

Computational intelligence approach for modeling hydrogen production: a review

Sina Faizollahzadeh Ardabili, Bahman Najafi, Shahaboddin Shamshirband, Behrouz Minaei Bidgoli, Ravinesh Chand Deo & Kwok-wing Chau

To cite this article: Sina Faizollahzadeh Ardabili, Bahman Najafi, Shahaboddin Shamshirband, Behrouz Minaei Bidgoli, Ravinesh Chand Deo & Kwok-wing Chau (2018) Computational intelligence approach for modeling hydrogen production: a review, Engineering Applications of Computational Fluid Mechanics, 12:1, 438-458, DOI: [10.1080/19942060.2018.1452296](https://doi.org/10.1080/19942060.2018.1452296)

To link to this article: <https://doi.org/10.1080/19942060.2018.1452296>



© 2018 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group



Published online: 28 Mar 2018.



Submit your article to this journal [↗](#)



Article views: 8678



View related articles [↗](#)




View Crossmark data [↗](#)



Citing articles: 32 View citing articles [↗](#)

Computational intelligence approach for modeling hydrogen production: a review

Sina Faizollahzadeh Ardabili^a, Bahman Najafi^a, Shahaboddin Shamshirband ^{b,c}, Behrouz Minaei Bidgoli^d, Ravinesh Chand Deo^e and Kwok-wing Chau^f

^aDepartment of Biosystem Engineering, University of Mohaghegh Ardabili, Ardabil, Iran; ^bDepartment for Management of Science and Technology Development, Ton Duc Thang University, Ho Chi Minh City, Vietnam; ^cFaculty of Information Technology, Ton Duc Thang University, Ho Chi Minh City, Vietnam; ^dDepartment of Computer Engineering, Iran University of Science and Technology, Tehran, Iran; ^eSchool of Agricultural, Computational and Environmental Sciences, Institute of Agriculture and the Environment (IAg&E), University of Southern Queensland, Springfield, Australia; ^fDepartment of Civil and Environmental Engineering, Hong Kong Polytechnic University, Hong Kong, People's Republic of China

ABSTRACT

Hydrogen is a clean energy source with a relatively low pollution footprint. However, hydrogen does not exist in nature as a separate element but only in compound forms. Hydrogen is produced through a process that dissociates it from its compounds. Several methods are used for hydrogen production, which first of all differ in the energy used in this process. Investigating the viability and exact applicability of a method in a specific context requires accurate knowledge of the parameters involved in the method and the interaction between these parameters. This can be done using top-down models relying on complex mathematically driven equations. However, with the raise of computational intelligence (CI) and machine learning techniques, researchers in hydrology have increasingly been using these methods for this complex task and report promising results. The contribution of this study is to investigate the state of the art CI methods employed in hydrogen production, and to identify the CI method(s) that perform better in the prediction, assessment and optimization tasks related to different types of Hydrogen production methods. The resulting analysis provides in-depth insight into the different hydrogen production methods, modeling technique and the obtained results from various scenarios, integrating them within the framework of a common discussion and evaluation paper. The identified methods were benchmarked by a qualitative analysis of the accuracy of CI in modeling hydrogen production, providing extensive overview of its usage to empower renewable energy utilization.

ARTICLE HISTORY

Received 17 January 2018
Accepted 10 March 2018

KEYWORDS

Alternative fuels;
computational intelligent;
hydrogen production;
modeling

Nomenclatures

Adaptive neuro-fuzzy inference system	ANFIS	Fluidized bed	FB
Anaerobic sludge blanket reactor	ASBR	Fuel cell power plants	FCPP
Analytic hierarchy process	AHP	Fuzzy support vector machine	FSVM
Artificial immune system	AIS	Fire fly algorithm	FFA
Artificial neural network	ANN	Fault semantic network	FSN
Back propagation neural network	BPNN	Genetic algorithm	GA
Batch hydrogen production	BHP	Genetic programming	GP
Biomass gasification	BG	Granule-based	GB
Binary-coded swarm optimization	BCSO	High temperature gas cooled	HTGC
Combined heat, power, and hydrogen	CHPH	Hydraulic retention time	HRT
Commercial dual fluidized bed	CDFB	Influent bicarbonate alkalinity	IBA
Cost benefit analysis	CBA	Imperialist competitive algorithm	ICA
Coal gasification process	CGP	Levenberg marquardt	LM
Chemical looping technology	CLT	Molten carbonate fuel cell power plants	MCFCPP
Dark fermentation process	DFP	Multi layered perceptron	MLP
Extreme learning machine	ELM	Monte carlo simulation	MCS
		Multi-way principal component analysis	MPCA

CONTACT Shahaboddin Shamshirband  shahaboddin.shamshirband@tdt.edu.vn

Natural-gas	NG
Neuro-fuzzy	NF
Non-dominated sorting genetic algorithm	NSGA
Nuclear power electrolysis	NPE
Organic loading rate	OLR
Particle swarm optimization	PSO
Probability distribution functions	PDF
Pareto optimal method	POM
Proton exchange membrane	PEM
Photo-electrochemical cell	PEC
Photo voltaic	PV
Correlation coefficient	r
Radiative transfer equation	RTE
Root mean square error	RMSE
Roulette wheel mechanism	RWM
Rotating gliding arc	RGA
Steam gasification plant	SGP
Steam methane reforming	SMR
Self-adaptive gravitational search algorithm	SAGSA
Support vector machines	SVM
Self-adaptive learning bat-inspired algorithm	SAL-BIA
Structural risk minimization principle	SRMP
Standard error of prediction	SEP
Teacher-learning algorithm	TLA
Total organic carbon	TOC
Up flow anaerobic sludge blanket	USAB
Wind electrolysis	WE

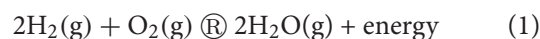
1. Introduction

Welfare and comfort of human life directly depends on the progress achieved in science and technology. This progress is likely to generate environmental and energy crises mainly due to its dependence on the energy needs of developed and first world nations (Mahmudul et al., 2017; Najafi, Pirouzpanah, Najafi, Yusaf, & Ghobadian, 2007). Declining fossil fuels and the impacts of CO₂ emission remain a concerning GHG emissions reduction task (Faizollahzadeh_Ardabili, Najafi, Ghaebi, Shamshirband, & Mostafaeipour, 2017) and a major global-warming issue (Franco, Mandla, & Rao, 2017). Therefore, a major task to be implemented by environmentally sustainable nations is to shift their energy use trend toward alternatives, mainly clean energy generated from renewable sources (Najafi, Pirouzpanah, Ghobadian, & Sadeghpour, 2007).

There is no doubt that heavily utilization energies such as wind, solar, biomass, hydro power, tidal, geothermal and hydrogen are the most well-known renewable energies that provide viable solution not only to solve future energy needs but also, to empower alternative measures to ameliorate the growing concern about environmental

degradation due to conventional fossil fuel. In last few years, it has been observed that an increasing interest on alternative energy sources has been mounting in the energy sector. Based on a report of British Petroleum statistical review of global energy usage in June 2017, the universal primary energy consumption appears to have increased by about 1% (in 2016), after a growth of about 0.9% in 2015 and about 1% in 2014. However, the 10-year average value was estimated to be about 1.8% per year. It was also noticeable that the renewable power (excluding hydro) has grown by about 14.1% in 2016 and that wind energy is expected to provide more than 50% of the growth of the renewable energies, while almost 18% of total energy value has been accounted for solar energy. The global NPE has increased by about 1.3% in 2016, whereas hydroelectric power generation has elevated by about 2.8% in 2016 (leading to a value of 27.1 mtoe) (Global, 2017).

While there have been previous reviews on other forms of renewable energies (e.g. (Kannan & Vakeesan, 2016; Thakur, Panigrahi, & Behera, 2016)), this paper is focused on hydrogen, a unique and an alternative energy resource that has a low pollution footprint released from its combustion (in the presence of sufficient oxygen) that produces only water and energy, and its subsequent utilization in fuel cells. The chemical process of energy extraction accords to (Eq. 1) to advocate the use of hydrogen as a future energy resource (Castillo, Magnin, Velasquez, & Willison, 2012; Perna, 2007).



It is important to be note that fuel generated from hydrogen has the largest 'higher heat value' (HHV) (approximately 141.9 MJ/kg) and a 'lower heat value' (LHV) (approximately 119.9 MJ/kg) compared to the conventional energy constituents such as methane (approximately 55.5 and 50 MJ/kg, respectively for HHV and LHV), Ethane (approximately 51.9 and 47.8 MJ/kg, respectively for HHV and LHV), Gasoline (approximately 44.5 and 47.5 MJ/kg, for LHV and HHV), Diesel (approximately 44.8 and 42.5 MJ/kg, for HHV and LHV) and methane (approximately 20 and 18.1 MJ/kg, for HHV and LHV) (Nikolaidis & Poullikkas, 2017). These comparisons show a great potential of hydrogen to be amicably embraced as a future energy resource in respect to the other forms of competing energy counterparts.

Despite the opportunities offered by hydrogen (as an alternative energy resource), it is imperative to note that hydrogen is not available as a single elemental source of energy, but it needs to be detached from potential compound including hydrocarbon fuels, boron hydride, water, chemical elements, hydrogen sulfide, and biomass (Dincer & Joshi, 2013). The techniques applied for the

production of hydrogen can be placed in four classes: biochemical (Sivagurunathan, Kumar, Kobayashi, Xu, & Kim, 2017), electrical (Hosseini & Wahid, 2016), thermal (Hbaieb, Rashid, & Kooli, 2017) and photonic (Vagia et al., 2017). Nuclear, fossil, and other renewable energies, can be the sources for the production of hydrogen but on the other hand, hydrogen can also be produced by recovered energy through various other chemical processes (Dincer & Joshi, 2013).

Figure 1 presents a flowchart of the hydrogen production methods.

In few last years, there was an increasing interest production of hydrogen production studies through a number of techniques, some of which are as analyzed and presented as follows.

Cao et al. (2016) employed an FB reactor to generate hydrogen from chicken manure with supercritical water gasification, Kraussler, Binder, Schindler, and Hofbauer (2016) produced hydrogen from a CDFB biomass SGP through a lab scale process and Cesar et al. (2016) produced hydrogen during steam reforming from ethylene glycol in the presence of Ni and Ni-Pt hydrotalcite-derived catalysts Saadi, Becherif, and Ramadan (2016) studied hydrogen production using Proton Exchange

Membrane (PEM) electrolyzer by applied solar energy to the production system while Hu, Zhang, Jing, and Lee (2016) produced bio-hydrogen from maize straws, pretreated with micro grinding technique and a photo-fermentation process. Lin, Leu, and Lee (2016) studied a two-stage ($H_2 + CH_4$) fermentation and CH_4 reforming process to increase hydrogen production with an environment-friendly approach where wastewater was used. This followed many researchers who used different methods, and they clearly depict a broad range of tools used for direct extraction of hydrogen without detrimental influence on the environment and the resulting burden of carbon footprint.

From the viewpoint of understanding hydrogen production there certainly appears to be a need for modeling the production process, to enable real-time production to be mapped with feasibility studies and forward planning of the entire renewable energy extraction and capital investment strategy. In recent years, artificial intelligence or soft computing (denoted as 'computational intelligence', CI) has been employed in scientific and energy engineering studies. For example, Sefeedpari, Rafiee, Akram, Chau, and Pishgar-Komleh (2016) employed ANFIS and MLP to emulate the production

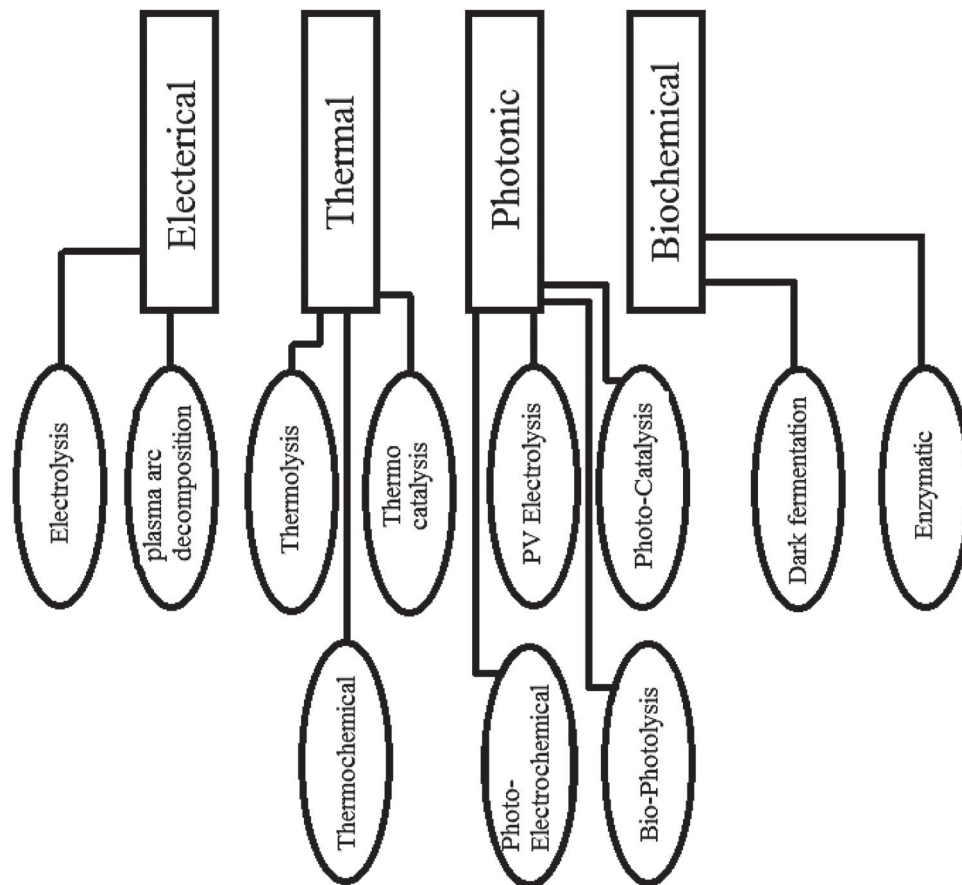


Figure 1. Hydrogen production method.

of eggplants based on actual energy consumption. ANN methodology was used to estimate the fluctuation in groundwater level simulated by dendrochronology by Gholami, Chau, Fadaee, Torkaman, and Ghaffari (2015), while ANN methodology was also selected to estimate base flow separation in an experiment. In this study, the computational run time was seen to be reduced with ELM algorithm. In another study the inputs and model identification was performed with the BCSO (Taormina, Chau, & Sivakumar, 2015), revealing the utility of CI in scientific experiments in a practical implementation framework. A hybrid improved complete ensemble empirical model decomposition model integrated with PSO-SVR was applied to emulate short-term electricity demand by Al-Musaylh, Deo, Adamowski, and Li (2018b) while Salcedo-Sanz, Deo, Cornejo-Bueno, Camacho-Gómez, and Ghimire (2018) applied a neuro-evolutionary hybrid mechanism to estimate daily solar radiation in Australia.

In published literature, it is evident that the use of CI acts to reduce the complexity of the system to be modeled and it can provide a high level of simulated accuracy of the overall system. To name a few such studies, we note that the CI method can be classified into these algorithms: GA, PSO, NF, AIS, FSVM and ANN applied to optimize the entire modeling process (Faizolahzadeh_Ardabili, Mahmoudi, & Mesri Gundoshmian, 2016; Kalantari et al., 2017). Known as artificial intelligence methods, CI has an excellent ability to learn the patterns embedded in the input-target dataset, and thus are able to recognize the complex (and potentially concealed) behavior in such data to model the objective variable. Using computer-based method research shows that CI approaches are able to employ significantly large volume of data to attain a high level of accuracy. More importantly, with the help of computer-assisted facilities, CI approaches can also enable a variety of decision-making options modeled by realistic estimates of processes that need to be implemented in real-life scenario (O'Leary, 2013).

Like many other fields, CI has attained a respectable place in the production, optimization and evaluation of hydrogen energy mainly because the generation of this energy is a relatively complex process involving large volume of data with several (and sometimes highly convoluted) input parameters. Such input parameters can be analyzed carefully to successfully model and extract hydrogen energy in a real system. Shi, Gai, Zhao, Zhu, and Zhang (2010) employed ANN for bio-hydrogen production in a steady-state performance bioreactor whereas Gabbar, Hussain, and Hosseini (2014) developed a new method using FSN for the propagation analysis and fault diagnosis in the presence of evolutionary technique such as the GP and ANN to uncap the interactions between

hydrogen production process variables. The rest of the studies, as presented in Table 1, can be categorized based on the respective CI approach.

The aim of this review is to survey the state-of-the-art CI approaches used in hydrogen production in terms of their context of application, accuracy and sensitivity to the model's input datasets. An extensive review, analysis and interpretation is expected to provide comprehensive information on the utilization of CI in hydrogen production, which is useful for researchers to optimize their approach, and renewable energy engineers to embrace such methods in modeling hydrogen energy systems. This review study contains five primary stages. The first stage is a comprehensive introduction about hydrogen energy and its production process. Secondly, the review provides a classification of studies based on the developed CI method in a greater detail, while stage three introduces CI and the hydrogen production methods. Stage four defines the criteria for evaluation of models and the final stage develops the comparison based on evaluation criteria and the overall conclusion reached in the review paper and the synthesis of state-of-the-art studies in hydrogen production studies.

2. Methodology

In this review we adopt a state-of-art where 21 recent articles on CI methods for hydrogen production are collected from cited archival literature including Science Direct, IEEE and Springer. The papers are reviewed in terms of hydrogen production method, modeling technique(s) and the obtained result. Table 1 provides a list of studies that deal with CI technique. This is arranged as a comprehensive overview of the aims and objectives, and the developed modeling method. The table also contains the method in the horizontal section with 4 vertical sections that are the title of the paper, publication year, author(s) and objective(s).

3. Characteristics of the studies

Table 2 presents the characteristics of the studies, *i.e.* the employed methodologies for each study in detail, the hydrogen production method, modeling method and the input and output datasets of each CI approach.

4. CI Approach Evaluation Criteria

The effectiveness of previous CI approach applied in a problem of hydrogen production has been evaluated based on a comparison of the output of the developed model and the target values, used for most accurate prediction, detection, and optimization and monitoring of

Table 1. Publications on CI techniques in field of hydrogen production between 2007 and 2017.

Row	Published Year	Author(s)	Objective
Artificial neural network			
1	2017	(Jha, Kana, & Schmidt, 2017)	To optimize the hydrogen yield and Chemical Oxygen Demand removal efficiency in a UASB bioreactor
2	2016	(Hossain, Ayodele, Cheng, & Khan, 2016)	To estimate the produced hydrogen-rich syngas through methane dry reforming process over Ni/CaFe ₂ O ₄ catalysts
3	2016	(Karaci, Caglar, Aydinli, & Pekol, 2016)	To model the thermochemical conversion process (i.e. hydrogen gas production from waste materials)
4	2014	(Whiteman & Kana, 2014)	To predict the bio-hydrogen production process
5	2014	(El-Shafie, 2014)	To estimate the bio-hydrogen yield
6	2010	(Rosales-Colunga, García, & Rodríguez, 2010)	To estimate the biohydrogen production during fermentative processes
ANFIS and other fuzzy methods			
1	2017	(Shabanian, Edrisi, & Khoram, 2017)	To estimate the hydrogen production and to optimize the production process for reaching the maximum production yield and energy efficiency
2	2016	(Aghbashlo, Hosseinpour, Tabatabaei, Younesi, & Najafpour, 2016)	Exegetically optimization of the operational conditions of the photo-bioreactor for bio-hydrogen production during water gas shift (WGS) reaction using a multi-objective hybrid optimization technique
3	2014	(Woo, 2014)	To analyze the safety of nuclear power plants production of hydrogen
4	2011	(Chang, Hsu, & Chang, 2011)	To choose the most appropriate hydrogen production technology using an evaluating method: application in Taiwan
5	2012	(Huang et al., 2012)	To develop an online system for bio-hydrogen production through monitoring control approach.
6	2012	(Heo, Kim, & Cho, 2012)	To evaluate the hydrogen production using six alternative methods include: biomass gasification (BG), NPE, coal gasification (CG), steam methane reforming (SMR), wind electrolysis (WE), and by-product hydrogen
7	2014	(Thengane, Hoadley, Bhattacharya, Mitra, & Bandyopadhyay, 2014)	To compare different hydrogen production methods from view point of cost benefit approach
GA and related algorithms			
1	2007	(Mu & Yu, 2007)	To model the steady-state performance of a GB hydrogen production through UASB reactor
2	2009	(Wang & Wan, 2009)	To increase the hydrogen production yield
3	2016	(Li & Lu, 2017)	To obtain the optimal value of the varying temperatures (i.e. room temperature (T1), hydrolysis temperature (T2) and oxygen decomposition temperature (T3)) in nuclear-based hydrogen Production process
4	2013	(Niknam, Bornapour, & Gheisari, 2013)	To consider the placement of Combined sources of Power, Heat, and Hydrogen fuel cell power plants without assuming the devices preparing cost
5	2015	(Bornapour & Hooshmand, 2015)	To plan the placement and the operation of MCF CPPs in distribution networks in case of using for CHPH production
6	2013	(Niknam, Bornapour, Ostadi, & Gheisari, 2013)	To optimize the planning of MCF CPPs for CHPH production
7	2012	(Niknam, Fard, & Baziar, 2012)	To evaluate the operation of hydrogen production, thermal load and electrical energy by FCPP
Support Vector Machine (SVM) method			
1	2016	(Monroy, Guevara-López, & Buitrón, 2016)	To develop a model for evaluating and estimating BHP during photofermentation process

the process in term of their statistical performance accuracy. Table 3 presents the evaluating factors that have been employed for comparing the efficiency of the CI approach. The second column describes the parameters used in the performance indices.

5. State-of-the-art of CI approaches in Hydrogen Production

5.1. Fuzzy method

This method was first introduced by Zadeh (1965). The method contains valued logics in which the variables are assigned as the actual number between or equal to 0 and 1 to classify data into an orderly manner (Faizollahzadeh_Ardabili et al., 2016; Kalantari et al., 2017). This method has since become prominent for handling

non-deterministic data concepts, for example, where the goal value has a magnitude between completely true or the completely false case (Novák, Perfilieva, & Mockor, 2012). Fuzzy method has been successfully applied to many research fields, including control theory and spanning to artificial intelligence-based applications, as presented below.

5.1.1. Fuzzy analytic hierarchy process approach (FAHP)

AHP method was first used by Saaty (1980) in multi-criteria decision making. This aims to employ the theory of measurements through pairwise comparisons by using both quantitative and qualitative data. This means that the FAHP is able to apply pairwise comparisons to benchmark the possibilities based on their importance over each other. The comparisons made are able to indicate

Table 2. Modeling characteristics.

No.	Methodology	Production Method	Modeling method/ classification method	Input(s) /objective function (s)	Output (s)/ Criteria	References
1	Using immobilized cell volume (ICV), Hydraulic Retention Time (HRT) and process temperature as input variables (independent variables) for developing the ANN and RSM	Anaerobic Sludge Blanket (UASB) bioreactor	ANN	Hydraulic retention times, immobilized cell volumes and temperatures	hydrogen yield and COD (Chemical Oxygen Demand) removal efficiency	(Jha et al., 2017)
2	Applied radial basis function (RBF) and multi layered perceptron (MLP) to predict the production process in presence of the catalyst metal loadings, feed ratio and the reaction temperature as inputs and H ₂ yield, CO yield, CH ₄ conversion and CO ₂ as output of process	Methane reforming	ANN	Feed ratio, Reaction Temperature and Metal loading	CH ₄ conversion, CO ₂ conversion, H ₂ yield and CO yield	(Hossain et al., 2016)
3	Pyrolysis process was modeled using MLP network using LM algorithm with 13 neurons on hidden layer by employing catalyst amount, type, biomass diversity, and temperature	pyrolysis of waste materials	ANN	catalyst amount, type, biomass diversity, and temperature	Hydrogen rich gas production yield	(Karaci et al., 2016)
4	concentration of molasses, pH, temperature and inoculum concentration were considered as input variables and hydrogen production yield was considered as output variable	Fermentation process	ANN	concentration of molasses, pH, temperature and inoculum concentration	Hydrogen production	(Whiteman & Kana, 2014)
5	Sixty data set were collected from batch type reactor. Reaction temperature, initial medium pH and the initial substrate were considered as input of ANN and the output was the hydrogen production yield.	Fermentation process	ANN	Reaction temperature, initial medium pH and the initial substrate	Hydrogen production yield	(El-Shafie, 2014)
6	A BPNN with 12 nodes in hidden layer with the conjugated gradient algorithm was employed to model the hydrogen production (as target parameter) using oxidation-reduction potential, pH dissolved CO ₂ .	Fermentation process	BPNN	oxidation-reduction potential, pH dissolved CO ₂	Hydrogen production	(Rosales-Colunga et al., 2010)
7	In first stage, ANFIS method was employed to predict the hydrogen yield and conversion efficiency of butanol and jet fuel and ICA methodology was developed to optimize the above mentioned processes from view point of production yield and energy efficiency	noncatalytic filtration combustion to be used in fuel-reforming process	ANFIS	Inlet velocity and equivalence ratio	hydrogen yield and conversion efficiency of butanol and jet fuel	(Shabaniyan et al., 2017)



8	The objective function of study was developed by ANFIS, and then the NSGA was applied to find the highest energy efficiency and the lowest destructed energy	Photo bio reactor	NSGA with ANFIS	culture agitation speed and syngas flow rate	normalized energy destruction, rational energy efficiency, and process energy efficiency	(Aghbashlo et al., 2016)
9	The assessment of HTGC reactor was modeled using fuzzy algorithm for the stabilized hydrogen production using nuclear energy	Nuclear energy-based hydrogen production	Modified Fuzzy method	In five scenario for evaluation the system: Long-term cooling using conduction Shutting down the cooling system, Flow coast down and power equilibrium, Trip of pre-turbine, Re-criticality achievements,		(Woo, 2014)
10	Linguistic scores prepared by Delphi questionnaire, were used to collect the technology rating and weights. The prepared linguistic scores were fuzzified, and the ideas of decision makers (on related weights and rates) was exported using fuzzy Delphi method (FDM). The developed model was employed to study hydrogen production based on different technologies.	NG reforming, NG reforming with CO2 storage, using net Electricity for producing Hydrogen, Using PV electricity for producing Hydrogen, using electrolysis by wind power for producing Hydrogen, using biomass gasification for producing Hydrogen, using fermentation process for producing Hydrogen	Fuzzy Delphi method	linguistic variables for Energy efficiency, CO2 emission, Fossil fuel consumption, Technological maturity, Technology development potential, Technological/industrial support, Feedstock, Capital, and Hydrogen production costs, Domestic market demand, Global market demand, Land use, Safeguard and social acceptance	Evaluating and presenting the best hydrogen production technology	(Chang et al., 2011)
11	<ul style="list-style-type: none"> pH and temperature were employed as fermentation environmental factors to control the feeding pump speed and heater performance fuzzy control was employed in lab-view software to develop a real time controller on hydrogen production process 	Fermentation	Fuzzy controller for controlling the production process	PH and temperature	feeding pump operating speed and heater status/ Hydrogen production	(Huang et al., 2012)
12	The fuzzy AHP method were employed to evaluate the studied system based on Twelve factors and their weights include: Ripple effect to other industries, Market size, Environmental contribution, Human resource development, Operation, Equipment, Infrastructure, and Distribution costs, Technological Reliability, dependency, acceptability and Stability.	SMR, gasification of biomass and coal, NPE and wind electrolysis, and by-product of hydrogen	Fuzzy AHP	Risks, Opportunities, Benefits, Costs, and Concepts	Evaluating and presenting the best hydrogen production technology	(Heo et al., 2012)

(continued).

Table 2. Continued.

No.	Methodology	Production Method	Modeling method/ classification method	Input(s) /objective function (s)	Output (s)/ Criteria	References
13	AHP and Fuzzy-AHP methods were employed to evaluate eight hydrogen production technologies including: partial biomass and coal gasification, SMR, oxidation of hydrocarbons, hydro-based, wind based and photovoltaic-based electrolysis, water splitting by chemical looping.	partial biomass and coal gasification, SMR, oxidation of hydrocarbons, hydro-based, wind based and photovoltaic-based electrolysis, water splitting by chemical looping	CBA using AHP and Fuzzy-AHP approaches	Common inputs of each method	Hydrogen production, utilities and raw material consumption greenhouse gas emissions, energy scalability and efficiency	(Thengane et al., 2014)
14	Applied ANN and GA by the input parameters of OLR, HRT, and IBA and the output parameters of H ₂ production rate, concentration, and yield, effluent total organic carbon and effluent aqueous products, separately	ASBR	ANN and GA	OLR, HRT, and IBA	H ₂ production rate and yield, H ₂ concentration in the biogas, and TOC, acetate, valerate, propionate, butyrate, caproate in the reactor effluent	(Mu & Yu, 2007)
15	Developed the neural network-based GA and RSM based on, initial PH, temperature and glucose concentration as the input variables and the hydrogen production as the target value.	Fermentation process	ANN-GA	initial PH, temperature and glucose concentration	Hydrogen yield	(Wang & Wan, 2009)
16	GA-MCS approach is employed to find the optimal temperature ranges	nuclear-based through Cu-Cl cycle	Genetic Algorithm and Monte Carlo Simulation	room temperature, hydrolysis temperature and oxygen decomposition temperature	Hydrogen production	(Li & Lu, 2017)
17	Employed the h-Self Adaptive Gravitational Search algorithm to achieve the optimal locating for FCPPs and daily optimal active powers.	Fuel Cell Power Plants (FCPPs)	⊖-SAGSA	Cost, emission and voltage deviation	heat produced by FCPP in bus I, bus during time t, equivalent electrical energy, equivalent electrical energy of saved, the maximum power of FCPP and equivalent electric power for hydrogen production during time t	(Niknam, Bornapour, & Gheisari, 2013)
18	The study scenarios were defined and the RWM-PDF was employed to generate scenarios based on input random variables. This approach helped define the problem as a cost-function. FFA and POM were employed to reduce the costfunction.	MCFCPP	FFA	Cost, emission and voltage deviation	Achieving the best response for developed scenarios	(Bornapour & Hooshmand, 2015)



19	<ul style="list-style-type: none"> The objective function included: electrical energy production cost, thermal energy, and hydrogen production, and voltage deviation The optimal planning for production of heat power and hydrogen with nonlinear nature was considered as study problem, accordingly a SLA-BIA was employed for solving the mentioned issue 	MCFCPP	SLA-BIA		Several scenarios for management of thermal energy and hydrogen production, total emission of MCFCPPs and achieving the best optimal set	(Niknam, Bornapour, Ostadi, et al., 2013)
20	TLA to take the optimal operation management of PEM-FCPPs and the optimal configuration of the system	FCPP	TLA		scenarios of PEM-FCPPs managements	(Niknam et al., 2012)
21	<ul style="list-style-type: none"> Using experimental photo-fermentations to obtain Kinetic parameters experimentally determining the Optimal conditions for light intensities, pH and Temperature, as state variables, as variables in the mechanistic model - employing MPCA technique and a classification stage using SVM 	Photo fermentation process	Mathematical modeling/Support Vector Machine	I, pH and Temperature	Hydrogen production	(Monroy et al., 2016)
22	Employing a method for fault diagnosis and propagation analysis using ANN and GP to uncover the interactions between hydrogen production process variables.	Cu-Cl thermochemical cycle	FSN	A/C ratioFeed D flow rateSeparator liquid flow	Explosion	(Gabbar et al., 2014)

Table 3. Model evaluation criteria

Accuracy and Performance Index	Description
$MSE = \frac{1}{N \times p} \sum_{i=1}^p \sum_{j=1}^N (T_{ij} - L_{ij})^2$	<ul style="list-style-type: none"> • P, the number of data set patterns • N, the number of output units • T_{ij} and L_{ij} are target and output values
$RMSE = \sqrt{\frac{1}{N \times p} \sum_{i=1}^p \sum_{j=1}^N (T_{ij} - L_{ij})^2}$	<ul style="list-style-type: none"> • P, the number of data set patterns • N, the number of output units • T_{ij} and L_{ij} are target and output values
$MAE = \frac{1}{N \times p} \sum_{i=1}^p \sum_{j=1}^N T_{ij} - L_{ij} $	<ul style="list-style-type: none"> • P, the number of data set patterns • N, the number of output units • T_{ij} and L_{ij} are target and output values
$MAPE = 100 \times \frac{1}{N \times p} \sum_{i=1}^p \sum_{j=1}^N \left \frac{T_{ij} - L_{ij}}{T_{ij}} \right $	<ul style="list-style-type: none"> • P, the number of data set patterns • N, the number of output units • T_{ij} and L_{ij} are target and output values
$r = \frac{\sum_{i=1}^n [(P_{Mi} - \bar{P}_M)(P_{Pi} - \bar{P}_P)]}{\sqrt{\sum_{i=1}^n [(P_{Mi} - \bar{P}_M)^2 \sum_{i=1}^n (P_{Pi} - \bar{P}_P)^2]}}$	<ul style="list-style-type: none"> • P_{Mi} is the target power • P_{Pi} is the output power • P_M is the average power • n is the number of the samples;

the sensitivity and the influence of an element relative to the other element by taking into account the particular attribute using an absolute scale theorem. Due to the nature of the indefinite judgment for the importance of each criteria, the FAHP model is able to exhibit a good fit with the fuzzy sets or the fuzzy numbers model, which is based on the vague thinking of humans. Therefore many studies have explored the fuzzy AHP (FAHP) approach in practical applications (e.g. (Dožić, Lutovac, & Kalić, *in press*; Shahbod, Mansouri, Bayat, Nouri, & Goddousi, 2017)). This method is one of the most popular approaches used in analyzing and modeling renewable energies. For example, Kumar et al. (2017) employed the fuzzy AHP approach to predict the best biodiesel production method whereas Singh, Vats, and Khanduja (2016) employed the FAHP approach to estimate the potentiality index (PI) and the relevant ranking of different Indian states for using solar energy in more efficient manner.

5.1.2. Fuzzy Delphi (F-D)

F-D is an analytical tool first introduced by Ishikawa et al. (1993). In terms of its origin, this method has been derived from the fuzzy set theory and Delphi techniques. This method is primarily grounded as a decision-making tool where an expert opinion is based on the writing

of the questionnaire surveys. In the last few years, the F-D method has been employed in various fields by different researchers and in a variety of research contexts (Suganthi, Iniyan, & Samuel, 2015).

5.2. Artificial neural network (ANN)

ANNs have a good ability to learn and analyze data features and subsequently, to implement non-linear approximation function (Faizollahzadeh_Ardabili et al., 2016) and are considered as one of the most efficient methods compared to statistical techniques (Naderloo et al., 2012). ANNs operate on the basis of the biological neural network and this has led to their successful applications in many areas such as pattern recognition, adaptive controls, image analysis etc. (Chen & Zhang, 2014). ANNs do not require any initial assumption about the nature of the fitting function or the data distribution, and this is a primary advantage of the model over its statistical counterparts. On the other hand, ANN can be trained with experimental data; therefore it is classified superior among the popular modeling tools. Importantly, ANN method has the ability to model complex systems in a more user-friendly way, requiring no parametric form of data assumption, complex physical equations and initial or boundary conditions compared to mathematical-type models (e.g. linear regression) (Pahlavan, Omid, & Akram, 2012). Recent papers have used ANN to model wind speed and global solar radiation with nearest neighbor datasets (Deo et al., 2018; Deo & Sahin, 2017).

5.2.1. Multi-layered-perceptron (MLP)

This model is a feed forward ANN that uses back-propagation, and supervised learning for the training of the network. The method contains input, hidden and output layers and the model aims to map input data onto an output space (Rosenblatt, 1961). Due to the simplicity of the design of an MLP, the model has successfully been employed to predict the production of biofuels, in many studies. For example, Maran and Priya (2015) employed MLP network and compared its performance with the RSM model for analyzing FAME conversion process in biodiesel production, reporting the MLP method with a better efficiency compared to the RSM. Akbaş, Bilgen, and Turhan (2015) employed MLP to predict biogas production from wastewater treatment, and found a relatively good ability to model the process, while another study applied MLP model integrated with Firefly Optimizer algorithm to model wind speed using neighboring station wind speed dataset without any other climate-based input (Deo et al., 2018).

5.2.2. Radial basis function (RBF)

The production of hydrogen has also been modeled with a Radial Basis Function (RBF) model that contains three data analysis layers similar to an MLP network but unlike the MLP the RBF employs only one hidden layer. RBF can be used as a kernel function in support vector classification or support vector regression models (e.g. (Al-Musaylh, Deo, Adamowski, & Li, 2018a)). Moreover, RBF-based model has a simpler structure compared to the MLP, and it usually presents efficient learning and modeling capabilities compared to the MLP-based model. This was evident from some studies showing that this model can provide more precise output (relative to the input) compared to the MLP-based model due to its architectural design, and accordingly, providing a highly adaptable network for modeling different types of energy systems (Tatar, Barati-Harooni, Partovi, Najafi-Marghmaleki, & Mohammadi, 2016).

5.3. ANFIS

ANFIS is a well-established tool that integrates the features and merits of ANN and the Fuzzy method. ANFIS model contains a number of adaptive nodes that are connected through the directional links that progress and model the input features through the fuzzy logic and the neural network approaches (Yaseen et al., 2017). Similar to the ANN model, the ANFIS model is able to generate the outputs using adaptive nodes, but on the other hand, it also uses the features of learning rules to minimize the training errors of the resulting predictive model. In fact, the ANFIS model is able to generate a hybrid intelligent system (*i.e.* combining ANN and Fuzzy Logic) where the merits of both the fuzzy logic and neural networks are used into a unified predictive model (Faizollahzadeh_Ardabili et al., 2017). As such, the ANFIS model has been one of the most accurate prediction methodologies considered in the field of renewable energies.

5.4. Genetic algorithm (GA)

GA is a prediction tool that aims to generate high-quality solutions in optimization and global search problems (Salcedo-Sanz et al., 2018). This model is able to deduce the closest optimal solution by searching through a feature space (Kennedy & Optimization, 1995). In GA model, a solution needs to be selected as the candidate solution (CS) and its population is set to evolve towards a better solution. Each CS contains a set of properties. This properties have the ability to mutate and change, therefore the evolution generally begins from a population of randomly generated individuals, and is progressed

as a duplicate process. In each generation (*i.e.* the population in each iteration), the objective function (for the optimization problem) is calculated. The new generation of the candidate solutions is then used in the next iteration of the algorithm. When a maximum number of generations have been produced, the algorithm stops and utilizes the final model to make the predictions. Recent applications include studies on evaporation modeling (Deo & Samui, 2017) and feature selection in energy prediction problems (Salcedo-Sanz et al., 2018).

5.4.1. *h*-Self adaptive gravitational search algorithm (*h*-SAGSA)

h-SAGSA has been acquired from a set of concepts related to Newton's law of gravity (Formato, 2007). According to the behavior of gravity and the Newton's Second law, the gravitational force between any two bodies depends on their mass and the acceleration of the body only depends on the force acting and its mass. In this algorithm, a similar notion is used where the bodies or particles are considered to be objects and their masses are the value objective functions in the optimization problem, while their positions are solutions.

5.4.2. Firefly algorithm (FFA)

FFA proposed by Yang (2010a), is an innovative modeling and optimization tool inspired by the flashing behavior of the fireflies. The conceptualization involves the notion that the light generated from the firefly acts as a signal to attract the other fireflies and the brightness level is dependent on the objective function. Recent work has used the FFA as a tool integrated with the MLP model for pan evaporation modeling (Ghorbani, Deo, Yaseen, Kashani, & Mohammad, 2017), modeling and uncertainty evaluation of dissolved biochemical oxygen demand (Raheli, Aalami, El-Shafie, Ghorbani, & Deo, 2017) as well as wind speed prediction without the use of large-scale climate datasets (Deo et al., 2018).

5.4.3. Bat-inspired algorithm (BiA)

BiA developed by Yang (2010b), is an innovative tool used for goal optimization. This is based on microbats behaviors, and it operates by considering the variation of the emitted pulse rates and their loudness such that it considers a bat that is flying at a velocity, position and frequency. As the algorithm progresses to find bait, its loudness, frequency and pulse emission change. This technique is used to control the motion behavior of bats.

5.4.4. Teaching-Learning (T-L) based optimization algorithm (OA)

T-LOA is an algorithm based on population which is developed by Rao, Savsani, and Vakharia (2011) used

for Optimization purposes. This algorithm represents the imitation of the T-L ability of the teacher and the students. In this method, the population considered for modeling purpose is a group of students and the offered topics to the student are as design variables of the model. A student's result is similar to the fitness value of the model and the value of objective function is used to represent the knowledge of a particular student. As the teacher is considered to be the most learned option than others, the best solution attained is similar to teacher in the T-LOA model. The process of Teaching and Learning-Based Optimization is divided in to two category.

5.5. SVM

SVM is considered as a popular CI method. This methodology is applied in accordance with statistical learning theory, which has a wide application in many fields of science and engineering including classification and regression problems (Ebtehaj, Bonakdari, Shamshirband, & Mohammadi, 2016; Ghorbani, Shamshirband, et al., 2017). SVM aims to reduce the generalized upper bound error rather than the local training error. This is one of the main advantages of the SVM model compared to the traditional machine learning methods. Moreover, the SVM model uses SRMP and presents a good generalization capability to overcome the shortcomings of the conventional ANN algorithm that utilizes the empirical risk minimization in modeling a given variable. SVM models have thus been applied in a number of energy problems (e.g. (Al-Musaylh et al., 2018a; Deo, Wen, & Feng, 2016; Salcedo-Sanz et al., 2018)).

6. Hydrogen production method

In accordance with literature, green energy solutions based on hydrogen production methods are separated into four categories from the viewpoint of utilizing this as a primary energy in renewable energy systems. These four categories, as focused in this study, are: electrical, thermal, photonic and biochemical energies. The remaining methods are a combination of these four production methods (Dincer & Joshi, 2013).

In this section of the review a brief description of each hydrogen production method is presented. This descriptions of the methodologies have been collected from primary references (Dincer, 2012; Dincer & Joshi, 2013; Rajeshwar, McConnell, & Licht, 2008; Turner, 2004; Van de Krol & Grätzel, 2012).

In accordance with the findings, the review identifies that electrical energy is considered as the primary energy resource for the electrolysis and plasma arc decomposition methods. In the electrolysis method,

passing a direct current from water and then decomposing water into O_2 and H_2 is facilitated. In the plasma arc decomposition method, the hydrogen is also generated by passing the natural gas through an electrically produced plasma arc. In this process, the carbon soot is also produced along with the production of hydrogen. ezzahra Chakik, Kaddami, and Mikou (2017) employed zinc alloys as the cathodes in water electrolysis process for hydrogen production in the presence of NaOH as the primary electrolyte. Grigoriev et al. (2017) implemented Clathrochelate-based electrocatalysts in proton exchange membrane (PEM) water electrolysis to facilitate the hydrogen production process. In a study by Zhang et al. (2014), the hydrogen production from methane decomposition process was investigated. In this study, an atmospheric pressure RGA discharge reactor was employed, which was co-driven by a tangential flow and a magnetic field.

The next category of hydrogen production utilizes thermal energy as a primary energy source, and this contains the Thermolysis, Thermo-catalysis and the Thermochemical processes. In principle, Thermolysis uses water as the raw material resource, and accordingly, the water steam is then brought to the temperature of over 2,500 K and its molecules are decomposed thermally. Hydrogen sulfide is the material resource of Thermo-catalysis process, which is cracked thermo-catalytically into H_2 and S as the byproducts. In another stage, the material source is biomass, which is converted through the Thermo-catalytic process into usable hydrogen and the thermochemical process entails the splitting of water, followed by gasification and reformation that results in H_2S after the final splitting stage. Here, the water is the material source in the splitting process, which utilizes chemical reactions to disintegrate the water molecules. Gasification, on the other hand, uses biomass as the material resource where H_2 is extracted through the conversion of biomass into the syngas. The reforming process, converts liquid biofuels to H_2 such that the H_2S slitting process uses hydrogen sulfide in the presence of cyclical reactions to split the H_2S molecule, and accordingly to release usable hydrogen.

In terms of existing studies, the work by Cong et al. (2016) has developed a reaction mechanism for the H_2S thermolysis process. A reaction path analysis is applied to determine the reactions that were responsible for the formation of H_2 and S_2 from the hydrogen sulfide. Yeheskel and Epstein (2011) developed a volumetric reactor in order to produce hydrogen through a solar thermolysis of methane in the presence of carbon particles cloud, which were a priory seeded or chemically produced. Naterer et al. (2015) developed a new solubility model for $CuCl-CuCl_2-HCl-H_2O$ quaternary system where

a new integrated process for-electrochemical hydrogen production was used to increase the speed and efficiency of electrolysis. Nakamura, Miyaoka, Ichikawa, and Kojima (2013) employed the thermochemical water splitting process using lithium redox reactions below 800 °C for the production of hydrogen while Ferrandon et al. (2010) investigated the hydrogen production prospects in a Cu–Cl thermochemical cycle to study the key steps of hydrolysis of CuCl_2 into Cu_2OCl_2 and HCl in the thermochemical Cu–Cl cycle. Sahraei, Larachi, Abatzoglou, and Iliuta (2017) studied the hydrogen production using Ni-UGS as a catalyst (which was prepared from metallurgical residues by the impregnation of Ni in a solid state) through a glycerol steam reforming (GSR) process and Wang, Fan, and Wang (2016) studied hydrogen production through chemical looping reforming process by using the reactivity of NiMn_2O_4 , employing bioethanol as a renewable liquid fuel. In this process, CO was also generated, along with H_2 as a major product.

The other hydrogen production methods are as follows: Photo Voltaic electrolysis, Photo-catalysis, Photo-electrochemical and bio-photolysis. These processes can be placed in the category of Photonic energy (as a primary energy required for the production of hydrogen). For these hydrogen production methods, water is normally the material resource required to facilitate the hydrogen generation process. Accordingly, in PV electrolysis, the electrolyser can be activated by the electricity generated from a PV panel. In the photo-catalysis method, however, the photo-initiated electrons are collected in the presence of homogeneous catalysts that generate hydrogen from water. In photo electrochemical process, water electrolysis process is activated by means of photovoltaic electricity generated by a hybrid cell and in the bio-photolysis process, the generation of hydrogen is facilitated by biological systems based on the cyanobacteria in a controlled way. In a study by Tebibel (2017), researchers investigated the hydrogen production using an off grid PV electrolyser system by analyzing the effect of PV array, tilt angle and battery DoD where the developed mathematical model of the system was also used. Dahbi et al. (2016) investigated a PV electrolyser system using the Simulink tool in MATLAB software in order to maximize the hydrogen production by considering the proportionality among the water flow, electrical power of PV system and the hydrogen production.

The PV module performance and average hydrogen production through water electrolysis process were considered in a study by Bhattacharyya, Misra, and Sandeep (2017) whilst also investigating the system based on energy and energy analyses. Moreover, Gobara, Nassar, El Naggar, and Eshaq (2017) studied the splitting of water (*i.e.* hydrogen production) induced by solar energy

using different Nanocrystalline ferrites and Boudjema et al. (2016) studied the relation of hydrogen production and $\text{A}_{0.2}\text{Zn}_{0.8}\text{Fe}_2\text{O}_4$, synthesized by co-precipitation method, through the heterogeneous photo-catalyst process. Yu, Meng, Li, and Li (2013) studied hydrogen production in the presence of CuO and carbon fiber co-modified TiO_2 nano-composite through photo-catalyst process. Casallas, Dincer, and Zamfirescu (2016) studied and developed a PEC in presence of electro-deposition of CuO/Cu₂O semiconductor photo-catalysts for hydrogen production. Qureshy, Ahmed, and Dincer (2016) developed numerical simulations of transport phenomena based on the Navier–Stokes equation, and the respective energy equation for electrolyte, and RTE in the PEC reactor where the hydrogen yield and the conversion efficiency were predicted. Rabbani, Dincer, and Naterer (2016) developed a photo electrochemical reactor to produce hydrogen, which utilized zinc sulfide as a photo catalyst. The effect of applied voltage value, amount of catalyst, and light intensity on hydrogen production was also studied. In addition to studying the effects of using a conical photo-bioreactor on bio-hydrogen yield, the work of Ainas et al. (2017) investigated bio-hydrogen production from *Spirulina platensis* under continuous illuminations.

It is apparent that biochemical energy source production contains two methods; dark fermentation and enzymatic method, both of which use biomass and water as the material resource, respectively. The dark fermentation process, is used to produce hydrogen in the absence of light during a fermentation process and the enzymatic method is used to produce hydrogen from water in the presence of polysaccharides. In the study of Noblecourt, Christophe, Larroche, and Fontanille (2017) hydrogen was produced from pre-fermented substrates (*i.e.* food waste) during the DFP where the hydrogen yield was simulated with the Gompertz model. Srivastava et al. (2017) employed *Clostridium pasteurianum* and hydrolyzed rice straw to generate hydrogen through DFP, and studied the optimum condition of the production process. Khongklian, Kongjan, Utarapichat, Reungsang, and Sompong (2017) investigated thermophilic dark fermentation and microbial electrolysis to produce hydrogen in the optimum conditions from cassava starch processing wastewater, while the study of Argun and Onaran (2017) considered hydrogen production from waste paper through the dark fermentation process. The latter study also investigated the effect of P/C, N/C, and Fe/C ratios on the production of hydrogen yield.

Evident through this review paper, there appears to have been a notable degree of prior studies on the production processes of hydrogen gas. These can be investigated in through separate research tasks, but in general, based

on the results of these studies, we can aver that water electrolysis, photo-electrochemical, biomass gasification and photo-fermentation process are the primary processes used for an efficient hydrogen production.

Based on the results by Kapdan and Kargi (2006) it can be synthesized from this review that, among the different hydrogen production methods, the methods SMR, electrolysis of water, and the auto-thermal processes, are the well-known methods. However, these methods require high energy, therefore, they cannot be considered as effective hydrogen extraction procedures. On the other hand, the production of hydrogen gas through biological production methods can have a significant advantage compared to the chemically based methods.

7. Synthesis of Results and Concluding Remark

This section synthesizes the findings and discusses the results of hydrogen production in previous studies. Figure 2 presents the distribution of CI methodologies applied in Hydrogen production during 2007 to 2017. This tree has been categorized based on type of methods grouping (single or hybrid) and publication year, and they are employed for various duties such as

developing, diagnosing, estimating, designing and optimizing in hydrogen production fields. This tree also describes the application trends for each methods in each year. As is clear, 2016 has the most trends for applying CI methods in hydrogen production. Also, the share of using single methods (61.9%) is higher than that of the hybrid methods (28.1%), on the other hand the diversity of single methods is higher than that of the hybrid methods. In case of method type, MLP (19.04%) has the highest usage among other methods (both single and hybrid methods).

Table 4 presents a list of results based on the selected paper number, collected in terms of the accuracy of the CI approaches and their effects on the hydrogen production process.

To provide further insights Table 5 has been extracted from Table 4, which presents the efficiency of each CI methods in greater detail.

Based on Table 5, using it is apparent that the use of MLP and ANFIS presents the highest correlation coefficient and the lowest modeling error encountered in the prediction of the hydrogen production process. In studies Referenced as 1, 2, 3, 5, 6 and 7, the employed methods (*i.e.* MLP and ANFIS models) resulted the correlation coefficient values of about 0.99, 0.97, 0.955, 0.98, 0.955

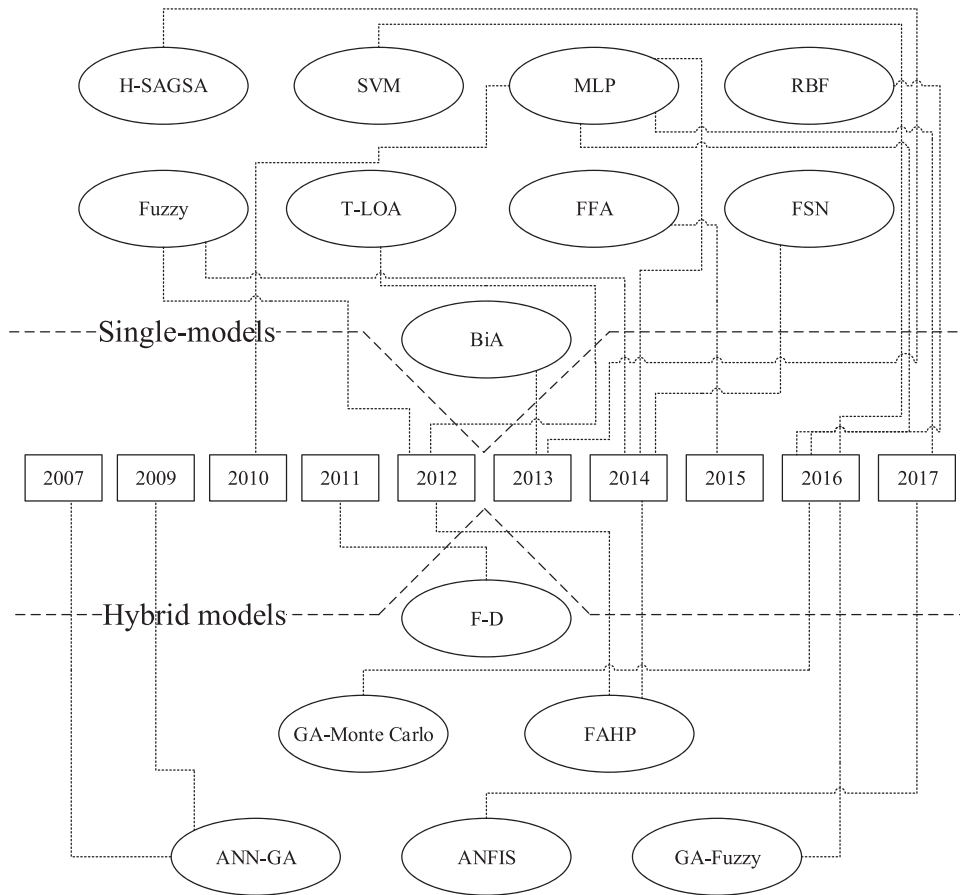


Figure 2. Distribution of CI methods in hydrogen production.

Table 4. Total results of the presented studies.

Paper. No.	Results and evaluation	Paper. No.	Results and evaluation
1	Based on the results, ANN presented the highest accuracy and reliability for modeling and optimization the studied parameters compared to RSM method. Accordingly, a higher molar bio hydrogen yield (0.90 mol-H ₂ /mol glucose) and COD removal efficiency (84.81%) in the UASB system was obtained, optimized by the ANN model.	12	<ul style="list-style-type: none"> Based on the results, the most important indexes were able to achieve economic feasibility and lowering risks. SMR was selected the appropriate hydrogen production method.
2	MLP method by presenting the highest R ² value for the simulated output of the selected variable as the best predictor compared to the RBF method	13	Based on results (from view point of cost-benefit analysis), the splitting of water by CLT had the most acceptable results compared to the renewable approaches.
3	Based on the results the developed network was able to estimate the hydrogen rich gas ratio with little error.	14	Based on the results, the developed model was able to estimate the daily variation of the performance of UASB reactor, and could predict the reactor performance at various HRTs
4	RSM and ANN models resulted the R ² values of 0.75 and 0.91, respectively. Based on the results in the validation process, the prediction errors of 15.12 and 119.08% prediction were calculated for the ANN and the RSM based on the volume of hydrogen.	15	Based on the results, the performance of the ANN-based GA was much better than that for RSM, and this concluded that the ANN model had a much higher predicting accuracy compared to that of the RSM model
5	Based on the results, the developed ANN model provided significantly high predicting performance	16	Based on the results GA-based MCS method could be applied to find the optimal temperature ranges such that this method found temperature ranges of [25.705, 25.809], [433.595, 434.245] and [521.645, 528.415] for T1, T2 and T3, respectively.
6	Based on the results, the BPNN with correlation coefficient of 0.955 between the target and the output values successfully estimated the hydrogen production with a potential to be used in other hydrogen production systems	17	Based on the simulation results, a satisfactory performance of the developed model was found, being an effective algorithm with a shorter convergence time.
7	Based on the prediction results, the R ² value of ANFIS model was calculated to be about 0.998, 0.998, 0.999 and 0.999, respectively for estimating the hydrogen yield and conversion efficiency of jet fuel and butanol.	18	The developed method led to a reduced voltage deviation, cost and emission. On the other hand, based on the simulation results, the algorithm had a significant advantage compared to the other comparative methods.
8	The culture agitation speed of 383.33 rpm and the syngas flow rate of 13.34 ml/min provided the optimal condition by rational exergy efficiency of 85.64%, yielding process exergy efficiency of 21.66% and exergy destruction of 1.55	19	Based on the results, the developed algorithm decreased the convergence time for optimally planning the location and operation. The simulation results validated the performance of the proposed approach.
9	Based on results, a frequency of 8% was obtained for successful long-term cooling by conduction.	20	The simulation results demonstrated satisfactory performance of the developed method, with a potential for greater efficiency in the thermal energy and hydrogen production process.
10	Based on the results, we aver that the use of wind power and photovoltaic electricity were the two appropriate approaches used for hydrogen production in Taiwan	21	Based on the results, both data-driven models had strong outputs for further usage.
11	<ul style="list-style-type: none"> Based on the results, the use of the fuzzy controller acted to reduce the energy consumption in hydrogen production process and provided an appropriate condition for growth of microorganisms by providing the best environmental condition maximum production in the case of using fuzzy controller was 13.44 L/Day 		

and 0.998 for prediction of hydrogen yield. This values of correlation show the highest prediction ability of the developed approaches.

On the other hand using hybrid CI methods (such as the GA-ANN method) led to an improved and optimized opportunity for the production of hydrogen. For example, in study of Reference 14 that used the GA-ANN method, the result showed a prediction accuracy with a correlation coefficient of 0.966 and in the study of reference 15, the use of the GA method led to an increase in the hydrogen production compared to their RSM method. That is, the GA-ANN model led to a predicted value of 360.5 ml/g of hydrogen produced, which

was higher than that of the GA-RSM method (at a value of 289.8 ml/g of hydrogen).

In studies Referenced as 12 and 13, the authors have used a fuzzy AHP for the classification of the production methods. This study showed that the steam methane was reformed with the weights of 0.529 and a byproduct hydrogen with a weight of 0.366 that were the most and the least effective methods. Based on the studied factors of Reference 12 and 13, the splitting of water by a chemical looping process (WS-CL) and the biomass gasification (BG) methods, the results yielded a score of 0.1945 and 0.0627, respectively, as the most and the least effective hydrogen production methods.

Table 5. The values of the model evaluating factors.

Paper No.	method	Efficiency factor	Value
1	ANN-MLP	R^2	0.99 for hydrogen production yield
2	RSM	R^2	0.90 for hydrogen production yield
	ANN-MLP	R^2	0.9726, 0.8597, 0.9638 and 0.9394 for H ₂ yield, CO yield, CH ₄ conversion
3	ANN-RBF	R^2	0.9218, 0.7759, 0.8307 and 0.7425 for H ₂ yield, CO yield, CH ₄ conversion
		r	0.955 for hydrogen production yield
4	ANN-MLP	MSE	6.97 for hydrogen production yield
		R^2	0.91 for hydrogen production yield
5	RSM	R^2	0.75 for hydrogen production yield
6	ANN-MLP	R^2	0.98 for hydrogen production yield
7	BP ANN	r	0.955 for hydrogen production yield
8	ANFIS	R^2	0.998, 0.998, 0.999 and 0.999, respectively for hydrogen yield and conversion efficiency of jet fuel and butanol.
		MAPE	0.9, 0.97 and 0.92 for normalized exergy destruction, rational exergy, and process exergy efficiencies
		MSE	0.019, 0.0029, 0.0228 for normalized exergy destruction, rational exergy, and process exergy efficiencies
9	Modified fuzzy algorithm	frequency	8% of successful long-term conduction cooling
12	Fuzzy AHP	Overall weights of each production method based on risk, cost and opportunities	0.529, 0.46, 0.449, 0.331, 0.395 and 0.366 for SMR, CGP, BG, WE, NPE, and hydrogen yield, respectively.
13	Fuzzy AHP	Final score of each production method based on GHG emission, raw material, energy efficiency, scalability, wastes and emission	0.1945, 0.1648, 0.1474, 0.1385, 0.1151, 0.0908, 0.0863 and 0.0627 for WS-CL, H-EL, SMR, W-EL, POX, PV-EL, CG and BG, respectively.
14	GA-NN	R^2 for Training	0.966, 0.81, 0.882 and 0.92 for H ₂ concentration in the biogas, production rate, yield, and effluent TOC.
		R^2 for validation	0.719, 0.806, 0.843 and 0.854 for H ₂ concentration in the biogas, production rate, yield, and effluent TOC.
15	ANN-MLP	RMSE, and SEP	16.6% and 38.4%, respectively for RMSE and SEP for hydrogen production
	RSM	RMSE, and SEP	7.7% and 17.8% respectively for RMSE and SEP for hydrogen production
	GA-ANN	Maximum hydrogen production	360.5 ml/g of glucose
	GA-RSM	Maximum hydrogen production	289.8 ml/g of glucose

In Figure 3, we present the history of CI methods, defining some results originated from other methods to sustain the modeling efficiency and productiveness. In the present review article, a total of 21 state-of-the-art research papers related to application of computational intelligence (CI) techniques for hydrogen production were collected from highly cited publications, Science Direct, IEEE and Springer databases, and these were reviewed in terms of the production method, modeling techniques and the obtained results. The relatively low number of articles in the case of using CI methods for hydrogen production, shows a high research potential in this field, particularly for embracing cleaner energy as a solution to combat climate change and also to address the challenges that are faced in respect to the rapid depletion of fossil reserves and environmental and health repercussions.

The literature concerning to the issues and challenges of the hydrogen production data and the production methods and applications of CI methods on production process have also been discussed. Due to a plethora of

studies performed in the use of CI methods, this article was not categorized into hybrid and single-based CI methods. However, the present evaluation has been conducted using previous results of the most relevant papers using on different datasets in terms of the accuracy and sensitivity of the final prediction. Based on the synthesis of the results, the use of hybrid methods such as GA-ANN or GA-RSM leads to an improvement and optimization of the process of hydrogen production whereas the use of MLP and ANFIS methods leads to the highest correlation and the lowest error for prediction of the hydrogen production. Despite numerous papers on various CI methods in hydrogen production field, there appears to have been a lack of studies in case of accessing a comprehensive dataset, classification and analyzing the CI methods in the case of hydrogen production. The present review study can only partly compensate for this need for future researchers to focus in a greater depth on the issues raised in this paper. Our future viewpoint is to develop a multi-factor system-based CI applied to hydrogen production methods to reach the high performance in estimating and

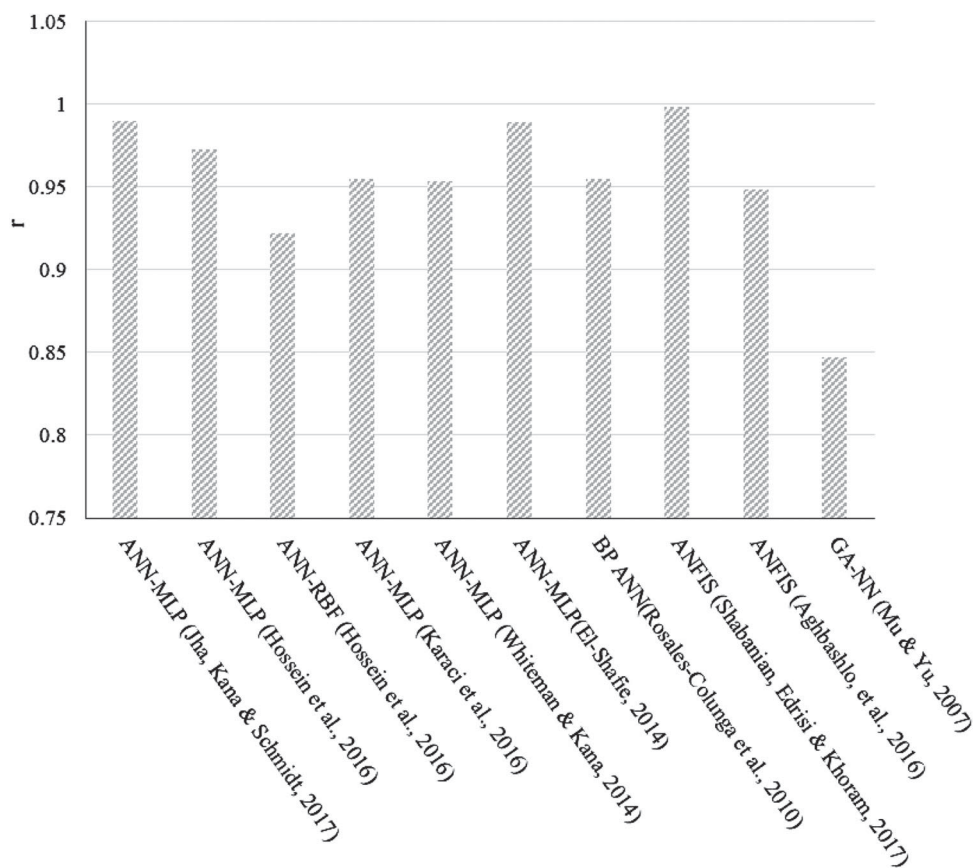


Figure 3. Comparing of prediction models in terms of R².

modeling and to design a platform which contains accurate and powerful methods for unsupervised learning on hydrogen production data.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This research is funded by the Foundation for Science and Technology Development of Ton Duc Thang University (FOSTECT), website: <http://fostect.tdtu.edu.vn>, under [grant number FOSTECT.2017.BR.19].

ORCID

Shahaboddin Shamshirband  <http://orcid.org/0000-0002-6605-498X>

References

- Aghbashlo, M., Hosseinpour, S., Tabatabaei, M., Younesi, H., & Najafpour, G. (2016). On the exergetic optimization of continuous photobiological hydrogen production using hybrid ANFIS-NSGA-II (adaptive neuro-fuzzy inference system–non-dominated sorting genetic algorithm-II). *Energy*, 96, 507–520.
- Ainas, M., Hasnaoui, S., Bouarab, R., Abdi, N., Drouiche, N., & Mameri, N. (2017). Hydrogen production with the cyanobacterium *Spirulina platensis*. *International Journal of Hydrogen Energy*, 42(8), 4902–4907.
- Akbaş, H., Bilgen, B., & Turhan, A. M. (2015). An integrated prediction and optimization model of biogas production system at a wastewater treatment facility. *Bioresour Technol*, 196, 566–576.
- Al-Musaylh, M. S., Deo, R. C., Adamowski, J. F., & Li, Y. (2018a). Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia. *Advanced Engineering Informatics*, 35, 1–16.
- Al-Musaylh, M. S., Deo, R. C., Adamowski, J. F., & Li, Y. (2018b). Two-phase particle swarm optimized-support vector regression hybrid model integrated with improved empirical mode decomposition with adaptive noise for multiple-horizon electricity demand forecasting. *Applied Energy*, 0, 0. doi:10.1016/j.apenergy.2018.02.140
- Argun, H., & Onaran, G. (2017). Effects of N/C, P/C and Fe/C ratios on dark fermentative hydrogen gas production from waste paper towel hydrolysate. *International Journal of Hydrogen Energy*, 42(22), 14990–15001.
- Bhattacharyya, R., Misra, A., & Sandeep, K. (2017). Photo-voltaic solar energy conversion for hydrogen production by alkaline water electrolysis: Conceptual design and analysis. *Energy Conversion and Management*, 133, 1–13.
- Bornapour, M., & Hooshmand, R.-A. (2015). An efficient scenario-based stochastic programming for optimal planning

- of combined heat, power, and hydrogen production of molten carbonate fuel cell power plants. *Energy*, 83, 734–748.
- Boudjemaa, A., Popescu, I., Juzsakova, T., Kebir, M., Helaili, N., Bachari, K., & Marcu, I.-C. (2016). M-substituted (M = Co, Ni and Cu) zinc ferrite photo-catalysts for hydrogen production by water photo-reduction. *International Journal of Hydrogen Energy*, 41(26), 11108–11118.
- Cao, W., Cao, C., Guo, L., Jin, H., Dargusch, M., Bernhardt, D., & Yao, X. (2016). Hydrogen production from supercritical water gasification of chicken manure. *International Journal of Hydrogen Energy*, 41(48), 22722–22731.
- Casallas, C., Dincer, I., & Zamfirescu, C. (2016). Experimental investigation and analysis of a novel photo-electrochemical hydrogen production cell with polymeric membrane photocathode. *International Journal of Hydrogen Energy*, 41(19), 7968–7975.
- Castillo, P., Magnin, J.-P., Velasquez, M., & Willison, J. (2012). Modeling and optimization of hydrogen production by the photosynthetic bacterium *Rhodospirillum rubrum* by the methodology of design of experiments (DOE): interaction between lactate concentration and light luminosity. *Energy Procedia*, 29, 357–366.
- Cesar, D. V., Santori, G. F., Pompeo, F., Baldanza, M. A., Henriques, C. A., Lombardo, E., . . . Nichio, N. N. (2016). Hydrogen production from ethylene glycol reforming catalyzed by Ni and Ni-Pt hydrotalcite-derived catalysts. *International Journal of Hydrogen Energy*, 41(47), 22000–22008.
- Chang, P.-L., Hsu, C.-W., & Chang, P.-C. (2011). Fuzzy Delphi method for evaluating hydrogen production technologies. *International Journal of Hydrogen Energy*, 36(21), 14172–14179.
- Chen, C. P., & Zhang, C.-Y. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on big data. *Information Sciences*, 275, 314–347.
- Cong, T. Y., Raj, A., Chanaphet, J., Mohammed, S., Ibrahim, S., & Al Shoaibi, A. (2016). A detailed reaction mechanism for hydrogen production via hydrogen sulphide (H₂S) thermolysis and oxidation. *International Journal of Hydrogen Energy*, 41(16), 6662–6675.
- Dahbi, S., Aboutni, R., Aziz, A., Benazzi, N., Elhafyani, M., & Kassmi, K. (2016). Optimised hydrogen production by a photovoltaic-electrolysis system DC/DC converter and water flow controller. *International Journal of Hydrogen Energy*, 41(45), 20858–20866.
- Deo, R. C., Ghorbani, M. A., Samadianfard, S., Maraseni, T., Bilgili, M., & Biazar, M. (2018). Multi-layer perceptron hybrid model integrated with the firefly optimizer algorithm for windspeed prediction of target site using a limited set of neighboring reference station data. *Renewable Energy*, 116, 309–323.
- Deo, R. C., & Sahin, M. (2017). Forecasting long-term global solar radiation with an ANN algorithm coupled with satellite-derived (MODIS) land surface temperature (LST) for regional locations in Queensland. *Renewable and Sustainable Energy Reviews*, 72, 828–848.
- Deo, R. C., & Samui, P. (2017). Forecasting evaporative loss by least-square support-vector regression and evaluation with genetic programming, Gaussian process, and minimax probability machine regression: Case study of Brisbane city. *Journal of Hydrologic Engineering*, 22(6), 05017003–05017015.
- Deo, R. C., Wen, X., & Feng, Q. (2016). A wavelet-coupled support vector machine model for forecasting global incident solar radiation using limited meteorological dataset. *Applied Energy*, 168, 568–593.
- Dincer, I. (2012). Green methods for hydrogen production. *International Journal of Hydrogen Energy*, 37(2), 1954–1971.
- Dincer, I., & Joshi, A. S. (2013). *Solar based hydrogen production systems*. Oshawa: Springer.
- Dožić, S., Lutovac, T., & Kalić, M. (in press). Fuzzy AHP approach to passenger aircraft type selection. *Journal of Air Transport Management*.
- Ebtehaj, I., Bonakdari, H., Shamshirband, S., & Mohammadi, K. (2016). A combined support vector machine-wavelet transform model for prediction of sediment transport in sewer. *Flow Measurement and Instrumentation*, 47, 19–27.
- El-Shafie, A. (2014). Neural network nonlinear modeling for hydrogen production using anaerobic fermentation. *Neural Computing and Applications*, 24(3-4), 539–547.
- ezzahra Chakik, F., Kaddami, M., & Mikou, M. (2017). Effect of operating parameters on hydrogen production by electrolysis of water. *International Journal of Hydrogen Energy*, 42(40), 25550–25557.
- Faizollahzadeh_Ardabili, S., Mahmoudi, A., & Mesri Gundoshmian, T. (2016). Modeling and simulation controlling system of HVAC using fuzzy and predictive (radial basis function, RBF) controllers. *Journal of Building Engineering*, 6, 301–308.
- Faizollahzadeh_Ardabili, B., Najafi, H., Ghaebi, S., Shamshirband, A., & Mostafaeipour. (2017). A novel enhanced exergy method in analysing HVAC system using soft computing approaches: A case study on mushroom growing hall. *Journal of Building Engineering*, 13, 309–318.
- Ferrandon, M. S., Lewis, M. A., Tatterson, D. F., Gross, A., Doizi, D., Croize, L., . . . Carles, P. (2010). Hydrogen production by the Cu-Cl thermochemical cycle: Investigation of the key step of hydrolysing CuCl₂ to Cu₂OCl₂ and HCl using a spray reactor. *International Journal of Hydrogen Energy*, 35(3), 992–1000.
- Formato, R. (2007). Central force optimization: A new meta-heuristic with applications in applied electromagnetics. *Progress In Electromagnetics Research*, 77, 425–491.
- Franco, S., Mandla, V. R., & Rao, K. R. M. (2017). Urbanization, energy consumption and emissions in the Indian context A review. *Renewable and Sustainable Energy Reviews*, 71, 898–907.
- Gabbar, H. A., Hussain, S., & Hosseini, A. H. (2014). Simulation-based fault propagation analysis—application on hydrogen production plant. *Process Safety and Environmental Protection*, 92(6), 723–731.
- Gholami, V., Chau, K., Fadaee, F., Torkaman, J., & Ghaffari, A. (2015). Modeling of groundwater level fluctuations using dendrochronology in alluvial aquifers. *Journal of Hydrology*, 529, 1060–1069.
- Ghorbani, M. A., Deo, R. C., Yaseen, Z. M., Kashani, M. H., & Mohammad, B. (2017). Pan evaporation prediction using a hybrid multilayer perceptron-firefly algorithm (MLP-FFA) model: Case study in North Iran. *Theoretical and Applied Climatology*. doi:10.1007/s00704-017-2244-0.
- Ghorbani, M. A., Shamshirband, S., Haghi, D. Z., Azani, A., Bonakdari, H., & Ebtehaj, I. (2017). Application of firefly algorithm-based support vector machines for prediction of field capacity and permanent wilting point. *Soil and Tillage Research*, 172, 32–38.

- Global, B. P. (2017, June). BP statistical review of world energy. Gobara, H. M., Nassar, I. M., El Naggar, A. M., & Eshaq, G. (2017). Nanocrystalline spinel ferrite for an enriched production of hydrogen through a solar energy stimulated water splitting process. *Energy*, *118*, 1234–1242.
- Grigoriev, S., Pushkarev, A., Pushkareva, I., Millet, P., Belov, A., Novikov, V., ... Voloshin, Y. (2017). Hydrogen production by proton exchange membrane water electrolysis using cobalt and iron hexachloroethylenes as efficient hydrogen-evolving electrocatalysts. *International Journal of Hydrogen Energy*, *42*(46), 27845–27850.
- Hbaieb, K., Rashid, K., & Kooli, F. (2017). Hydrogen production by autothermal reforming of dodecane over strontium titanate based perovskite catalysts. *International Journal of Hydrogen Energy*, *42*(8), 5114–5124.
- Heo, E., Kim, J., & Cho, S. (2012). Selecting hydrogen production methods using fuzzy analytic hierarchy process with opportunities, costs, and risks. *International Journal of Hydrogen Energy*, *37*(23), 17655–17662.
- Hossain, M. A., Ayodele, B. V., Cheng, C. K., & Khan, M. R. (2016). Artificial neural network modeling of hydrogen-rich syngas production from methane dry reforming over novel Ni/CaFe 2 O 4 catalysts. *International Journal of Hydrogen Energy*, *41*(26), 11119–11130.
- Hosseini, S. E., & Wahid, M. A. (2016). Hydrogen production from renewable and sustainable energy resources: Promising green energy carrier for clean development. *Renewable and Sustainable Energy Reviews*, *57*, 850–866.
- Hu, J., Zhang, Q., Jing, Y., & Lee, D.-J. (2016). Photosynthetic hydrogen production from enzyme-hydrolyzed micro-grinded maize straws. *International Journal of Hydrogen Energy*, *41*(46), 21665–21669.
- Huang, S.-R., Chen, H.-T., Chung, C.-H., Wu, C.-C., Tsai, T.-Y., Chu, C.-Y., & Lin, C.-Y. (2012). Fermentative hydrogen production using a real-time fuzzy controller. *International Journal of Hydrogen Energy*, *37*(20), 15575–15581.
- Ishikawa, A., Amagasa, M., Shiga, T., Tomizawa, G., Tatsuta, R., & Mieno, H. (1993). The max-min Delphi method and fuzzy Delphi method via fuzzy integration. *Fuzzy Sets and Systems*, *55*(3), 241–253.
- Jha, P., Kana, E., & Schmidt, S. (2017). Can artificial neural network and response surface methodology reliably predict hydrogen production and COD removal in an UASB bioreactor? *International Journal of Hydrogen Energy*, *42*(30), 18875–18883.
- Kalantari, A., Kamsin, A., Shamshirband, S., Gani, A., Alinejad-Rokny, H., & Chronopoulos, A. T. (2017). Computational intelligence approaches for classification of medical data: State-of-the-art, future challenges and research directions. *Neurocomputing*, *276*, 2–22.
- Kannan, N., & Vakeesan, D. (2016). Solar energy for future world:-A review. *Renewable and Sustainable Energy Reviews*, *62*, 1092–1105.
- Kapdan, I. K., & Kargi, F. (2006). Bio-hydrogen production from waste materials. *Enzyme and Microbial Technology*, *38*(5), 569–582.
- Karaci, A., Caglar, A., Aydinli, B., & Pekol, S. (2016). The pyrolysis process verification of hydrogen rich gas (H-rG) production by artificial neural network (ANN). *International Journal of Hydrogen Energy*, *41*(8), 4570–4578.
- Kennedy, J., & Optimization, R. E. P. S. (1995). *Ieee int. Conf. on Neural Networks*.
- Khongkliang, P., Kongjan, P., Utarapichat, B., Reungsang, A., & Sompong, O. (2017). Continuous hydrogen production from cassava starch processing wastewater by two-stage thermophilic dark fermentation and microbial electrolysis. *International Journal of Hydrogen Energy*, *42*(45), 27584–27592.
- Kraussler, M., Binder, M., Schindler, P., & Hofbauer, H. (2016). Hydrogen production within a polygeneration concept based on dual fluidized bed biomass steam gasification. *Biomass and Bioenergy*, *111*, 320–329.
- Kumar, K. A., Kumar, P. S., Madhusudanan, S., Pasupathy, V., Vignesh, P. R., & Sankaranarayanan, A. R. (2017). A simplified model for evaluating best biodiesel production method: Fuzzy analytic hierarchy process approach. *Sustainable Materials and Technologies*, *12*, 18–22.
- Li, B., & Lu, L. (2017). Genetic-algorithm-based fault detection of the heat transfer process in nuclear-based hydrogen production based ON Cu-Cl cycle. *International Journal of Hydrogen Energy*, *42*(6), 3863–3875.
- Lin, C.-Y., Leu, H.-J., & Lee, K.-H. (2016). Hydrogen production from beverage wastewater via dark fermentation and room-temperature methane reforming. *International Journal of Hydrogen Energy*, *41*(46), 21736–21746.
- Mahmudul, H., Hagos, F., Mamat, R., Adam, A. A., Ishak, W., & Alenezi, R. (2017). Production, characterization and performance of biodiesel as an alternative fuel in diesel engines—A review. *Renewable and Sustainable Energy Reviews*, *72*, 497–509.
- Maran, J. P., & Priya, B. (2015). Comparison of response surface methodology and artificial neural network approach towards efficient ultrasound-assisted biodiesel production from muskmelon oil. *Ultrasonics Sonochemistry*, *23*, 192–200.
- Monroy, I., Guevara-López, E., & Buitrón, G. (2016). A mechanistic model supported by data-based classification models for batch hydrogen production with an immobilized photo-bacteria consortium. *International Journal of Hydrogen Energy*, *41*(48), 22802–22811.
- Mu, Y., & Yu, H.-Q. (2007). Simulation of biological hydrogen production in a UASB reactor using neural network and genetic algorithm. *International Journal of Hydrogen Energy*, *32*(15), 3308–3314.
- Naderloo, L., Alimardani, R., Omid, M., Sarmadian, F., Javadikia, P., Torabi, M. Y., & Alimardani, F. (2012). Application of ANFIS to predict crop yield based on different energy inputs. *Measurement*, *45*(6), 1406–1413.
- Najafi, B., Pirouzpanah, V., Ghobadian, B., & Sadeghpour, R. A. (2007). Experimental investigation of diesel engine performance parameters and pollution using biodiesel.
- Najafi, B., Pirouzpanah, V., Najafi, G., Yusaf, T., & Ghobadian, B. (2007). Experimental investigation of performance and emission parameters of a small diesel engine using CNG and biodiesel.
- Nakamura, N., Miyaoka, H., Ichikawa, T., & Kojima, Y. (2013). Hydrogen production via thermochemical water-splitting by lithium redox reaction. *Journal of Alloys and Compounds*, *580*, S410–S413.
- Naterer, G., Suppiah, S., Stolberg, L., Lewis, M., Wang, Z., Rosen, M., ... Secnik, E. (2015). Progress in thermochemical hydrogen production with the copper-chlorine cycle. *International Journal of Hydrogen Energy*, *40*(19), 6283–6295.
- Niknam, T., Bornapour, M., & Gheisari, A. (2013). Combined heat, power and hydrogen production optimal planning of

- fuel cell power plants in distribution networks. *Energy Conversion and Management*, 66, 11–25.
- Niknam, T., Bornapour, M., Ostadi, A., & Gheisari, A. (2013). Optimal planning of molten carbonate fuel cell power plants at distribution networks considering combined heat, power and hydrogen production. *Journal of Power Sources*, 239, 513–526.
- Niknam, T., Fard, A. K., & Baziar, A. (2012). Multi-objective stochastic distribution feeder reconfiguration problem considering hydrogen and thermal energy production by fuel cell power plants. *Energy*, 42(1), 563–573.
- Nikolaïdis, P., & Poullikkas, A. (2017). A comparative overview of hydrogen production processes. *Renewable and Sustainable Energy Reviews*, 67, 597–611.
- Noblecourt, A., Christophe, G., Larroche, C., & Fontanille, P. (2017). Hydrogen production by dark fermentation from pre-fermented depackaging food wastes. *Bioresource Technology*, 247, 864–870.
- Novák, V., Perfilieva, I., & Mockor, J. (2012). *Mathematical principles of fuzzy logic*. New York: Springer Science & Business Media.
- O'Leary, D. E. (2013). Artificial intelligence and big data. *IEEE Intelligent Systems*, 28(2), 96–99.
- Pahlavan, R., Omid, M., & Akram, A. (2012). Energy input–output analysis and application of artificial neural networks for predicting greenhouse basil production. *Energy*, 37(1), 171–176.
- Perna, A. (2007). Hydrogen from ethanol: Theoretical optimization of a PEMFC system integrated with a steam reforming processor. *International Journal of Hydrogen Energy*, 32(12), 1811–1819.
- Qureshy, A. M., Ahmed, M., & Dincer, I. (2016). Simulation of transport phenomena in a photo-electrochemical reactor for solar hydrogen production. *International Journal of Hydrogen Energy*, 41(19), 8020–8031.
- Rabbani, M., Dincer, I., & Naterer, G. (2016). Experimental investigation of hydrogen production in a photo-electrochemical chloralkali processes reactor. *International Journal of Hydrogen Energy*, 41(19), 7766–7781.
- Raheli, B., Aalami, M. T., El-Shafie, A., Ghorbani, M. A., & Deo, R. C. (2017). Uncertainty assessment of the multilayer perceptron (MLP) neural network model with implementation of the novel hybrid MLP-FFA method for prediction of biochemical oxygen demand and dissolved oxygen: A case study of Langat river. *Environmental Earth Sciences*, 76(14), 503. doi:10.1007/s12665-017-6842-z
- Rajeshwar, K., McConnell, R., & Licht, S. (2008). *Solar hydrogen generation. Toward a renewable energy future*. New York: Springer.
- Rao, R. V., Savsani, V. J., & Vakharia, D. (2011). Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems. *Computer-Aided Design*, 43(3), 303–315.
- Rosales-Colunga, L. M., García, R. G., & Rodríguez, A. D. L. (2010). Estimation of hydrogen production in genetically modified *E. Coli* fermentations using an artificial neural network. *International Journal of Hydrogen Energy*, 35(24), 13186–13192.
- Rosenblatt, F. (1961). *Principles of neurodynamics. Perceptrons and the theory of brain mechanisms*. Buffalo, NY: Cornell Aeronautical Lab INC.
- Saadi, A., Becherif, M., & Ramadan, H. (2016). Hydrogen production horizon using solar energy in Biskra, Algeria. *International Journal of Hydrogen Energy*, 41(47), 21899–21912.
- Saaty, T. L. (1980). The analytic hierarchy process: Planning, Priority setting. *Resource allocation* (p. 287). MacGraw-Hill, New York International Book Company.
- Sahraei, O. A. Z., Larachi, F., Abatzoglou, N., & Iliuta, M. C. (2017). Hydrogen production by glycerol steam reforming catalyzed by Ni-promoted Fe/Mg-bearing metallurgical wastes. *Applied Catalysis B: Environmental*, 219, 183–193.
- Salcedo-Sanz, S., Deo, R. C., Cornejo-Bueno, L., Camacho-Gómez, C., & Ghimire, S. (2018). An efficient neuro-evolutionary hybrid modelling mechanism for the estimation of daily global solar radiation in the sunshine state of Australia. *Applied Energy*, 209, 79–94.
- Sefeedpari, P., Rafiee, S., Akram, A., Chau, K.-w., & Pishgar-Komleh, S. H. (2016). Prophesying egg production based on energy consumption using multi-layered adaptive neural fuzzy inference system approach. *Computers and Electronics in Agriculture*, 131, 10–19.
- Shabaniyan, S. R., Edrisi, S., & Khoram, F. V. (2017). Prediction and optimization of hydrogen yield and energy conversion efficiency in a non-catalytic filtration combustion reactor for jet A and butanol fuels. *Korean Journal of Chemical Engineering*, 34(8), 2188–2197.
- Shahbod, N., Mansouri, N., Bayat, M., Nouri, J., & Goddousi, J. (2017). A fuzzy analytic hierarchy process approach to identify and prioritize environmental performance indicators in hospitals. *International Journal of Occupational Hygiene*, 9(2), 66–77.
- Shi, Y., Gai, G.-s., Zhao, X.-t., Zhu, J.-j., & Zhang, P. (2010). Back propagation neural network (BPNN) simulation model and influence of operational parameters on hydrogen bio-production through integrative biological reactor (IBR) treating wastewater. *Bioinformatics and biomedical engineering (iCBBE), 2010 4th international conference on*.
- Singh, A., Vats, G., & Khanduja, D. (2016). Exploring tapping potential of solar energy: Prioritization of Indian states. *Renewable and Sustainable Energy Reviews*, 58, 397–406.
- Sivagurunathan, P., Kumar, G., Kobayashi, T., Xu, K., & Kim, S.-H. (2017). Effects of various dilute acid pretreatments on the biochemical hydrogen production potential of marine macroalgal biomass. *International Journal of Hydrogen Energy*, 42(45), 27600–27606.
- Srivastava, N., Srivastava, M., Kushwaha, D., Gupta, V. K., Manikanta, A., Ramteke, P., & Mishra, P. (2017). Efficient dark fermentative hydrogen production from enzyme hydrolyzed rice straw by *Clostridium pasteurianum* (MTCC116). *Bioresource Technology*, 238, 552–558.
- Suganthi, L., Iniyan, S., & Samuel, A. A. (2015). Applications of fuzzy logic in renewable energy systems—a review. *Renewable and Sustainable Energy Reviews*, 48, 585–607.
- Taormina, R., Chau, K.-W., & Sivakumar, B. (2015). Neural network river forecasting through baseflow separation and binary-coded swarm optimization. *Journal of Hydrology*, 529, 1788–1797.
- Tatar, A., Barati-Harooni, A., Partovi, M., Najafi-Marghmaleki, A., & Mohammadi, A. H. (2016). An accurate model for predictions of vaporization enthalpies of hydrocarbons and petroleum fractions. *Journal of Molecular Liquids*, 220, 192–199.

- Tebibel, H. (2017). Off grid PV system for hydrogen production using PEM methanol electrolysis and an optimal management strategy. *International Journal of Hydrogen Energy*, 42(30), 19432–19445.
- Thakur, A., Panigrahi, S., & Behera, R. (2016). *A review on wind energy conversion system and enabling technology*. Electrical Power and Energy Systems (ICEPES), International Conference on.
- Thengane, S. K., Hoadley, A., Bhattacharya, S., Mitra, S., & Bandyopadhyay, S. (2014). Cost-benefit analysis of different hydrogen production technologies using AHP and fuzzy AHP. *International Journal of Hydrogen Energy*, 39(28), 15293–15306.
- Turner, J. A. (2004). Sustainable hydrogen production. *Science*, 305(5686), 972–974.
- Vagia, E. C., Muradov, N., Kalyva, A., Ali, T., Qin, N., Srinivasa, A. R., & Kakosimos, K. E. (2017). Solar hybrid photo-thermochemical sulfur-ammonia water-splitting cycle: Photocatalytic hydrogen production stage. *International Journal of Hydrogen Energy*, 42(32), 20608–20624.
- Van de Krol, R., & Grätzel, M. (2012). *Photoelectrochemical hydrogen production*. Boston, MA: Springer.
- Wang, W., Fan, L., & Wang, G. (2016). Study on chemical looping reforming of ethanol (CLRE) for hydrogen production using NiMn₂O₄ spinel as oxygen carrier. *Journal of the Energy Institute*, 90(6), 884–892.
- Wang, J., & Wan, W. (2009). Optimization of fermentative hydrogen production process using genetic algorithm based on neural network and response surface methodology. *International Journal of Hydrogen Energy*, 34(1), 255–261.
- Whiteman, J., & Kana, E. G. (2014). Comparative assessment of the artificial neural network and response surface modelling efficiencies for biohydrogen production on sugar cane molasses. *BioEnergy Research*, 7(1), 295–305.
- Woo, T. H. (2014). Modified fuzzy algorithm based safety analysis of nuclear energy for sustainable hydrogen production in climate change prevention. *International Journal of Electrical Power & Energy Systems*, 61, 192–196.
- Yang, X.-S. (2010a). *Nature-inspired metaheuristic algorithms*. Frome, BA: Luniver press.
- Yang, X.-S. (2010b). A new metaheuristic bat-inspired algorithm. *Nature Inspired Cooperative Strategies for Optimization (NICSO 2010)*, 284, 65–74.
- Yaseen, Z. M., Ghareb, M. I., Ebtehaj, I., Bonakdari, H., Siddique, R., Heddami, S., ... C, D. R. (2017). Rainfall pattern forecasting using novel hybrid intelligent model based ANFIS-FFA. *Water Resource Management*, In Press.
- Yehekel, J., & Epstein, M. (2011). Thermolysis of methane in a solar reactor for mass-production of hydrogen and carbon nano-materials. *Carbon*, 49(14), 4695–4703.
- Yu, Z., Meng, J., Li, Y., & Li, Y. (2013). Efficient photocatalytic hydrogen production from water over a CuO and carbon fiber comodified TiO₂ nanocomposite photocatalyst. *International Journal of Hydrogen Energy*, 38(36), 16649–16655.
- Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353.
- Zhang, H., Du, C., Wu, A., Bo, Z., Yan, J., & Li, X. (2014). Rotating gliding arc assisted methane decomposition in nitrogen for hydrogen production. *International Journal of Hydrogen Energy*, 39(24), 12620–12635.