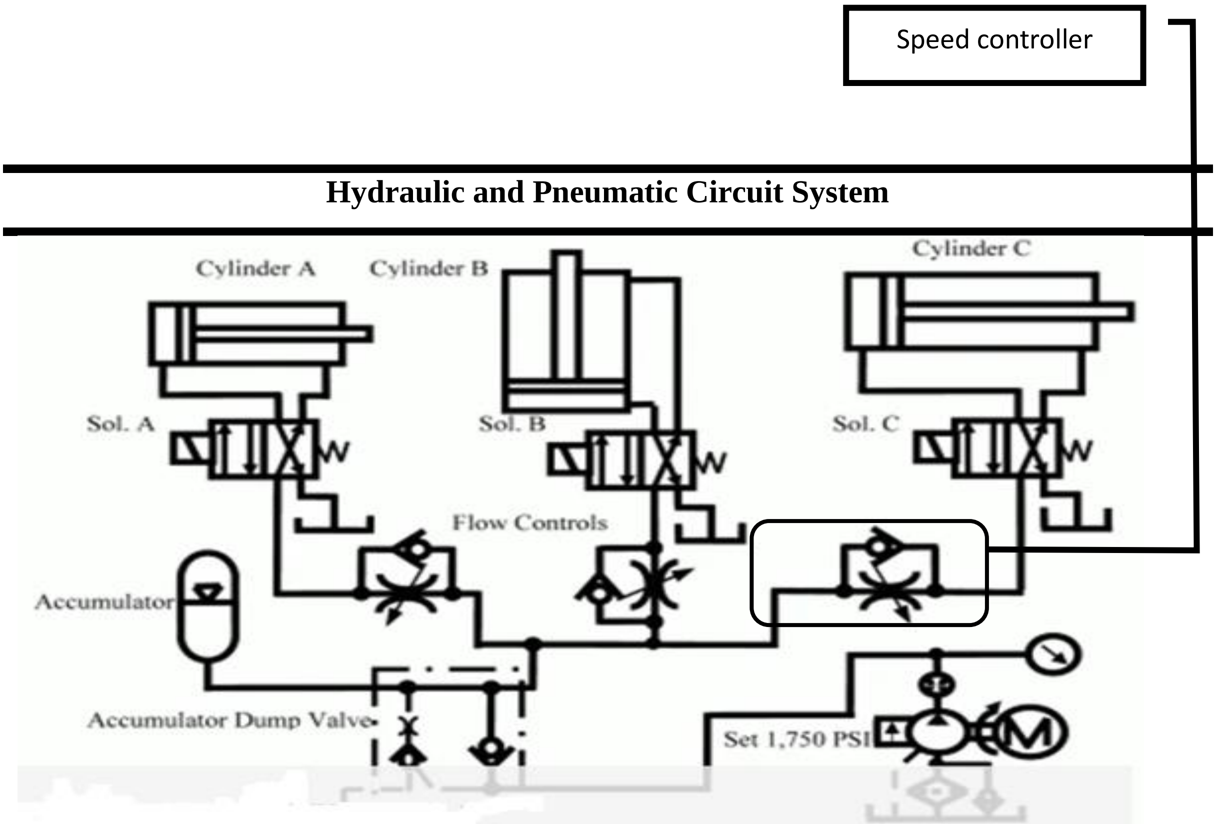


Figure A6.3 Sequence Control Valve with Limit (Parr, 2000)

APPENDIX A6 SEQUENCE CONTROL SHUTTLE VALVE

Hydraulic and Pneumatic Circuit System



Pneumatic Circuit	Hydraulic/Pneumatic Circuits
Second layer: for lightweight open/close issue	First layer: for heavyweight open/close issue

Figure A6.4 Sequence Control Hydraulic and Pneumatic Circuit (Hydraulic and Pneumatics, 2021)

Figure A6.4 shows one of the classic hydraulics and pneumatics circuits for effectively and efficiently opening/closing valving systems. The devices are in two layers.

Each layer is as follows:

- The First layer is for a speedy open/close valving system in 5 to 10 tonnes of dead weight of raw material above the valve seat when a mobile vessel links to the silo. The pneumatic cylinder associated with the hydraulic cylinder is one of the solutions because of its reliable design, allowing trimming mechanical type speed controller whatever in conditional maintenance and free from fire hazards. All devices move in a linear considered a linear regression equation (e.g., velocity multiple times equal to distance).

- The second layer has facilitated the pneumatic circuit for handling lightweight open/close tasks when the mobile vessel transports fly ash from the power station or construction site and considers no dead weight above the valve seat. (see Appendix 6.2 to 6.3).

Figures A6.2 to A6.4 can work in sequence control and have an interlock to each other and work in a robust environment and if possible are kept in a special design enclosure (see Appendices A6 and A12) free from dust, oil, grease, rust and moisture that can affect production facility performances and fly-ash quality; they can also damage the device if it is moved somewhere else because of relocating the vessels from the power station to cement plant for further treatment.

APPENDIX A7 WAVE MOTION AND VIBRATION AGAINST VESSEL (SHIBLI AND MARQUES, 2019; MATSON,2018; KOKINEN,2012)

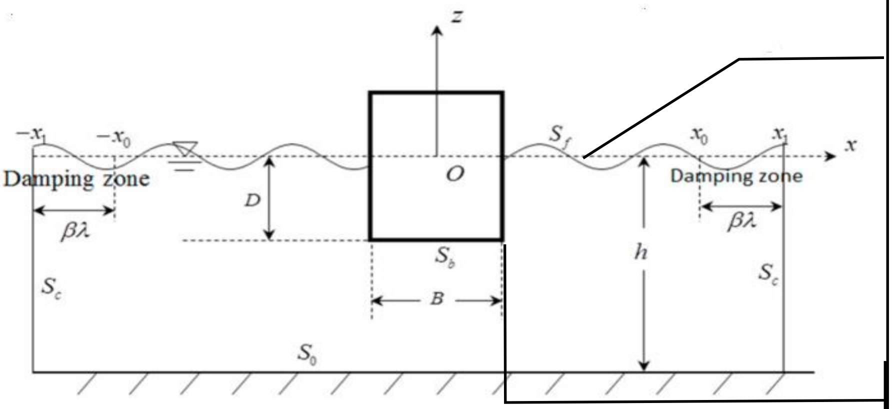


Figure A7.1 Wave Motion Against Vessel (Wave controller, 2021)

To improve productivity for small lot production and customers' needs, one company used an artificial wave in the pool instead of traditional mixers to accelerate and fully achieve the chemical reaction between fly ash/metakaolin particles in both dynamic and static statuses (Company Z, 2021). The mobile vessel works with regular and continuous sine/cosine waves to generate wave motion machines for mixing the correct ratio of sodium hydroxide/potassium hydroxide solutions with fly ash for geopolymer-based cement manufacturing. The maximum loading of the pool is six to eight tonnes in an upright position, as shown in Figure A8.1, using sodium hydroxide solution, the concentration and solution status of which is periodically checked by a chemical laboratory technician, ensuring quality (see Tables 4.1 to 4.3 and Table 4.9). Regarding trimming mechanical type valving speed and frequency setting, an engineer must avoid machine malfunction.

$$y(x_i, t_i) = A sin(kx_i \mp \omega_i t_i + \varphi) \ldots\ldots (A7.1)$$

Where

A = amplitude of the wave
S_i = distance travel; i=1,…n and S_c, S_0 = pool dimension and S_b = vessel dimension
t_i = time; i=1,…,n
ω = wave's angular frequency,
k = wavenumber
φ = phase of the sine wave given in radian
$\frac{c}{f} = \lambda; where\ c = 3 * 10^8\ {}^{m}/_{s}$; f =frequency and λ=wavelength

APPENDIX A8 CASE STUDY RESULTS OF CEMENT INDUSTRY IN AUSTRALIA

Case study 1: Consider $\beta_i + \beta_j \geq 1$. The production function has a constant return to scale. Assuming perfect competition, α, β_i, β_j can be shown to be labour and capital's share of output.

Table A8.1 Results Using Classic Cobb–Douglas Production Function Model Method

various parameters

Total Productivity(Q)	Total Factor Constant of Productivity, α	Output Elasticity of Labour Constant, β_i	Labour Cost(A$/Month)	Output Elasticity material and Energy Constant, β_j	Material and Energy Cost (A$/Tonne)
7,340,233	1	0.5	1,192,500	0.55	9,100,300.00
4,419,951,697	1.08	0.7	1,192,500	0.77	9,100,300.00
817,591,724,227	1.10	0.9	1,192,500	0.92	9,100,300.00

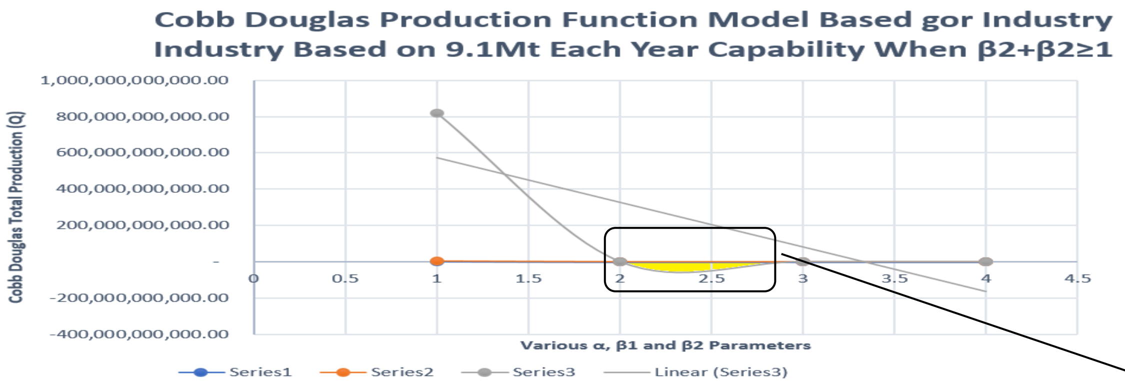


Figure A8.1 Classic Cobb–Douglas Production Function Model when $\beta_i + \beta_j \geq 1$ for Cement Production

This envelops decreased area due to change βi and βj parameters

Case Study 2

1) Consider $\beta_i + \beta_j \leq 1$. Examined production function in constant return to scale.

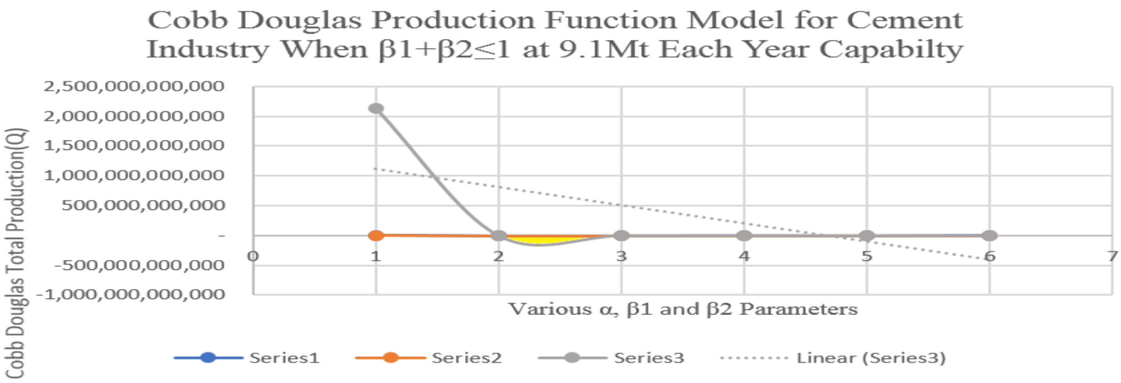


Figure A8.2 Classic Cobb–Douglas Production Function Model When $\beta_i + \beta_j \leq 1$ for Cement Production

Case Study 3

2) Consider $\beta_i + \beta_j = 1$. The production function in constant return to scale.

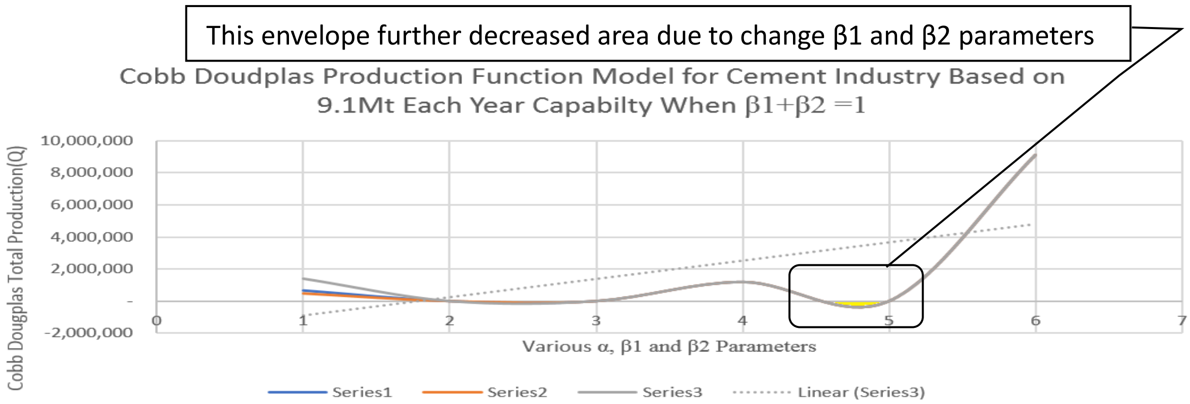


Figure A8.3 Classic Cobb–Douglas Production Function Model When $\beta_i + \beta_j = 1$ for Cement Production

In Figure A8.3, the envelope area in yellow occupies a smaller area and the gradient line has a less sharp decline compared with Figures A8.1 and A8.2; this is the result of improved labour and capital cost.

APPENDIX A9 CALCUALTION OF SM, AM AND LSF (CHAN, 2018, P.22)

(a) SM is commonly used in cement manufacturing to calculate the composition of Portland cement clinker, obtained as follows:

(b) SM = $\frac{S}{(A+F)}$ Where S = Silica, A = Alumina, F = Iron oxide

The SM is defined as the amount of liquid that is dependent on the value of this ratio. Typical values of SM are between 2.3 to 2.5. If the SM is too high, then the amount of liquid phase produced 'I' low, which results in not all the materials being converted into clinker modules. The remaining, not-yet-melted dusty materials clog the kiln and do not completely achieve (Gani, 1997) the formation of clinker materials and modulation.

(c) AM is defined as the temperature at which melting commences. Typical values are about 2, obtained as follows: AM = $\frac{A}{F}$

This equation shows that the lowest temperature at which liquid is formed occurs at AM = 1.6, which is optimum for the formation of clinker materials and modulation (Gani, 1997).

(d)The LSF method is also commonly used in cement manufacturing (Chan, 2018; Gani, 1997) to calculate the composition of Portland cement clinker:

$$\text{LSF \% at } 100°\text{C} = \frac{LSF}{(2.8S + 1.18A + 0.65F)}$$

LSF equation is used the completion reaction of the calcium oxide in the mix to form compounds. If the LSF is less than (e.g., < 0) 100% or the value is more than (e.g., > 0) 100%, there will always be some free lime left in the clinker (see Chapter 2, Table 2.1).

APPENDIX A10 LINEAR VIBRATING SCREEN

Table A10.1 Linear Vibration (Ultrasonic) Vibration Screen (Henan PingYuan Mining Machinery, n.d.)

Linear Vibrating Screen

Model:	ZS1020
Screening area:	1.00~6.48m2
Frequency:	960rpm
Amplitude:	3~5mm
Capacity:	3~120m3/h
Power:	0.37*2~7.5*2(kw)

Specifications

A linear vibrating screen is designed with a dual-vibration motor drive: two synchronous motors are reversely placed so that the exciter generates excitations force by eccentric block cancel each other out on the parallel direction of motor axis and stack together with the perpendicular direction of motor axis so its trajectory is linear.

APPENDIX A11 DATA COLLECTION QUESTIONAIRES

COVER LETTER
FOR
E-SURVEY

TO WHOM IT MAY CONCERN

Dear Sir/Madam

Thank you for taking some time to participate in this survey. The aim of this survey is data collection for Doctor of Business Administration research study “Evaluating Total Productivity of Cement Manufacturing Options with Mass Customisation Technologies”. The data collection for survey is divided into three parts.

- Part A - short questions related to small-lots of production.
- Part B - the small lots of production orders each year for customised agile flexible manufacturing production?
- Part C - plant operation including labour cost, machines cost, machines breakdown cost, idling time cost, small lots of production cost, etc.

Please complete the appropriate box of each question. Based on you gave me the data and information that I will be able to analyses, calculate, and validate my proposed framework. Further, the information you provide will be kept in completely confidential and used for academic purposes. Individual information will not be identified. This survey has been approved by Human Ethics Research committee of The University of Southern Queensland.

Thank you for your anticipation

Yours Sincerely,
Chi-Shing CHAN
DBA Candidate

Part A

Thank you for your participation involving completion of Part A is related to Doctor of Business Administration research study “Evaluating Total Productivity of Cement Manufacturing Options with Mass Customisation Technologies.” The Part A questions are as below:

1) How much small lots of production orders each year, its turnover and production life cycle?
2) How long cement manufacturers organise small lots of orders manufacturing, and any extra resources involve?
3) How long of idling time and how long to repair them?
4)How does it affect productivity?

Your participation in this project is voluntary. If you do not wish to take part, you are not obliged to. If you decide to take part and later change your mind, you are free to withdraw from the project at any stage. Please note, that if you wish to withdraw from the project after you have submitted your responses, the Research Team are unable to remove your data from the project (unless identifiable information has been collected). If you do wish to withdraw from this project, please contact the Research Team (contact details at the top of this form).

Your decision whether you take part, do not take part, or to take part and then withdraw, will in no way impact your current or future relationship with the University of Southern Queensland.

Thank you for your anticipation

Yours Sincerely,

Chi-Shing CHAN
DBA Candidate

Part B

1. What quantity of small lots of ordinary Portland cement do you produce each year?

☐ less than 100 tonnes

☐ between 100 and 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ______________________________

2. What quantity of small lots of high Portland cement do you produce each year?

☐ less than 100 tonnes

☐ between 100 and 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ______________________________

3. What quantity of small lots of high-early strength Portland cement do you produce each year?

☐ less than 100 tonnes

☐ between 100 and 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ______________________________

4. What quantity of small lots of sulfate-resisting Portland cement do you produce each year?

☐ less than 100 tonnes

☐ between 100 and 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ______________________________

5. What quantity of small lots of air-entraining Portland cement do you produce each year?

☐ less than 100 tonnes

☐ between 100 and 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ______________________________

6. What quantity of small lots of Portland-blast furnace slag cement do you produce each year?

☐ less than 100 tonnes

☐ between 100 and 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ______________________________

7. What quantity of small lots of Portland-pozzolan cement do you produce each year?

☐ less than 100 tonnes

☐ between 100 and 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ______________________________

8. What quantity of slag-based geopolymer cement do you produce each year?

☐ less than 5 million tonnes

☐ between 5 and 10 million tonnes

☐ greater than 10 million, but less than 20 million tonnes

☐ other ______________________________

9. What quantity of small lots of rock-based geopolymer cement do you produce each year?

☐ less than 100 tonnes

☐ between 100 and 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ______________________________

10. What quantity of FA-based geopolymer cement do you use each year?

☐ less than 100 tonnes

☐ between 100 to 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ____

11. What quantity of small lots of ferro-sialate based geopolymer cement do you produce each year?

☐ less than 100 tonnes

☐ between 100 and 200 tonnes

☐ above 300 but less than 400 tonnes

☐ other ____

Part C

1. What is the breakdown frequency of the vertical grinding machines each year?

   ☐ less than 5

   ☐ between 4 and 1

   ☐ none

   ☐ other ______________________________

2. What is the breakdown frequency of the horizontal ball grinding machines each year?

   ☐ less than 5

   ☐ between 4 and 1

   ☐ none

   ☐other ______________________________

3. What is the breakdown frequency of the wet type of kiln machines each year?

   ☐ less than 5

   ☐ between 4 and 1

   ☐ none

   ☐ other ______________________________

4. What is the breakdown frequency of the dry type of kiln machines each year?

   ☐ less than 5

   ☐ between 4 and 1

   ☐ none

   ☐ other ______________________________

5. What is the breakdown frequency of the material handling system each year?

   ☐ less than 5

   ☐ between 4 and 1

   ☐ none

   ☐ other ______________________________

6. What is the breakdown cost of the vertical grinding machine each year?

☐ less than 5

☐ between 4 and 1

☐ none

☐ other ____

7. What is the breakdown cost of the horizontal ball grind machine each year?

☐ less than 5

☐ between 4 and 1

☐ none

☐other ____

8. What is the breakdown cost of the wet type of machine each year?

☐ less than 5

☐ between 4 and 1

☐ none

☐ other ____

9. What is the breakdown cost of the dry type machines system each year?

☐ less than 5

☐ between 4 and 1

☐ none

☐ other ____

10. What is the breakdown cost of the material handling systems somewhere else in cement production systems each year?

☐ less than 5

☐ between 4 and 1

☐ none

☐other ____

11. What is the idling costs short supply of raw materials somewhere else for small lots of in cement production systems each year?

☐ less than 5

☐ between 4 and 1

☐ none

☐ other ______________________________

APPENDIX A12 MODULATING EXPLOSION PROOF LINEAR VALVE, LINEAR ELECTRIC ACTUATOR AND INTERLOCK

Appendix 12.1 Modulating Explosion Proof Electric Linear Valve

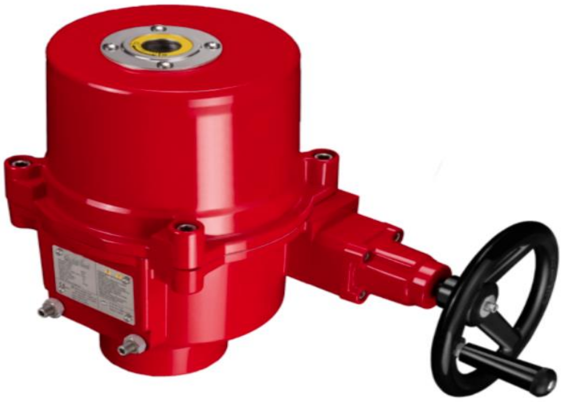


Figure A12.1 Modulating Explosive Proof with Spring Return Electric Valve (Process system, 2021)

this valving system is suitable for this research

Model	Torque (Nm)	Nominal Power (Watts)	Running Time (seconds)	Manual Override	Mounting (ISO 5211)	Shaft (mm)	Depth of Shaft (mm)
OME-1M	35	10	11	Allen Key	F03/F05	14	17
OME-AM	50	10	21	Allen Key	F07	17	20
OME-2M	90	40	18	Hand Wheel	F07	22	30
OME-3M	150	40	28	Hand Wheel	F07	22	30
OME-4M	400	80	20	Hand Wheel	F10	36	48
OME-5M	500	80	27	Hand Wheel	F10	36	48
OME-6M	650	80	36	Hand Wheel	F10	36	48
OME-7M	1000	120	52	Hand Wheel	F12 or F14	36	50
OME-8M	1500	120	54	Hand Wheel	F12 or F14	36	50

Figure A12.1 illustrates the general specifications of the modulating explosive proof with a return electric valve. Here, this study preferred a mechanical type of pneumatic and hydraulic actuator (Appendix 6) for open/close issue in black box due to the run time within design limit instead of electric actuator due to safety consideration. But at the end of the actuator uses rectangle shape valve the shape with guide slot to avoid leakage and quickly close/open the valve.

Appendix 12.2 Linear Electric Actuator

Figure A12.2 Modulating Explosive-Proof with Spring Return Electric Actuator (Process system, 2021)

Appendix A12. 3 Interlock

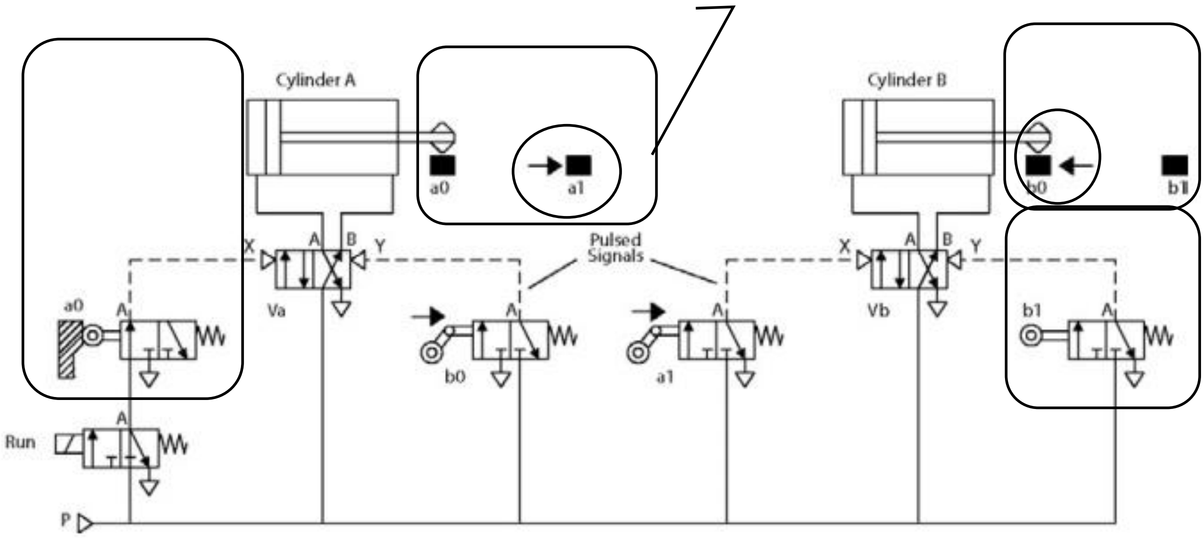


Figure A12.3 Interlock in One-Way Solution (Parr, 2000)

Cylinder A is in an actuating position, but cylinder B is in an extraction situation and vice versa, as shown in the black boxes in A12.3. They interlock when fly ash is changed to metakaolin or when the reverse occurs. This strategy prevents unnecessary mix proportion in line changing and minimises downtimes, accomplishing this process by the simulation model. This device is identified as a linear regression equation for empirical stochastic frontier analysis.

APPENDIX A13 VERTICAL INTEGRATION PLANT LAYOUT (COMPANY X,2021)

Figure A13.1 Vertical Integration Geopolymer-based Plant Layout (Company X, 2021)

Facilitated with silo with valving systems

Figure A13.1 is one of the practical examples of vertical integration for geopolymer-based production plants, enabling them to minimise delivery times. The four-tonne vessel in the black box is specially designed and can be relocated from the power station to the alkali solution pool for further processing to prepare FA-based geopolymer cement. The device can be used many times. For effective handling of this device without any impact on the environment due to the leak of fly ash particles, Company X (2021) uses two sets of shuttle valves, as shown in Appendix A6. The vessel consists of a set of valving with a hydraulic and pneumatic valving system, ensuring it can open/close freely because the maximum dead-weight is four tonnes of fly ash. The lower shuttle valving system is facilitated with the pneumatic and hydraulic systems with manual operational valves in case of valve jamming (see Appendix A12). The aim is to open/close as quickly as possible to prevent workers from breathing in the particles fly ash/metakaolin particles (e.g., occupation and health safety).

APPENDIX A14 SODIUM HYDROXIDE SOLUTION CONTAINER (VESSEL) POOL AND TRANSPORT

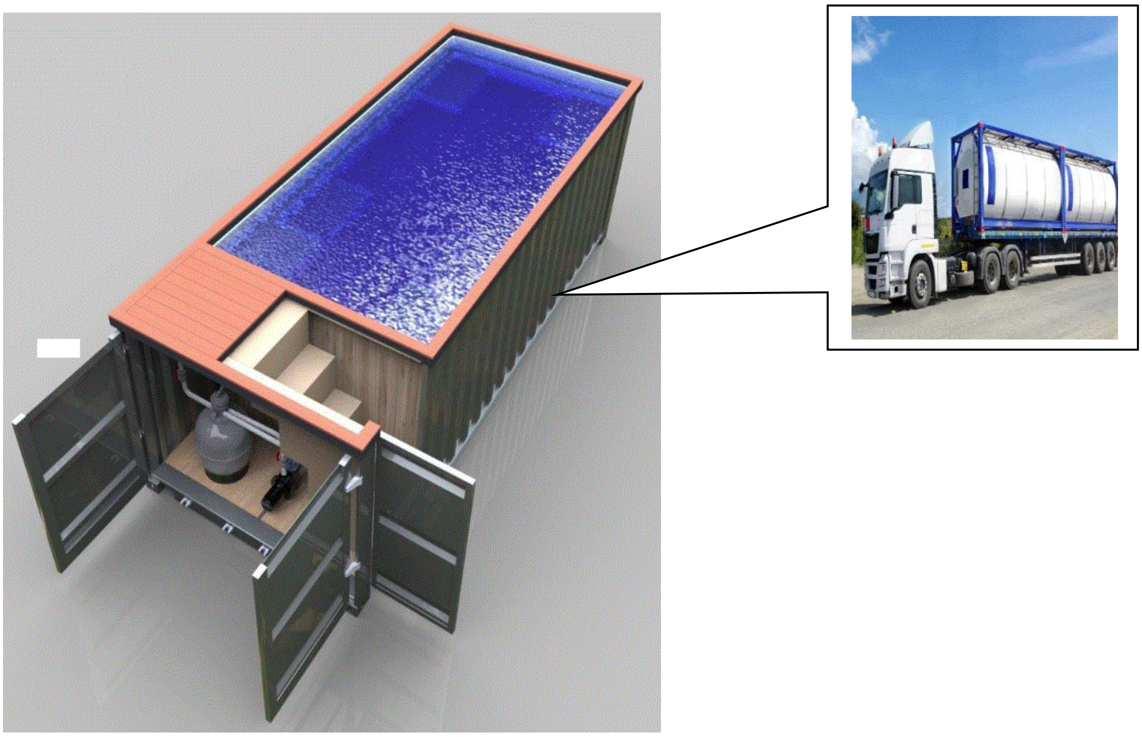


Figure A14.1 Sodium Hydroxide Solution Container Pool and Transport (Alibaba, 2022)

Figure A14.1 shows an advanced specially design container to store the sodium hydroxide solution. The main advantage of this design is that it fits the top-bottom integration manufacturing method.

The pumping system is placed in the left-most corner, circulating a sodium hydroxide solution. A mobile vessel in the right-most corner icon transported fly ash from the power station and a chemical solution with the potential of hydroxide ion, Ph value, in 9.8, which achieves the required mixture for geopolymer-based cement manufacturing and then the cement goes directly to a construction site for further processes (see Appendix A16). This is one of the methods of productivity improvement.

Additionally, the rectangular shape of the pool allows another fly ash enclosure to mix with sodium hydroxide solution. This considers the linear motion with respect to the empirical stochastic frontier analysis equation.

APPENDIX A15 MODULAR INTEGRATION CONSTRUCTION

A construction free-standing integrated modules is manufactured in a prefabrication factory and transported to site for installation in a building resulting in completion with finishes fixtures and fitting.

Figure A15.1 One Example of Modular Integration Construction (Hong Kong Government, 2022, 2023)

Sectional modular of a pe-casting concrete

Figure A15.2 Modular Integration Construction Method (Courtesy Image from Hong Kong Government, 2022, 2023)

Figure A15.3 Modular Integration Construction Method (Chung and Chan, 2021)

Figures A15.1 to A15.3 are examples of the Hong Kong Government Special Administration Region using modular integration construction methods to achieve optimum productivity for the housing industry. The contractors use designs created by architects and structural engineers pre-fabricating the standardised modules and parts in the factory and come with complete finishes and fixtures. The modules are precast and then transported to a project site to be lifted and installed in their final position. The advantages of modular integrated construction are that it saves and minimises cost, leading to faster project completion times.

APPENDIX A16 THREE-DIMESNIONAL PRINTER

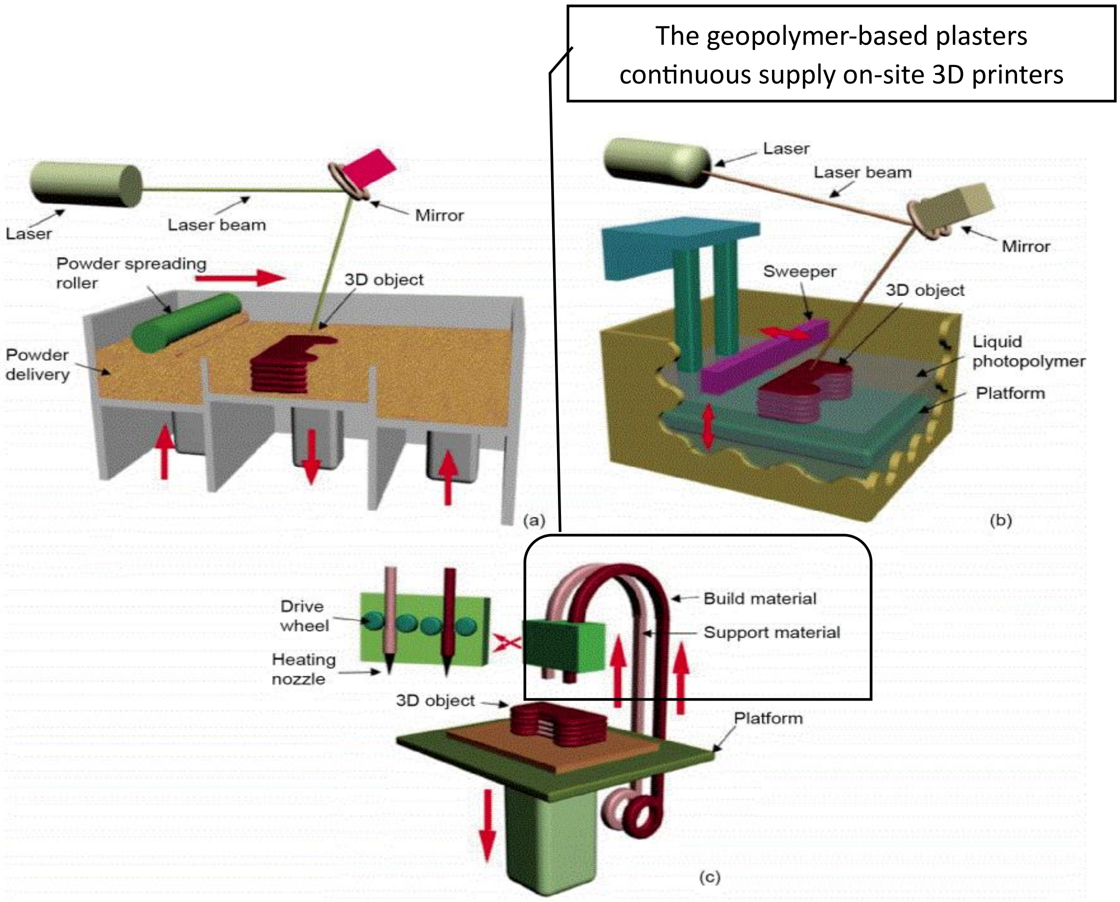


Figure A16.1 The Three-Dimensional Printer (Alibaba, 2022)

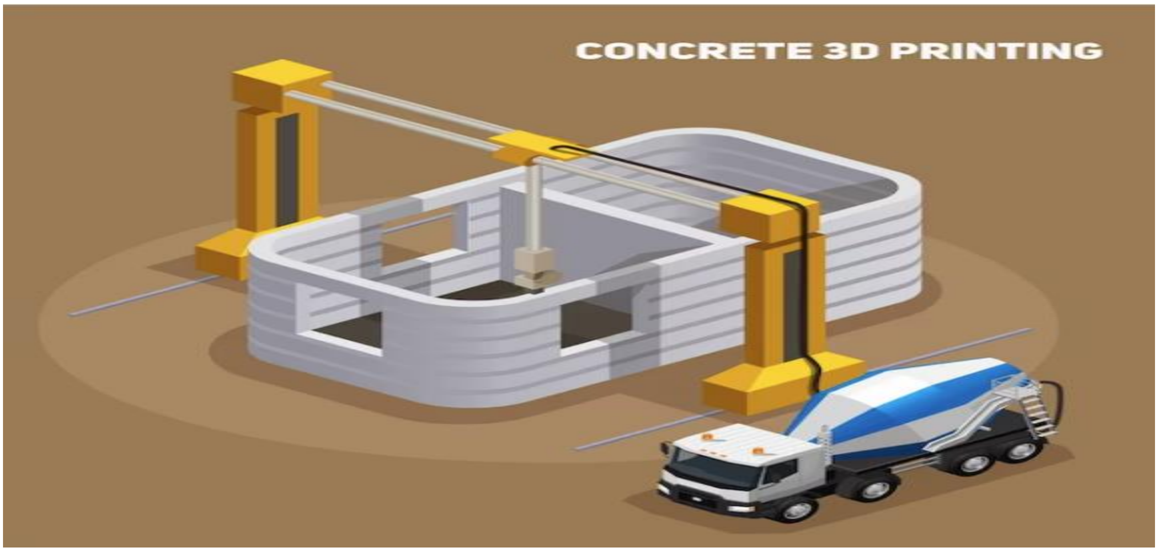


Figure A16.2 The Three-Dimensional Construction Printer (Alibaba, 2022)

Figures A16.1 and A16.2 illustrate from a front process, a mobile vehicle, which supplies enough slurry geopolymer-based pastes to a downstream 3D printer process to fabricate customised building parts. It is one of the fastest completion times for housing projects like the University of Hong Kong precinct solving Hong Kong Housing problems. As a result, a combination of modular integration construction and mix-&-add-in modular approaches are either on-site or in-house for optimal productivity and building costs down. It is an advantage of hybrid modular methods. Due to the technology-intensive in this case, the empirical stochastic frontier analysis can measure how much per cent productivity improvement, including technical efficiency in manufacturing customised modular building parts.

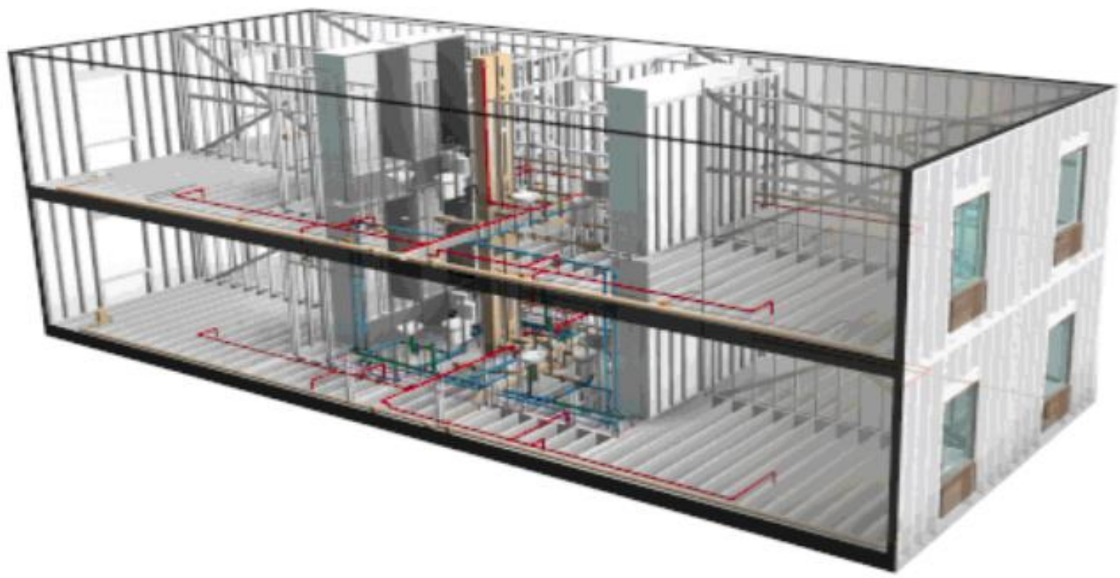


Figure A16.3 Sectional Modular Integrated Construction (Hong Kong Government, 2022)

Figure A16.3 shows a typical example of the internal revocation of mechanical, electrical, and plumbing for either an on-site or in-house fit-out for optimum housing completion time and resources use.

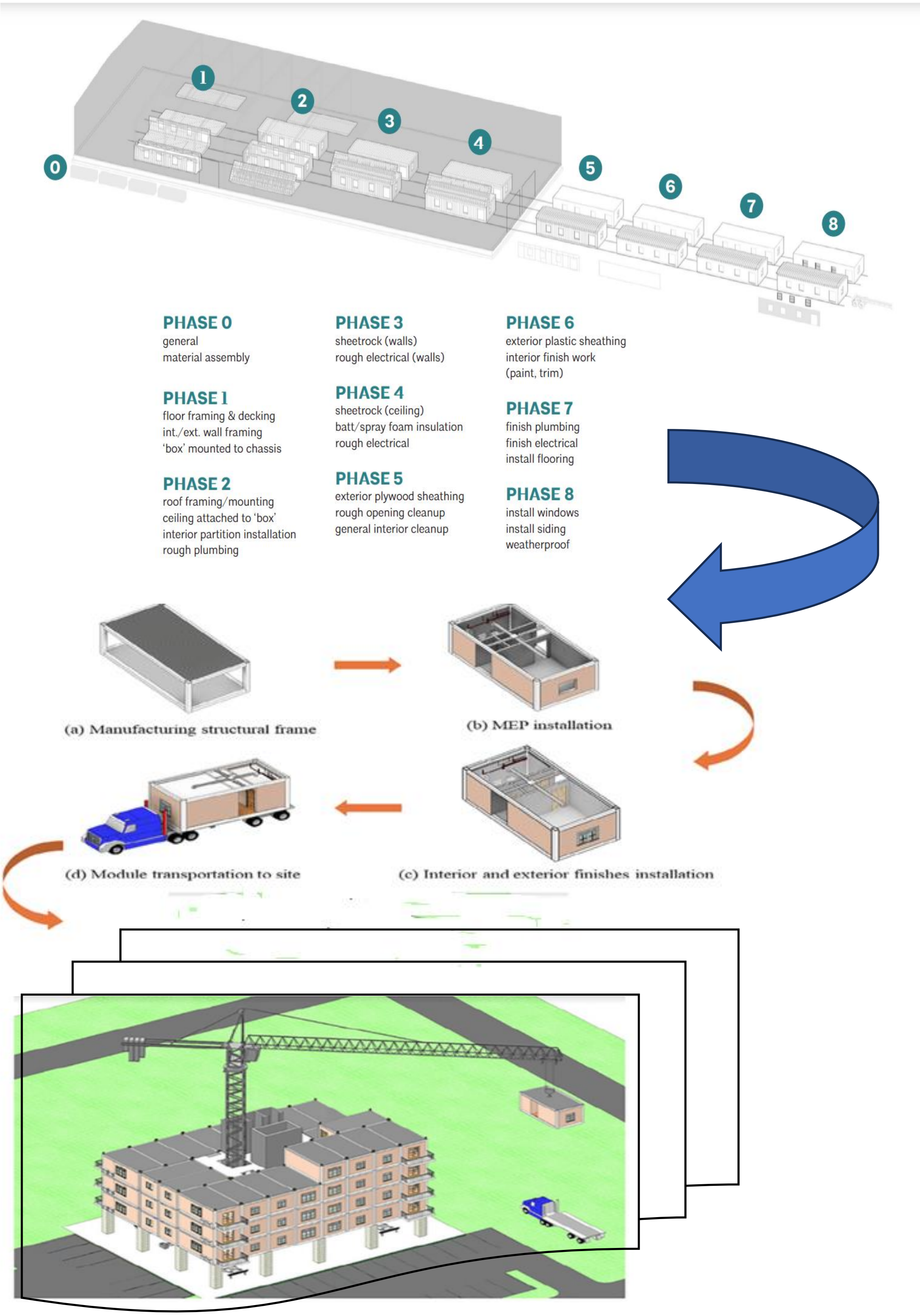


Figure A16.4 Essential Operational Modular Integrated Construction (Hong Kong Government, 2022)

Figures A16.3 to A16.4 illustrate the modular integrated construction operation, including the geopolymer-based pastes from the factory using mobile containers continuously supply material on-site for the downstream process installation based on architect drawings and project schedules. This is one of the typical pull-and-push (Hajifathalian et al., 2012) and sectional modularity manufacturing methods that can lead to earlier project completion because of optimum productivity, meeting Hong Kong's high demand for housing problems for low-income citizens and reducing carbon footprint in construction. Further, each sectional modularity can be de-assembled and reused for another housing project (Hong Kong Government, 2022).

The advantages of integrating the two modular methods are as follows:

- shorten product life cycle timeframe, including development, installation, delivery time and cost, leading to early completion of building projects.
- maximining resource use due to machine-intensive work, resulting in less material cost fluctuation and minimising labour cost.
- minimising footprint because of reduced carbon emissions from vehicles and in the production process for fabricating geopolymer-based cement and concrete, resulting in more environmentally conscious cement and construction.

APPENDIX A17 PYTHON AND RSTUDIO™ SNAPSHOT AND FLOWCHART

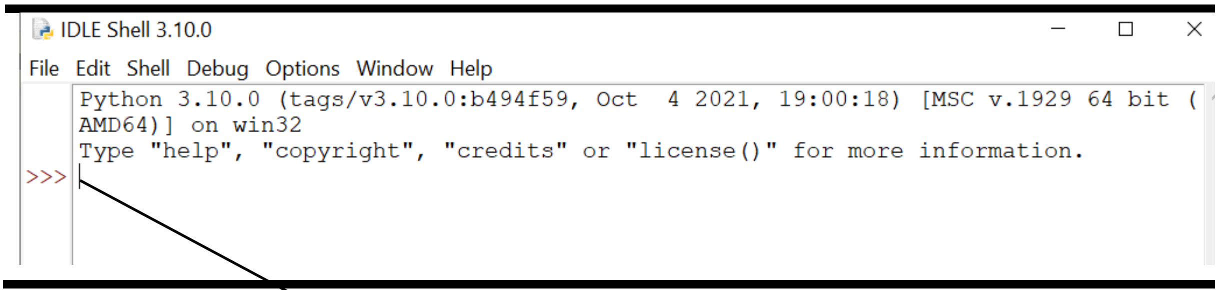


Figure A17.1 Python™ Snapshot

Python™ here is customised codes for avoiding calculation mistakes and better online monitoring production performances.

Enabling to capture spreadsheet-based file for further data analysis from

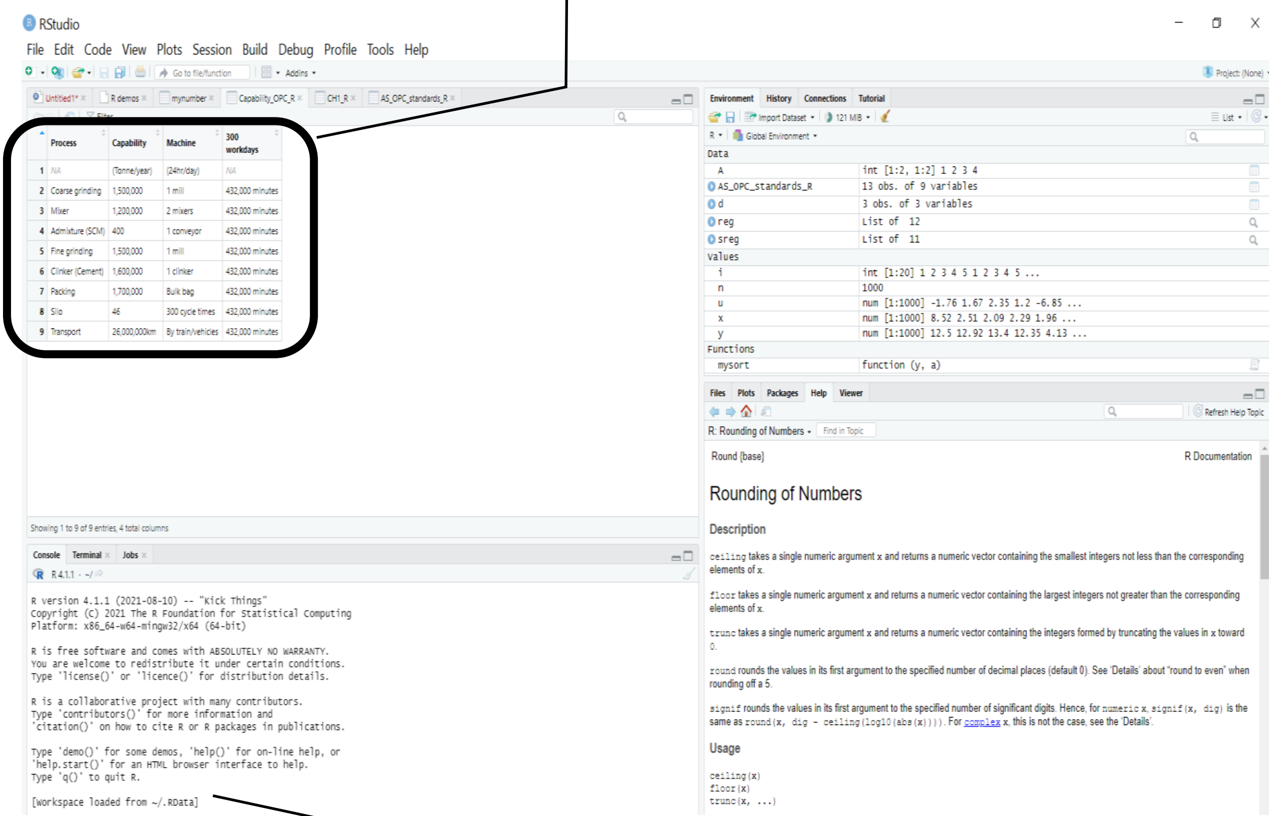
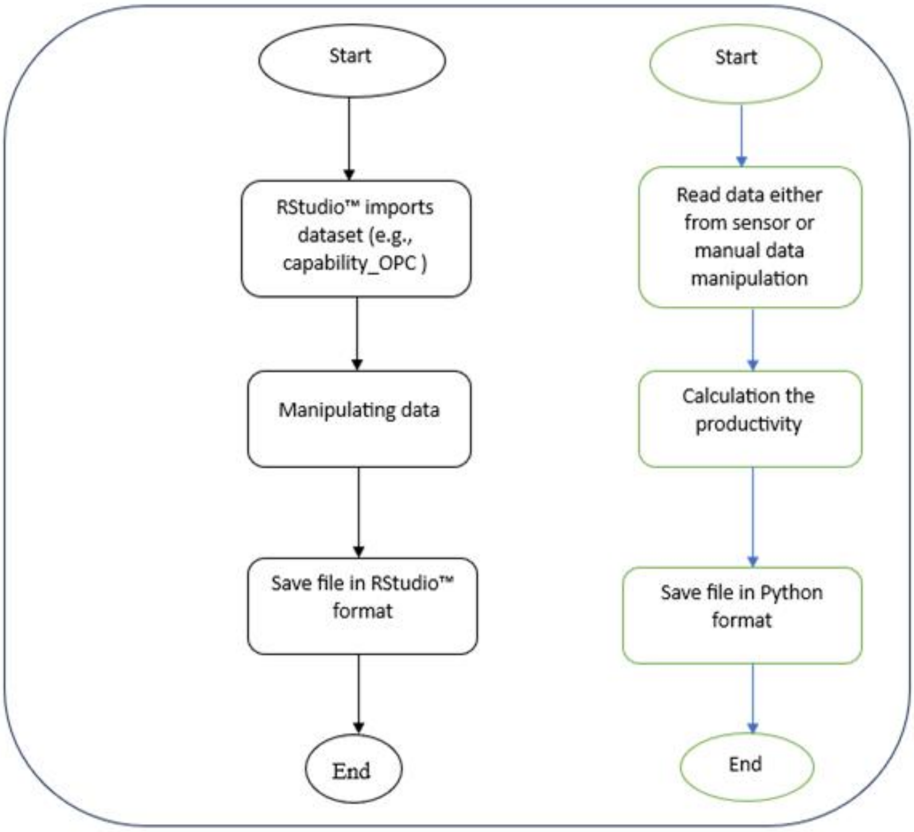


Figure A7.2 Data Editor for RStudio™ Snapshot

RStudio™ is enabling to be captioned of every single process data, ensuring in optimisation process as shown in the black box (top left)



Flow Chart for RStudio™	Flow Chart for Python™

Figure A17.3 Flow Chart for RStudio™ and Python™