Energy Strategy Reviews 26 (2019) 100372

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

Benefit assessment of battery plus solar for customers and the grid

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ARTICLE INFO

Keywords:
Agent-based modelling
Storage
Renewable energy communities
Low voltage network

ABSTRACT

A method that can assess the benefit for both the customers and the distribution grid when household or community batteries are installed without central control is presented. An agent-based model is used where the household assets' characteristics and behaviours are modelled and linked to a network model. Electricity data from dwellings on one street in Townsville, Australia, was used to populate the models, and simulations were run under three battery scenarios. The scenarios considered were a) "Business as usual" when no battery storage is installed, b) individual batteries are installed at each household, c) a community battery that would supply all the households is installed. Customer benefits are calculated from the operational costs savings using two types of tariffs available in Queensland. The network assets' health is assessed considering load, current and voltage levels at the distribution transformer. These simulations lead to a better informed decision for the customer, and give the utility insight into how such technologies might impact their assets.

1. Introduction

The electricity sector is going through a transformation phase driven by customers as they take up new technologies and are being more involved in managing their energy usage [1]. One such technology is energy storage devices (ESD), which present many opportunities for the distribution network service providers (DNSP), the community at large and individual customers. ESD can provide power system services (e.g. frequency control), act as an alternative supply source during outage events, provide local services and deferral of infrastructure upgrades [2–4], absorb the excess energy supplied by solar photovoltaics (PV) on low voltage networks during the middle of the day, and avoid high voltages issues on low voltage (LV) networks [5]. In addition they can preserve the atmosphere and natural resources, limiting carbon emissions by not relying on the grid which is mainly dependent on fossil fuel, especially in Australia [6]. Finally, when powered by renewable energy sources, ESD have the potential to reduce electricity bills for customers by optimising their consumption [7].

With high electricity costs, high penetration rates of solar PV [8] and the recently growing affordability of batteries [9,10], the market of privately owned batteries is expected to undergo a rapid increase in the near future in Australia [11]. While some customers might be able to afford their own battery, investing in a shared battery might be an alternative option until the cost of batteries becomes low enough for mass uptake. As customers are presented with the option of installing privately-owned batteries, whether they are individually owned or shared amongst users, they need to consider how this technology might benefit them. One question these customers are faced with is then: "*how would a battery system benefit me given my lifestyle and the current electricity tariffs?*"

In parallel, as greater numbers of privately-owned batteries are installed independently, the DNSP might not have much control over their installation and operation. The DNSP are very aware of the risk batteries present to their business, in terms of partial or full grid defection [12], and are preparing for change to ensure they remain relevant. Unexpected behaviours might be observed on their network in terms of load, voltage and current fluctuations which could affect the health of their assets, and the provision of electricity. A question that the DNSP might then have is: *"what is the impact on the network of privately-owned and operated battery systems without central control?"*

This paper presents a method to assess the benefits to both the individual consumers and the DNSP when household or community batteries are installed without central control. This research aims at providing the customer with a custom-tailored analysis to make an informed choice, and the DNSP with a way to plan their system as more batteries are being installed.

To achieve this, a custom-developed agent-based modelling and simulation (ABMS) software, called MODAM (MODular Agent-based

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https://doi.org/10.1016/j.esr.2019.100372
Received 25 January 2019; Received in revised form 4 June 2019; Accepted 13 June 2019
Available online 11 July 2019

Model) [13], was extended and used. MODAM, was initially developed to assess the impact of different trajectories of consumption at different locations of the electricity distribution grid over many years on the medium voltage (MV) network [14,15]. In here reported work, MODAM has been extended to perform simulations at the LV network where individual circuits within the home and assets on the LV network are described within the model. The extension of the model to the LV network and its validation are described in this paper. MODAM was then used to run simulations for a specific LV network. This was done using data from a case study conducted by Ergon Energy, a DNSP in Queensland, Australia. The set up and results of the simulations are presented in this paper, demonstrating the application of the agent-based model (ABM) and answering the two questions raised above. The simulations investigate two types of battery settings that the customers might consider for installation: a) the battery is owned and operated by each individual house or b) the battery ownership and its operation are shared between residents. The customer assessment compares the operational costs of these two arrangements under two tariff structures, while the network assessment considers the performance for the distribution feeder or transformer in terms of power consumption, voltage and current levels.

This paper's contribution is threefold:

- **An ABM of electrical flows over household circuits, LV and MV networks.** The ABM captures information about the electrical equipment in terms of their specifications, their operation and their connection to one another within the home and on the network. This ABM allows modelling at a fine level of detail and performing simulations at varying scales, from within the home up to the zone substation;
- **Integration of various models and data-types, including metered data, within one framework**, facilitated by the modular and compositional approach in building the ABM and the simulations [13,16]. The models link the loads and generation on the system, the performance of the physical system/network infrastructure, the tariff structures driving the operations of the battery systems, and energy management systems. By capturing the complex interactions between the different elements composing the system, integrated analyses can be performed;
- **Simulations to support decision-making for individual customers and network planning for the DNSP.** These can guide the decision-making process of the customer by comparing the operational costs of different battery systems, while the DNSP can assess how their usage might impact their network. Different viewpoints of technological uptake are consequently assessed simultaneously. Simulations output can also be used by the DNSP to enter an engagement process with their customers seeking the installation of a new technology to reach a mutually beneficial outcome.

This paper is structured as follows: Section 2 places this work in relation to other work. Section 3 describes the extension of the model to the LV network and its validation. The simulations setup and the results are presented in Section 4. A discussion follows in Section 5, with conclusion and future work in Section 6.

2. Related work

A growing number of studies of the integration of ESD into the grid can be found in the literature, especially in the context of smart-grids. In many cases, agent-based approaches have been used [17] for their capacity to represent the different entities of the system at a fine level of detail, and see the impact of their actions and interactions at the system level. They have been especially popular when studying the management of distributed ESD within a distribution network [18–23]. This is due to the fact that the rules governing their functioning and the communication to other assets can be described in detail so that a desired goal can be achieved for the grid overall.

Often a central control system is used to coordinate an aggregation of independently owned batteries by means of communication. This central control aims at reaching a desired goal, such as reducing losses over the network [18], increasing the reliability of the micro-grid [19], maximising houses self-consumption [20], enhancing locally generated power usage [19,21], reducing the customers energy bills with minimal network investment [23] or maximising their profits [19,22]. This approach aligns with the agent-based control systems subclass of multi-agent systems (MAS). Another subclass of MAS showing similarities with agent-based control systems is agent-based modelling (ABM). Similarly, agent-based models are a class of computational models that represent a system as a collection of individual entities, called agents that are autonomous, self-directed, self-contained and social [24]. The main difference between these two MAS is that agent-based control systems are built to achieve a desired emergent state of the system while agent-based modelling aims at discovering the emergent state of the system. In both cases, the agents interact with one another and their environment but the agent-based control systems rectify the situation if the system's emergent behaviour does not align with the desired goal. As the expected number of ESD uptake increases, having a centralised control might become a real challenge, especially as the integrity of the whole system can become compromised [25]. The work presented in this paper belongs to the class of agent-based modelling, where the focus is on understanding how the electricity system might be impacted over time by the different agents' evolution without central control. The only “control” that might be considered is an exogenous one, where different interventions or policies are implemented, such as a change in tariff structure, which might impact the agent's decision rules.

Agent-based modelling has been used for many energy applications, such as design of power markets [26,27], demand response management [28], adoption of energy technology [29–33], or transition in large-scale sociotechnical system [34]. Lately, it has been used to model the adoption of PV and batteries with examples of case studies in Ontario [35], and Germany [36]. These studies investigate how the wider adoption of PV and battery impact the grid in terms of load required. This estimation is however made for the overall area under study, without considering the actual network configuration. While such studies are valuable in terms of understanding the changing energy demand over an area, they do not explain how it might affect the assets over which the power flows. Such consideration is necessary when planning the system, or simply maintaining it under evolving requirements. With new technologies, pockets of technology adoption appear on the network resulting from the social interactions of the people [29]. These might lead to great fluctuations in the voltages and currents that can potentially damage system assets. There is currently, however, little published ABM work that addresses the issues of system design and planning [37].

In terms of battery systems investigated for the integration of ESD into the grid [18–23], the term “community battery” often refers to the aggregation of individually owned-batteries that are managed through a central system, as opposed to one single technical system that is shared amongst residents. An example of such shared system is currently being trialled in Western Australia [38], where 52 households can feed-in and draw energy from a 420 kWh battery that has been connected to the grid. It is expected that we will see more and more of these systems over the next few years, due to a growing popularity of the sharing economy, but also because sharing resources might be the only option for some, such as those living in strata. However, in order for the customers to choose the best technological option, they need to understand the cost savings that can be achieved. By comparing the effect of tariffs on the performance of different types of batteries coupled with PVs such as in the work presented in Ref. [39], the customer can better choose which technology to adopt. The different types of batteries presented in Ref. [39] however only compare individually owned batteries. A comparison of a community energy storage to storage owned by individual houses is presented in Ref. [40]. In their work, the authors compare the two storage settings in terms of the required capacity of the battery systems in communities with solar generation and how much they reduce exports to the community. They show that community energy storage is more beneficial than individually owned batteries especially in communities with high solar PV installation, however their results are not linking the energy flows to the network assets.

The different studies presented above highlight that there is a need to understand how different battery systems installed with solar PV will impact the loads and the assets over the network. The work presented in this paper fills this gap, where the different assets consuming and producing electricity within the home are modelled and their usage impact on the LV network is assessed by linking the energy flows to the network infrastructure. Assessment of the benefits for the individual customers and the DNSP is done using agent-based modelling and simulation, which is a technique that has proven to be useful when modelling system evolution without central control.

2.1. The agent-based model – modelling at the low voltage network

MODAM, an agent-based modelling software developed using a dynamic agent composition [13] was used and extended for the purpose of this study.

An agent is defined in MODAM as

Agent = Asset + Behaviours

Where data can be used to populate either or both their attributes. The asset and its behaviours then come together dynamically to create an agent at simulation setup.

When extending the ABM, these three aspects needed to be considered. The extension of the asset and the behaviour models was guided by the simulation aim as well as the data available. Thanks to the compositional approach in building the ABM, existing assets and behaviours' definitions could be reused to answer the analyses aim, facilitating the task. Details about the model extension and its validation are given below.

2.2. Extension of the agent-based model

2.2.1. The data

With the growing number of installation of smart meters and home energy management systems (HEMS), electricity consumption and generation data is becoming more widely available. Our ABM takes advantage of available data when possible, making it a data-driven as well as a rule-based model. In some instances, data is used directly from logs; in other instances, data is used to populate rule-based descriptions of agents' behaviours or to develop sub models of agents' behaviours.

Ergon Energy, the DNSP partnering on this project, supplied two main types of data: 1) consumption data and generation data from solar PV, collected at the meter for three tariff types and by HEMS for different circuits within the homes, and 2) data describing the configuration of the LV network and the circuits within the homes.

This data had been collected and used for a case study that aimed at understanding consumers and their interactions with new technologies. The case study site consisted of one street in Townsville were 14 houses are connected to a 100 kVA transformer on a three phase LV network. Nine of these fourteen houses (labelled *S[1··14]* in the network configuration file) participated in the study and were supplied with solar panels, battery systems and HEMS. Data from the participating houses are described below (omitting non-participatory sites S01, S09, S10 and S14).

Both the data collected by the HEMS and at the meter point were recorded for every half hour over three weeks in January 2016. HEMS data was recorded in Excel spreadsheet with headers describing the household circuits. Because the HEMS were setup manually without following a naming convention, headers varied from file to file. For example, some headers read "A.C" or "AC" or "A.C.1" for air-conditioners. These names were consolidated manually to obtain consistently named categories, reducing the number of headers from 41 to 12 categories. These categories consisted in air-conditioning, battery, bore pump, hot water, light, outdoor building, oven, pool pump, power plugs, solar panels, spa, and stove. This data was used to inform the extension of the asset model, in terms of assets and their characteristics, see Section 3.1.2, as well as to populate the household load behaviour model. Fig. 1 shows the average hourly load consumed or generated for each of the circuits recorded by the HEMS for each household. The loads of all of the appliances within the home are displayed as stacked for every half hour, including the load generated by the solar panels displayed as a negative value. The overall consumption, being the sum of all the loads within the home, is also shown by a line. In some cases, the load from solar generation is greater than the household demand, resulting in excess generation which is then exported to the grid. This is the case for example for S04 who produces more on average than they consume between 8am and 4pm. Fig. 1 therefore highlights how the loads vary between the different households, in terms of patterns of daily consumption and overall daily consumption. It can also be used to understand which appliances contribute most to the load and when, in the aim of finding ways to reduce individuals' bills. For example S04 has its load peaking on average at 5am because of the load for the pool pump while they are exporting their solar energy during the middle of the day. Assuming that their feed-in tariff is lower than their load tariff, they would be better off switching the time of their pool pump from morning to the middle of the day to absorb their excess generation.

The data recorded at the meter point, also recorded in spreadsheets, was used for model validation. This data was available over a longer period of time, 18 months, and was limited to the same three weeks in January for the model validation. Fig. 2(a) shows the daily average consumption for the different households over the 18 months, broken down into the amount of PV exported to the grid (orange) and what is billed to the customer (grey). For example, S04 imports on an average day 17 kWh from the grid and exports around 13.4 kWh, leaving an average net import from the grid of 3.6 kWh while S11 imports on average 21.3 kWh, exports 2.5 kWh, giving an average net import of 18.7 kWh. This figure highlights how the households differ in the consumption and production despite being located in the same street. It further highlights how much of the energy produced by the PV panels is not used within the home on an average day. Misalignment between the solar generation and the demand, which is defined as the ratio of PV exported to the total PV generated as defined in Ref. [40], was further calculated using the HEMS data over three weeks. Fig. 2(b) shows a histogram of the misalignment values calculated for every half hour for all the households. The proportion of time when the solar panels export is displayed against the ratio of solar exported to the total solar generated. For example, between 10 and 20% of the solar generated by the PVs is exported for around 30% of the time when PVs generate. The average misalignment over the three weeks for all homes was 22%, which is not excessive. However, when calculating these values for individual households, the misalignment values ranged from 2% to 62%, as shown in Table 7. This means that for those with high

Fig. 1. Daily average patterns of consumption and generation for each circuit type over 3 weeks.

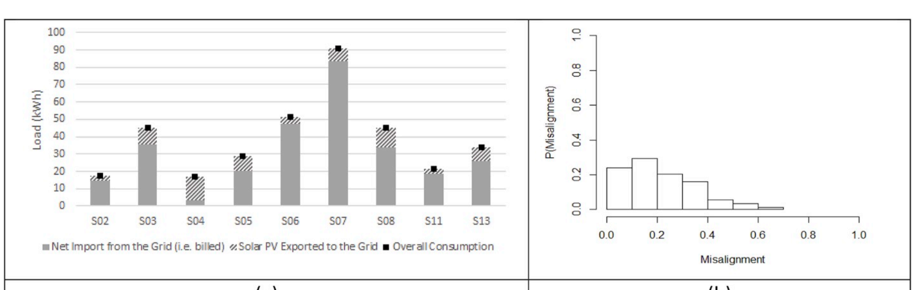

Fig. 2. (a) Households' daily average consumption. (b) Misalignment values between generation and consumption.

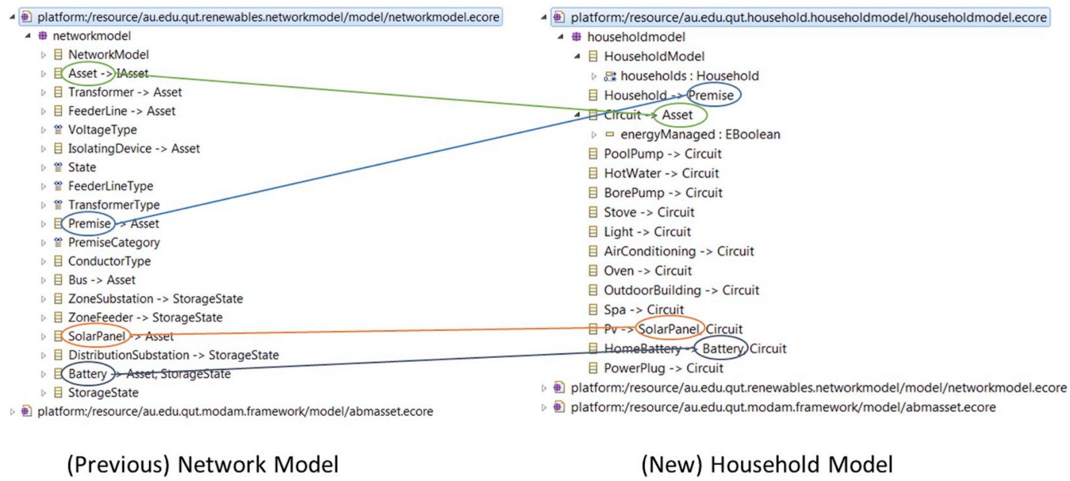

Fig. 3. Extension of the asset model. The (previous) network model and the (new) household model can work independently to perform simulations at the medium network level, or the household level, and together to perform simulations at the low and medium network level.

misalignment, e.g. 62%, only 38% of the electricity they produce matches their demand. If the feed-in tariff is much lower than the load tariff, customers are not benefiting much from the installation of their solar panels. In addition, if a large number of households have such high misalignment values on a LV network, the grid might see a drop in their load in the middle of the day and their voltages rise. Such high misalignment values give a case for both individuals and the DNSP to investigate the usage of batteries to absorb the excess PV generation.

The data describing the configuration of the LV network was also provided in spreadsheet, and was used to populate the asset model at simulation runtime. The configuration of the circuits within the home was described through a schematic representation. This data was used to define the connections between the different appliances, such as the connection between the battery and the solar panels when charging, and some selected circuits when discharging. It was also used to understand which appliances were connected to which meter points used for tariff charges. This data was used to guide the extension of the asset and behaviour models, but cannot be published due to confidentiality agreement.

2.2.2. Extension of the asset model

The first step in extending the software was to extend the Asset model. In MODAM, the assets are described in a data model, where their attributes and their relationship to one another are defined using the Eclipse Modelling Framework (EMF) [41]. Fig. 3 shows the network model, previously developed for the MV network, and the newly created household model that links it down to the LV network. In this figure, the models are defined at the top (*networkmodel* and *householdmodel*), and all their entities, classes or data types, are defined underneath. When an entity extends an existing one, it is specified by the arrow following its definition. For example, class *Premise* extends class *Asset* in *networkmodel*. Further, the two models are linked to each other through this system of class extension. Here, *networkmodel* is referenced in the *householdmodel*, with some of its classes extending ones defined in *networkmodel*. This is the case for the class *Circuit* which extends *Asset*, or *Pv* which extends *SolarPanel*, initially defined in *networkmodel*. Fig. 3 shows the different classes from the *householdmodel* that are extending those in *networkmodel*, through the highlighted lines.

Looking more closely at the *householdmodel*, it can contain zero or many households, where each *Household* extends *Premise* from the *networkmodel* (see blue line in Fig. 3). A *Circuit* is also defined, extending the entity *Asset* from the *networkmodel* (green line in Fig. 3). Then, the different circuit types, as described in the HEMS files after consolidating the names, are given. They all extend the entity *Circuit*, and can be attached to a *Premise* according to the hierarchy defined in the *networkmodel*. Other types of appliances defined in the *householdmodel*, such as the solar panels and the batteries are also linked to the *networkmodel* in a similar manner (see orange and black lines).

These links allow the two models to work together as one, achieving the goal of extensibility of the ABM within MODAM without having the cost of rewriting a new model specifically for the LV network. It is also possible to use the models independently depending on the type of analysis required, providing flexibility in the approach, as well as performing analyses at different levels of details.

2.2.3. Extension of the behaviour model

Following the creation of this data model, coding was undertaken in Java to define the behaviours of these new assets. Population of the assets' attributes was done using data in an automated manner, extracting this information from the network configuration files provided by the DNSP. Usage and generation data for the agents' behaviours were either populated from the HEMS files or calculated using rules or sub models.

As an example, household batteries had their behaviour implemented using an algorithm based on the time of the day. It was chosen to match the control algorithms implemented in the DNSP trials in the first instance and could therefore be used to validate the model, by comparing the outputs of the simulation and the recorded battery data. It was then kept for the simulations as it represents what is currently available commercially, in addition to being what customers might choose to use intuitively when looking at the tariff types currently available. For example, the shared community battery currently trialled in Western Australia [38] allows the customers to draw from the battery from 3pm every day, which corresponds to the start of the peak period. Other implementations of battery control systems are available in MODAM but are beyond the scope of this paper.

The battery scheduling algorithm used in this project is given in Pseudocode 1.

Initialisation by user input or data files:

ChargingTimes[1, .., N_c]	The times of charge for each day
DischargingTimes[1, .., N_D]	The times of discharge for each day
N_c	Total number of time steps over the charging period
N_D	Total number of time steps over the discharging period
N	The number of time steps within the simulation period
Δt	The time step duration as a proportion of an hour
ConverterRate	The converter rate of the battery (in kW)
η	The round trip efficiency of the battery [0..1]
Depth of Discharge	The percentage of the battery beyond which the battery cannot discharge (%)
SOC_{max}	Maximum State of Charge of the battery: the maximum level of energy the battery can charge up to; usually the total capacity of the battery (in kWh)
$SOC_{min} = SOC_{max}$ * *Depth of Discharge*	Minimum State of Charge of the battery: the lowest threshold under which the battery cannot discharge (in kWh)
C_r	A coefficient used when recharging the battery, that increases slightly the power transfer to ensure the battery is charged at the end of the day [0..1]
$ChargingCeiling$	The maximum load value to cover both the household demand and the charging of the battery

Computation

For $t = 1,2..N$, compute

$$\boldsymbol{Load(t)} = \sum_{i=1}^{n} \boldsymbol{Load_i(t)}$$

Where:

$\boldsymbol{Load_i(t)}$ is the load of each circuit connected to the battery at time step *t*; it can be positive when consuming or, negative when generating.

$\boldsymbol{Load(t)}$ is the load that needs to be covered by the battery or/and the grid; when positive, the battery can discharge and cover this load; when negative, this load can be used to recharge the battery.

And $\boldsymbol{SOC(t)}$ and $\boldsymbol{P^B(t)}$

Where:

$\boldsymbol{SOC(t)}$ is the state of charge of the battery, and $\boldsymbol{P^B(t)}$ is the battery power transfer at time step *t*.

They are calculated at each time step according to:

- $if(t \in DischargingTimes)$

$$SOC(t) = SOC(t-1) + P^B(t) * \Delta t \quad \text{Equation 1}$$

Where

$$P^B(t) = -\min(Load\ (t)\ , ConverterRate, SOC(t-1) - SOC_{min}) \quad \text{Equation 2}$$

- $else\ if(t \in RechargingTimes)$

$$SOC(t) = SOC(t-1) + P^B(t) * \eta * \Delta t \quad \text{Equation 3}$$

Where

$$P^B(t) = \min(ConverterRate, \frac{SOC_{max} - SOC(t-1)}{N_c} * C_r, ChargingCeiling - Load(t)) \quad \text{Equation 4}$$

Pseudocode 1 – Scheduling algorithm for the time dependent battery.

Pseudocode 1 – Scheduling algorithm for the time dependent battery.

In Pseudocode 1, the parameters are initialised either by the user in the command line, or in data files. The sets of *ChargingTimes* and *DischargingTimes* which are specified by the user are disjoint, meaning that the battery is either charging or discharging. Within each set of *ChargingTimes* or *DischargingTimes,* there can be many non-overlapping subsets, so that the battery can cycle from charging to discharging many times over a day. The two sets (*ChargingTimes* and *DischargingTimes*) consist of sets of integers which represent the different periods within a day. For example, the user can specify the times to discharge the battery to be between 6 and 9am, as well as between 2.30pm and 9pm. These will then be converted within the code to a set of integers indicating the time steps (e.g. Refs. [12–18,29–42] when the time step is half hour).

During the computation, the load ($\boldsymbol{Load(t)}$) and the state of charge ($\boldsymbol{SOC(t)}$) of the battery are calculated at each time step based on the previous time step and the power ($\boldsymbol{P^B(t)}$) either injected (at charging time) or released (at discharging time). Equation (3) differs from Equation (1) by an efficiency factor so that the losses due to the battery charging and discharging are taken into account.

The discharging of the battery aims at covering the load that is required by the appliances connected to it, unless such load exceeds the converter rate (*ConverterRate*) or the amount of energy left in the battery. During the set time for discharging, if the solar generation is greater than the load, the battery will still recharge. Indeed, the load

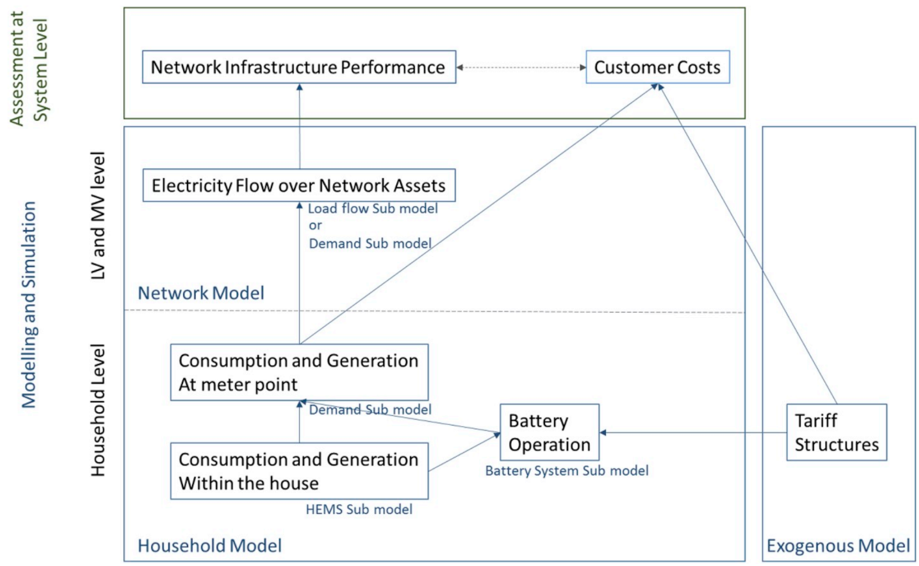

Fig. 4. Overall view of the models required to answer the aim of the study.

being negative, it will be the minimum value and will then be added to the state of charge (SOC).

The charging of the battery is such that it is constant over the recharging period and ensures that the battery is full at the end of it. It has to be noted that the charging will only happen if the household load, plus the one required to charge the battery is under a maximum demand value (*ChargingCeiling*), set by the user. This ensures that the overall load does not exceed an acceptable threshold, such as the capacity of the transformer when connected to it. A coefficient, C_r, is also set in Equation (4) to ensure that the battery is recharged at the end of the day, in case the maximum demand value is set and limits the charging over some time steps.

2.3. Bringing the models and sub models together at simulation runtime

Having extended the asset model and defined new behaviour models, simulations can then be set up. From the definition of the models and input parameters set by the user, the agents and their relationship to one another and the environment are created at simulation setup. The simulation then runs, letting the agents make their own decision at each time step according to what they perceive from their environment and other agents they are in relation with, and the rules they follow.

Fig. 4 shows the relationship between the different models that come together to answer the aim of the simulations. In order to assess simultaneously the benefits of installing a battery for individual customers and the DNSP (‘Assessment at the System Level’ block in Fig. 4), models describing the household loads and generation, the network assets, the battery system and the tariff structures needed to be defined (‘Modelling and Simulation’ block). Within each of these models, sub models were required such as the ones describing the loads over the household circuits or those specifying the battery operation.

Table 1
–Mean absolute deviation, mean squared error and maximum deviation for the households for model validation.

Household	Mean Squared Deviation (kWh)	Mean Absolute Deviation (kWh)	Maximum Deviation (kWh)
S02	0.25	0.39	2.4
S04	0.22	0.35	1.65
S05	0.15	0.26	2.34
S11	0.36	0.43	2.42

2.4. Validation of the model

Verification and validation of the model was undertaken. Verification was done using unit testing [42] in Java. Unit testing is a software method that consists in running a series of tests on the smallest parts of an application to ensure that they perform as designed. All the classes describing each agent's operations were therefore checked for correctness.

Validation was performed using quantitative methods [43]. Data recorded at the households were compared to simulation output. Because the data was obtained from a trial project for which one of the aim was to assess different types of batteries from different manufacturers, different settings had been used to define their control due to programming limitations of the control systems. The recorded data relevant to the battery control algorithm presented in Pseudocode 1 was then limited to 2 types of batteries, installed over 4 different households. This data was used for the validation of the model, by comparing the simulation output using the same battery settings and the data recorded from the HEMS. These battery control algorithms mimicked those implemented in the households’ installations. They covered the essential loads (lights and power circuits) at the household, after having been charged from the solar panels, as described in the circuit schematics provided by the DNSP.

The difference between the recorded and the simulated data was then calculated for these four households. Table 1 shows the mean absolute deviation, the mean squared deviation and the maximum deviation at each household. Time-series graphs were also plotted to illustrate the difference between simulated data and actual records for each point in time over the simulation period. Fig. 5 shows such time-series for one household, S05, and limited to one week for clarity purpose. It can be noted that for most households in Table 1 and Table S05 in Fig. 5, the difference between simulated and measured data is rather small, giving confidence in the implemented battery sub model, and the integration of the different models to represent the system overall.

3. Benefit assessment of battery installation for individual consumers and the DNSP

MODAM was then used to run simulations for the LV network over one street in Townsville, to answer the two questions mentioned in the introduction. In order to assess the benefits for both the customers and the DNSP when installing a battery system, simulations were performed under three scenarios:

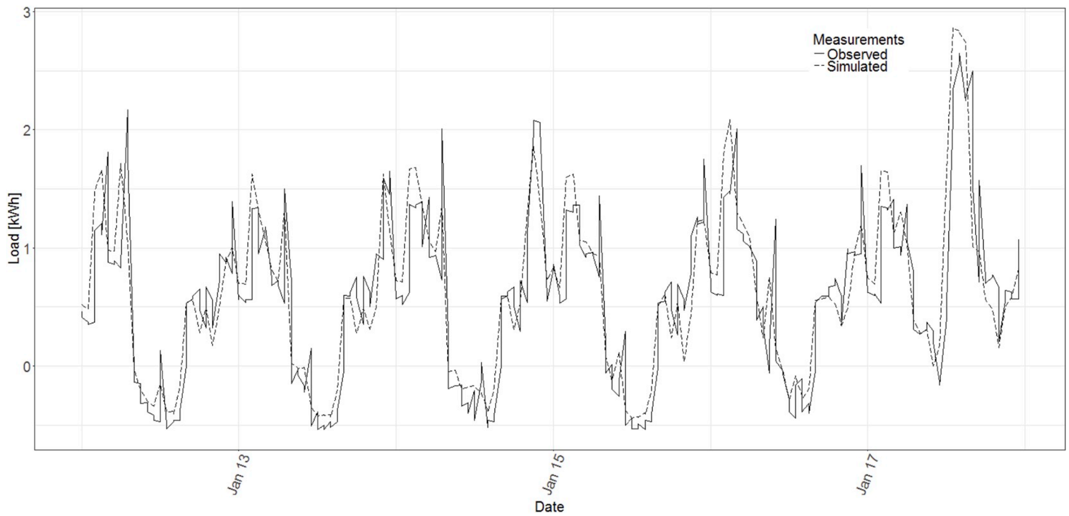

Fig. 5. Time-series of the observed and simulated overall consumption at household S05 for one week with battery.

Table 2
Tariff details as applied to the simulations (Financial Year 2016/17, GST inclusive).

	Tariff 12A – ToU Tariff	Tariff 11 – Single Rate Tariff
Off peak (c/kWh)	21.845	27.071
Peak (c/kWh)	61.452	27.071
Being between 15–21.30 in summer		
Supply charge (c per day)	111.437	98.529

- Scenario a) "Business as usual" when no battery is installed,
- Scenario b) Individual batteries are installed at each household,
- Scenario c) A shared community battery that would supply all the households is installed.

The first question was answered by assessing the benefit for individual customers by comparing the operational costs of these three arrangements using two types of tariffs. It has to be noted that capital and maintenance costs were not considered in this study. While omitting such costs impacts the economics overall, this choice was made to highlight the cost benefits when choosing between the two types of battery settings rather than limiting the results to a specific technology. In addition, the batteries considered in this project had already been chosen by the partner DNSP on this project, following an energy audit of the households. The work presented here can then be viewed as a second step when deciding on what technology setup to adopt. It can follow an optimisation process that identifies the type of individual battery to be installed according to their economics such as the one reported in Ref. [44].

The second question was answered by assessing the impact of such installations on the network assets looking at load, current and voltage levels at the transformer.

A description of the simulations set up is given below, followed by an assessment of their output.

3.1. The simulations

The simulations stem from the premise that a customer or a group of customers will consider installing a battery in the view to reducing their electricity costs. Whether a customer chooses to install an individual battery or to pool with others will depend on the electricity tariffs, the way electricity is consumed in the home, and the type of battery and its management system [39]. The simulations were therefore setup considering these four variables.

3.1.1. Input to the simulations

3.1.1.1. Tariffs. Different types of electricity tariffs currently exist in Australia. The most common ones for residential customers are single rate, time of use (ToU) and controlled load tariffs [45]. Single rate tariffs offer the same rate throughout the day and the year, while ToU tariffs have different costs depending on the time of the day which are often broken down into peak, off-peak and shoulder times. Finally, controlled load tariff is charged for specific appliances that are connected to dedicated circuits in the home, such as electric hot water systems.

The rates vary between each of these tariffs, and for the different retailers offering them. In some parts of Australia, however, where there is no competition, the prices can be specified by the regulator. This is the case, for example, in Queensland (except South East

Table 3
Solar PV size and battery energy system rating for each household.

Household	Solar PV Size (kW)	Scenario b)	Scenario c)
		Individual Battery Rating	Community Battery Rating
S02	2.4	3 kW, 10 kWh (Battery Type 1)	50 kW, 134 kWh
S03	4.6	5 kW, 20 kWh (Battery Type 4)	
S04	5 (2*2.5 kW)	3 kW, 10 kWh (Battery Type 1)	
S05	4.5	6 kW, 12 kWh (Battery Type 3)	
S06	3	5 kW, 20 kWh (Battery Type 4)	
S07	4.9	7.5 kW, 16 kWh (Battery Type 2)	
S08	4.9	7.5 kW, 16 kWh (Battery Type 2)	
S11	2.8	3 kW, 10 kWh (Battery Type 1)	
S13	4.9	5 kW, 20 kWh (Battery Type 4)	

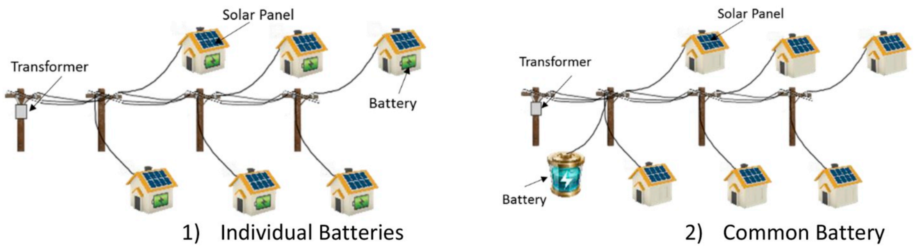

Fig. 6. Illustration of the network configuration under the two battery systems set up.

Table 4
Simulated battery properties.

Battery Properties	Community Battery	Battery Type 1	Battery Type 2	Battery Type 3	Battery Type 4
SOC_{max} (kWh)	134	10	16	12	20
SOC_{min} (kWh)	26.8	2	3.2	2.4	4
ConverterRate (kVA)	50	3	7.5	6	5
η (%)	85	85	85	85	85
Depth of Discharge (%)	80	80	80	80	80

Table 5
User input for simulations.

Simulation Parameter	Value
DischargingTimes[…]	15–21.5
ChargingTimes[…]	0–14.5
Charging Ceiling (kWh)	100 – for community battery only
Δt	0.5 (1/2 h)
N	1440 (= 30 days*48 timesteps)

Queensland), where the tariffs are set and reviewed every year by the regulator. An example of tariffs, taken from the Queensland Gazette [46], is given for the financial year 2016/17 in Table 2. It shows the price difference between a single rate tariff (Tariff 11) and a ToU tariff (Tariff 12A). These two tariffs were used in the simulations.

3.1.1.2. Consumption within the home. Consumption data recorded over the different circuits of each of the households was used as input to the simulation. While the households under study were all located in the same street, the consumption varied greatly between the different households, as shown in Section 3.1.1. In addition to the consumed load, data for the produced load from the solar panels for each of the houses was used. Details of the installed solar PV are given in Table 3.

While the validation of the simulation was done using the battery to cover the essential loads only, as set up in the experiments, the rest of the simulations are done such that the battery will cover as much of the households' needs as possible. The assumption was that all the circuits were on the same tariff, and that the battery would be used to cover these loads. This choice was done following current trends observed in the industry, where many people are switching some or all of their control loads to the main tariff, in order to maximise the use of their solar panels. This is so that they can limit or totally cancel the export of their PV generation to the grid. It is expected that once a battery is installed, this trend will be reinforced.

3.1.1.3. Types of battery. As mentioned earlier, two types of installations were considered for the batteries. The first one was such that each house had its own battery (scenario b) while the second one considered having a common battery installed under the distribution transformer (scenario c). Fig. 6 illustrates these two types of battery configuration with the connections of the households to the network.

The individual batteries were modelled as individual assets and attached to each of the household's assets in the ABM, while the community battery was attached below the transformer. Details of the individual and community batteries are given in Table 3. As mentioned previously, the individual battery types had been selected by the partner DNSP as part of their trial. The same four types of batteries (Battery Type 1 to 4 in Table 3) were considered in this study, using their characteristics to set up the battery parameters in the simulations. The community battery was chosen to be equivalent to the sum of the individual batteries in terms of capacity, resulting in a 134 kWh common battery. The size of the inverter was chosen to be 50 kW, upon looking at the average load of the transformer (around 50 kW), the transformer rating (100 kVA) and in line with the grid operated battery inverter sizes currently in use. It has to be noted that the size of the battery could have also been chosen as the maximum energy demand of all the households. This would have resulted in choosing a smaller size common battery while still ensuring that their load is always covered. However, the aim of these simulations was not to optimise the size of the batteries, but rather to provide a comparison between two equivalent types of installations in terms of capacity.

3.1.1.4. Management system - battery control algorithms. The battery

Table 6
Comparison over all the households of the demand, imports from the grid, exports to the grid and batteries charging loads for scenarios a) and b).

		Scenario a) No Battery		Scenario b) Individual batteries			
Household	Demand (kWh)	Exports (kWh)	Imports (kWh)	Battery usage (kWh)	Battery charge (kWh)	Exports (kWh)	Imports (kWh)
S02	882	31	913	310	36	10	927
S03	2310	13	2322	888	119	0	2429
S04	199	346	546	165	24	281	504
S05	755	82	837	243	32	29	816
S06	1470	72	1542	663	95	9	1573
S07	2846	20	2865	535	94	6	2945
S08	706	152	858	321	57	70	832
S11	297	257	555	273	35	149	481
S13	875	216	1091	440	66	129	1071

Table 7
Misalignment values between generation and consumption for each household, and percentage difference in imports from the grid for scenario a) and b) due to the charging needs from the batteries (efficiency factor).

	S02	S03	S04	S05	S06	S07	S08	S11	S13
Misalignment Value (%)	9	2	45	35	18	3	33	62	32
Change (%) in load imported from the grid between scenario a) and b)	1.5	4.6	−7.7	−2.5	2.1	2.8	−3	−13.3	−1.8
Change (%) in load exported to the grid between scenario a) and b)	−69.7	−98.7	−19	−64.5	−87.2	−71.7	−54.3	−42.3	−40

properties used for the simulation are summarised in Table 4 and the simulation parameters in Table 5.

As mentioned previously, the battery scheduling algorithm presented in Pseudocode 1 was dependent on the time of the day. Based on the ToU tariff described in Table 2, the battery discharging times were set from 3pm to 9.30pm. Different times for charging the battery were trialled. The one showing the least impact on the grid was chosen to be presented in this paper, being from midnight to 2.30pm. The *ChargingCeiling* value was set in this study to 100 kW for the common battery. This was chosen based on the rating of the transformer, ensuring that any additional load on the network during the battery charging would not overload it. The time step (Δt) for the simulations was set as 0.5, being for every half an hour, in line with the time frequency of the data supplied.

3.1.2. Types of simulations - simple sum of loads and load flow analysis

MODAM can perform simulations using a simple sum of loads over the network for each of the assets, as well as a load flow analysis. The simulations were performed using both these methods, and served different purposes. The simple sum of loads was used to calculate the overall electricity consumption for each of the households, allowing calculating the operational costs and savings for each scenario. The load flow analysis allowed understanding of the voltage and current fluctuations at the transformer, so that usage of the LV network assets could be assessed.

The load flow analysis was performed for each of the phases of the LV network in turn. The impact of each phase on the other was not taken into account due to the current software limitation. Simulation outputs gave the load, voltages and currents for each household and for the transformer simultaneously.

3.2. Simulations results

3.2.1. The network viewpoint - load, voltage and current over the LV network

For the three scenarios, the simulations output was analysed for each of the households as well as for the transformer. The results are summarised in Table 6, Table 7 and Table 8.

Table 6 shows for each of the households their demand, their imports from the grid and their exports to the grid from the excess solar generation for scenarios a) and b). When a battery is installed, the additional load required to recharge it due to the losses is shown in column ‘Battery charge’. In addition, a column labelled ‘Battery usage’ displays the load that is drawn from the battery during peak hour. It also corresponds to the load that is imported to recharge the battery at a different time during the day. As an illustration, household S02 has an overall demand of 882 kWh over the simulation period. Without a battery, this demand is supplied by importing 913 kWh from the grid, while 31 kWh are exported to the grid. When adding an individual battery, 310 kWh of its demand is shifted from the peak time to the recharging period. This shifted load was either covered by the solar panel, leaving an export to the grid of 10 kWh, or imported from the grid. An additional 36 kWh was also imported to cover the recharging needs of the battery due to its efficiency factor. This led to an overall import from the grid of 927 kWh. Results for scenario c) are not displayed in Table 6 as they are not very meaningful at the household level. Indeed, for scenario c), the excess solar generation of individual households is absorbed by the common battery most of the time and consequently shows 0 export to the grid by individual households. When the battery is full and the excess generation is exported to the grid, the origin of the electricity is not tracked to the individual households but amalgamated over all the households in the simulations. The results for scenario c) are consequently most meaningful when considering all the households together, and are shown in Table 8.

Table 7 summarises the change in load exported and imported for scenario a) and b) for all the households, using the data in Table 6 where scenario a) is the baseline. The reduction in solar export ranges from 19% to 99% when adding the individual batteries. As can be seen, not all the solar generation has been absorbed by the batteries, which is due to their settings. In some cases, the battery is nearly fully charged close to 3pm and cannot absorb the excess solar generation. This can be solved by having less load imported earlier, leaving a lower SOC in the battery just before 3pm that can be filled using the solar output. This however has the drawback that in case of low solar output, the battery might not be fully charged by 3pm or it might need to increase its draw from the grid, potentially creating a new peak. Also, in some cases, some solar generation is still observed during the discharging times of the battery – that is, after 3pm, when the households' demand is lower than the solar generated. Such outcome leads to question the way the tariff was designed which might not be optimal for the network. Having a narrower band for the peak period, might result in less export to the grid which translates into a reduced load to recharge the battery over the rest of the day. While the impact is quite minimal when looking at such a small case study, it can be expected to matter when studied over much larger areas.

Table 8 displays the same columns as Table 6 but summed over all the households, i.e. what is seen at the transformer, for the three scenarios. Regardless of the battery installed, the load exported from the excess PV generation, as seen as the transformer, is reduced by 67% with the individual battery and 94% with the community one. The load imported from the grid, however, has increased by 2.6% for scenario b) and 2.4% for scenario c) due to the additional load required to recharge the batteries because of losses.

Table 8
Imports from and exports to the grid, and battery usage and charge over all the households.

	Scenario a) No Battery	Scenario b) Individual batteries	Scenario c) Community battery
Imports (kWh)	10750	11032	11009
Exports (kWh)	410	135	25
Battery additional charge (kWh)	–	557	644
Battery usage (kWh)	–	3838	4386

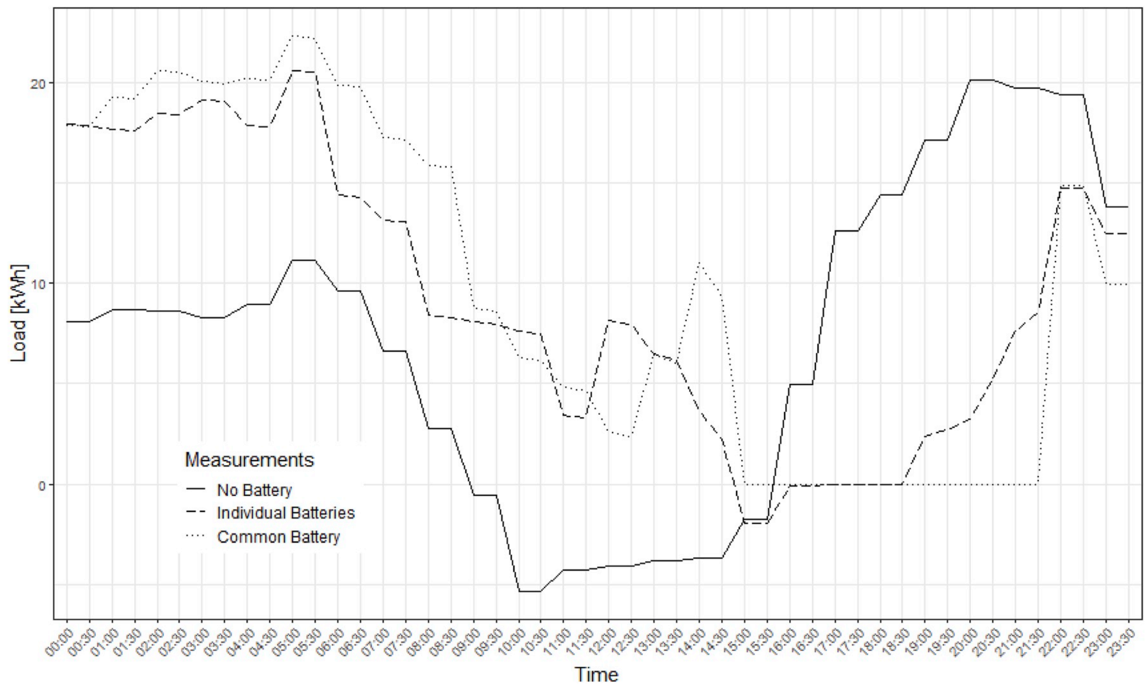

Fig. 7. Load for the peak day at the transformer for each of the scenarios over the simulation period.

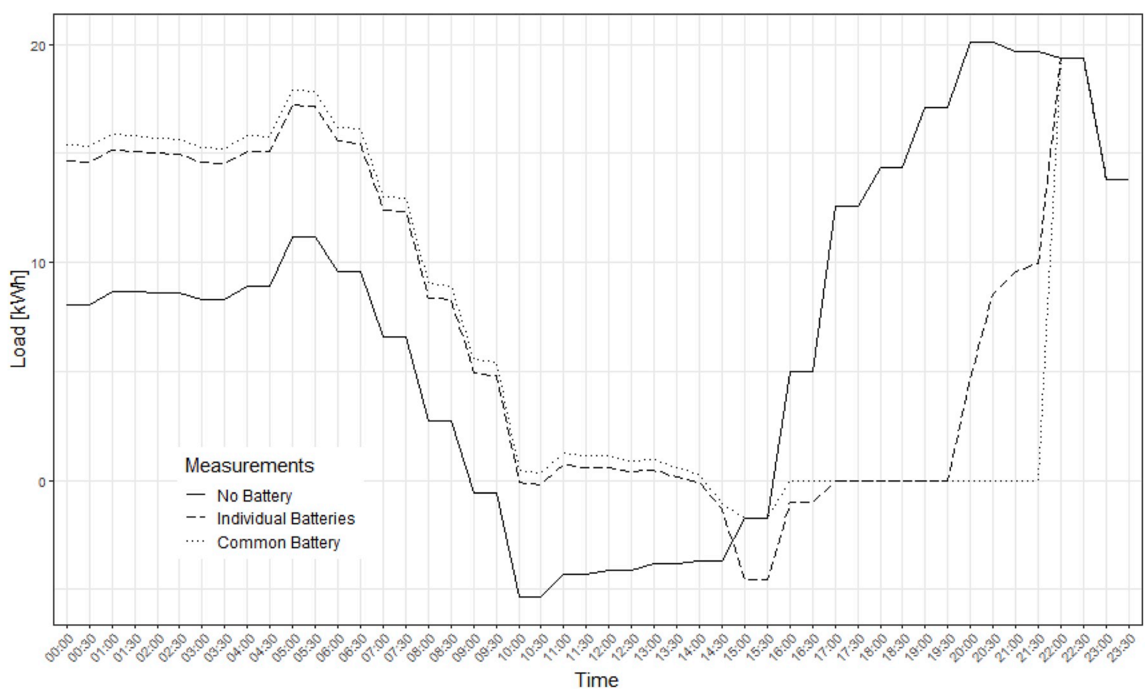

Fig. 8. Load for the peak day at the transformer under scenario a) "No Battery", and same day load for scenario b) "Individual Batteries" and c) "Common Battery".

From the grid viewpoint, there has been a slight increase overall in terms of the load supplied when adding the batteries. Understanding how the daily patterns of load, voltage and current have changed is then important to quantify the impact the addition of batteries has on the LV network.

The peak day, which is used as the metric when planning the network, was investigated for loads at the transformer, as shown in Fig. 7. A shift can be observed in the peak time from 8pm to 5am for both battery configurations. The new peaks, however, happened on different days. The three graphs of Fig. 7 are for the three days when the transformer peaked under each of the scenarios, which are different days. The peak at the transformer has now increased from 20.1 kWh over half an hour with scenario a) to 20.5 kWh with scenario b), and 22.2 kWh with scenario c). Despite an increase in the peak value with the installation of the batteries, this peak is not significantly greater than the base case scenario. In any case, it is far lower than the transformer rating.

Fig. 8 shows the new profile of the loads when looking at the peak day from scenario a). This graph illustrates how the batteries would change the profile of the load for a day that potentially would see other surrounding network transformers peak as well. This might be the case for example on a day of extreme temperatures, in this particular environment hot days, when many air-conditioners will be switched on. This graph shows that with the addition of batteries, the previous peak

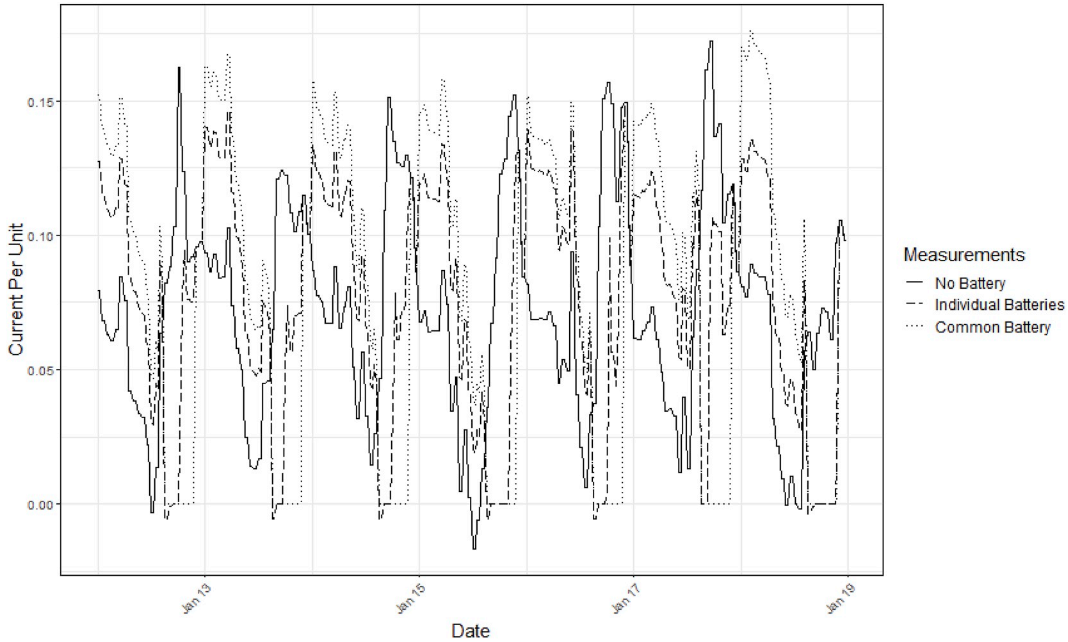

Fig. 9. Phase A current measured at transformer terminal for the three scenarios for one week over the simulation period.

load in the evening is shifted from 8pm to 10pm and is slightly lower. Another interesting point in Fig. 8 concerns the export of load in the afternoon, which is reduced under the two battery scenarios. Scenario b), however, shows a new dip in the curve at 3pm. This is because some of the households are exporting because their load needs are still lower than their PV production, and the batteries are all in discharge mode, meaning that this excess generation is not being absorbed by a neighbouring household. A similar dip can also be observed for scenario c). However, this dip is smaller because the excess PV of some of the households is absorbed by neighbouring households. Only then does the battery discharge, to cover the remainder of the load required under the transformer.

For each of the households of the study, voltage and current were also analysed. The voltages in all cases stayed the same at unity, with no significant deviation. Major differences in currents were, however, recorded in various cases. The maximum current of each load point for almost all cases stayed the same or was reduced with the addition of storage. However, for some periods of the day, the peak current at the households increased.

In order to investigate the battery operation impact on the whole network, the impact of each scenario on the total current passing through the transformer was also analysed. Fig. 9 presents the current of phase A at the transformer for the three scenarios over one week. The first message of the figure is that using battery storage in the network reduces the current in some points. However, at some other times the storage addition causes significant increase in the current.

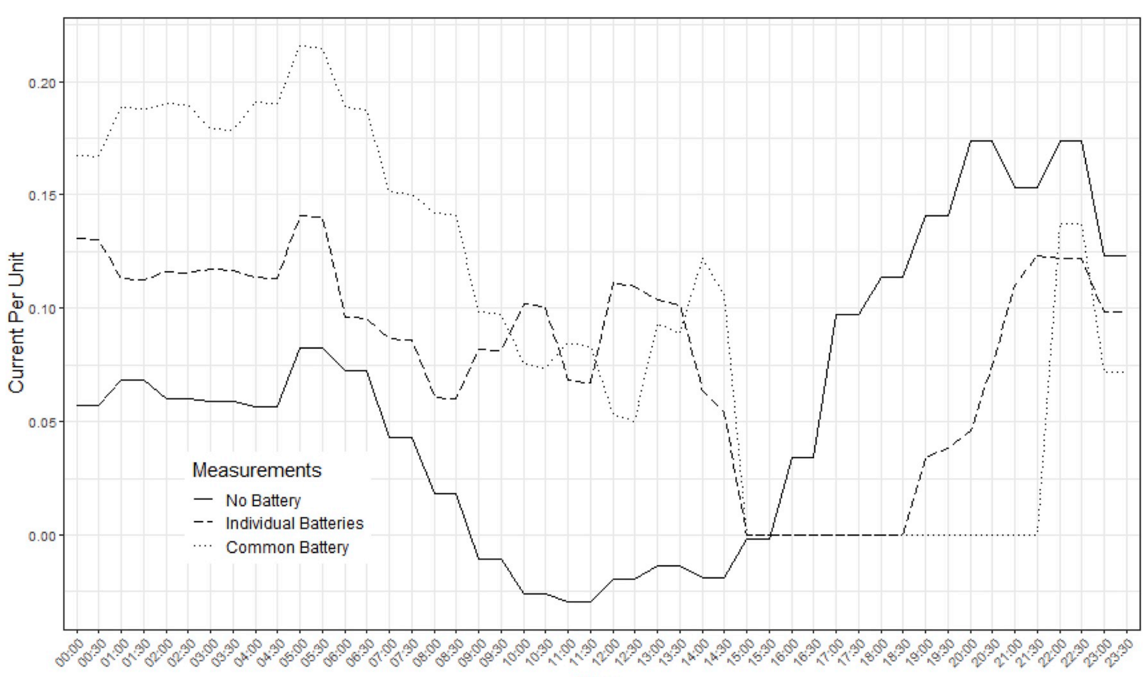

Fig. 10. Time of Day current per unit on phase A of transformer for the three scenarios for the peak day.

To investigate the current changes in more detail, Fig. 10 shows the time of day current of the transformer in phase A for the three scenarios for the peak day. In line with the results for the load, Fig. 10 shows that addition of storage to the network will result in a major decrease in peak hours' current at the transformer terminal. Comparing scenario b) and c) shows that scenario c) further reduces the peak period current. On the other hand, recharging storage from midnight to 2.30pm results in another peak current in the early morning. Consequently, the addition of storage will not increase the life cycle of the transformer in this case. This early morning peak probably corresponds to a time when controlled load appliances are turned on. To prevent this new peak from happening, the timing of either the battery or these controlled load appliances usage could be shifted. It has to be noted that the size of the transformer is quite large for the requirements of the households in that street, so this is not currently a concern. However, if the load at the transformer was to increase due to the addition of new dwellings, for example, this would have to be investigated further.

From this analysis, a few conclusions can be drawn regarding the impact of the installation of batteries without central control on the given LV network.

Simulations of the installations of either type of batteries have shown a shift in the peak time of the load, and currents on all three phases from the evening (8pm) to the early hours of the morning (5am), for the peak load day as well as some other days. In some instances, this peak is higher than the previous evening peak, although marginally. Despite this new peak, the ratings are still under the transformer's rating, and while batteries will not increase the life cycle of the transformer, they will not decrease it either in this case.

In terms of benefit of one type of battery compared to the other, the results indicate that the common battery has the advantage over the individual installation, as it cancels most feed-in from the solar PVs to the grid. Also, the load is at zero for the entirety of the peak period for the ToU tariff (3pm until 9.30pm), while the load starts increasing with individual batteries due to the limited capacity for some of the users. This gives the opportunity to free the network capacity for other areas that would need a greater load supplied during the evening peak.

3.3. The customer viewpoint - costs simulations

One of the main factors influencing people's decision when purchasing a new device is cost. Using the simulation output for every half hour, the cost of electricity for each of the households was calculated, applying a single rate tariff (Tariff 11) and a ToU tariff (Tariff 12A) currently available in Queensland. These tariffs are described in the Queensland Government Gazette [46], and summarised in Table 2. The calculations were done for 3 weeks in January, the hottest and wettest month in tropical Townsville. Doing these calculations for a whole year or more would give the customer a more realistic appreciation of the price difference between the different options; however, such data was not available.

The peak charges were applied to every day of the simulation because the peak time for the ToU is between 3pm and 9.30pm for every day during the summer months (1st of December until 28th of February). The off-peak charges were applied to the rest of the day, and the daily charge for each day of the observation period was then added.

Table 9
Contribution of each household to the battery when charging (from PV output surplus) and when discharging (from household consumption).

	S02	S03	S04	S05	S06	S07	S08	S11	S13
Contribution to battery recharge (%)	0.6	0.2	6.7	1.6	1.4	0.3	2.9	5.1	4.1
Contribution to battery discharge (%)	7.2	22.3	3.7	5.4	15	22.9	7.5	6.2	9.8

A 6c feed-in-tariff was also applied when the electricity generated by the solar panel exceeded the household's load requirements and the battery was fully charged.

With the community battery, two ways of sharing the costs were trialled, resulting in two costing scenarios, namely c1, and c2. In both cases, when discharging, the community battery tries to supply each household according to their demand without a cap. All the excess PV generated by the individuals is assumed to first be absorbed by their neighbours on the LV network and then by the community battery when recharging. When the solar output is not sufficient to cover the battery charging needs, the required load is then drawn from the grid.

When calculating the costs, the first approach (scenario c1) considers that the load drawn from the grid is divided amongst the users in an even manner. This means that each individual was charged an additional 558.9 kWh (= (4386 + 644)/9 from Table 8) to their consumption during the off-peak period.

Because the users have very different needs and load patterns as illustrated in Fig. 1, such approach might not be a fair way of sharing the common resources. During this study, the residents were interviewed regarding their electricity consumption and use of new technologies. When mentioning community batteries, most residents thought this was a good idea, however, the question of fairness around sharing the costs was raised on numerous occasions, highlighting this could be a real hurdle to their adoption. In light of this, another approach to sharing the costs was trialled.

In the second approach (scenario c2), the shareholders bank their excess solar output in the community battery. Once they have used their solar savings, the load to recharge the battery (what has been used and the additional needs due to losses) is divided amongst them proportionally to their usage of the battery, as shown in Table 9.

Costs for each of the households, for both tariffs and for the four costing scenarios (a, b, c1 and c2) were then calculated and are displayed in Table 10 and Fig. 11.

It can be seen that for scenario a) the costs of electricity are much higher for the ToU tariff than the single rate one. This is expected as most households consume a fair bit of electricity during the late afternoons, as shown in Fig. 1, which corresponds to the peak price. Under scenario c1) and c2), the costs are lower for the ToU tariff than for the single rate tariff for all the households. The same can be said for scenario b), except for S07. Such output was expected as the battery set up is such that it reduces, and most of the time cancels, the reliance on electricity coming from the grid during the peak charging period. Therefore, the unit price that is paid will be that of the off-peak tariff, which is cheaper than the unit price of the single rate tariff. The exception, for S07, is due to the fact that it is a high consumer, and its battery is not sufficiently large to answer its demand during the peak period. It therefore has to rely on the grid at times during the peak period when a higher rate is applied.

In scenario c1), the highest consumers receive most of the community battery benefits. The lowest consumer sees a 52% increase in their bills from an individual to a community battery under the ToU tariff, while the highest consumer has their bill reduced by 36% (S07). Using the second approach to sharing the costs is fairer as most consumers see a reduction in their costs from c1) to c2), apart from the three highest consumers (S03, S06, and S07). Overall, pooling together in a community battery under a ToU tariff will be cheaper than having their own battery for all consumers.

It has to be noted that these results look only at the operational costs; other considerations would need to be investigated further when investing in such battery. For example, in addition to sharing the load in a fair manner, some compensation by the highest users might need to be considered as they use the battery much more, thereby leading to a faster ageing of the battery.

Thanks to these simulations using actual electricity usage data, and the price calculations, the customer is able to better understand how an energy storage system would benefit him/her. In addition, when

Table 10
Operating costs in Australian dollars over the three weeks period for the three scenarios and the two tariffs.

	Scenario a) No Battery		Scenario b) Individual Batteries		Scenario c1) Common Battery – Even Share		Scenario c2) Common Battery – Share according to contribution	
	Single Rate Tariff	ToU Tariff	Single Rate Tariff	ToU Tariff	Single Rate Tariff	ToU Tariff	Single Rate Tariff	ToU Tariff
S02	274.9	359.3	280	240.8	333.8	280	278.3	233.8
S03	657.5	937.8	687.1	610.1	536.5	445	691.8	567.7
S04	156.6	197.3	149.2	126.7	228.9	192.7	110.2	92.9
S05	251.2	307.7	248.6	209.9	321.4	268.9	239.5	202
S06	442.6	633.2	455	381.3	400.9	333.9	449.4	371.5
S07	804	1066.1	826.6	872.8	674.8	555.5	839.3	686.7
S08	252.8	344	250.6	216	294.5	246.6	226.6	190.8
S11	164.3	249.1	150.8	131.3	203.4	173	107.4	93.4
S13	311.9	432.9	311.7	259.6	325	270.8	275.2	229.5

facilitating a group of people who are investigating the uptake of a common asset, such as a battery, this way of using the simulations can lead to a more informed and transparent decision-making process. This provides the customers with a way to understand the impact of a decision on their costs, as well as bring forward ways to share the profits fairly.

4. Discussion

The simulations presented in Section 4 highlighted the benefits in terms of electricity cost savings for individual customers, as well as the network asset usage in terms of voltage and current fluctuations for two types of battery installations. MODAM allowed to simultaneously assess the benefits for the different stakeholders by linking different models within one framework. These included models of the loads and generation on the system, the performance of the physical system, the tariff structures driving the operations of the battery systems and energy management systems. MODAM allowed performing detailed analyses at the individual household level, as well as make the assessment at the LV network level from finely defined entities and their operation. This scalability was performed without losing information or making broad assumptions about the network's entities under study because actual network configuration data and individuals' load data were used. Extending the ABMS was facilitated by the way MODAM is designed, using a compositional approach. The agents described in the model can be reused regardless of the level of detail at which the simulations are performed, avoiding unnecessary implementation and potential coding errors. It further allows moving from a micro to a macro representation of the system using the same rules and assumptions but bringing more information to the simulation according to the level of detail of the analysis aim. Having the various models and data-types at different scales and integrated within one framework provides a holistic view of the system while preserving the specific properties of the agents simulated.

The method presented in this paper can assist during the electricity sector transition. As new technologies and business models are being introduced, MODAM can be used by the DNSP as part of an engagement process with customers who have either been targeted or are voluntarily looking at installing new technologies. This has the potential to give the customer or group of customers, a personal insight into the cost savings they might realise while the network still achieves the specific outcomes it desires. For example, a group of users, such as a body corporate in a strata building or a group of neighbours seeking the installation of a battery system can quantify the benefit for each user and the common areas, using their own data. The DNSP or a third party can then devise a strategy for a fair sharing of costs and benefits amongst the users, as well as in terms of usage of their network. The DNSP can also ensure that the new technologies are set up in a way that is not going to hinder the network while still providing the benefits to the customers. For example, in this study, if left to their own device, the customers could have had any recharging times they chose. While the ones presented in this paper are from midnight to 2.30pm, they could have chosen to have the batteries recharging from 10pm until 2.30pm (that is, over the whole off-peak period) or from 6am until 2.30 p.m. (that is, only from when the solar panels produce). In both cases, this would have led to a higher peak to the one presented here; in the evening in the first case, and around 9.30am in the second case. By using the approach presented in this paper and understanding the

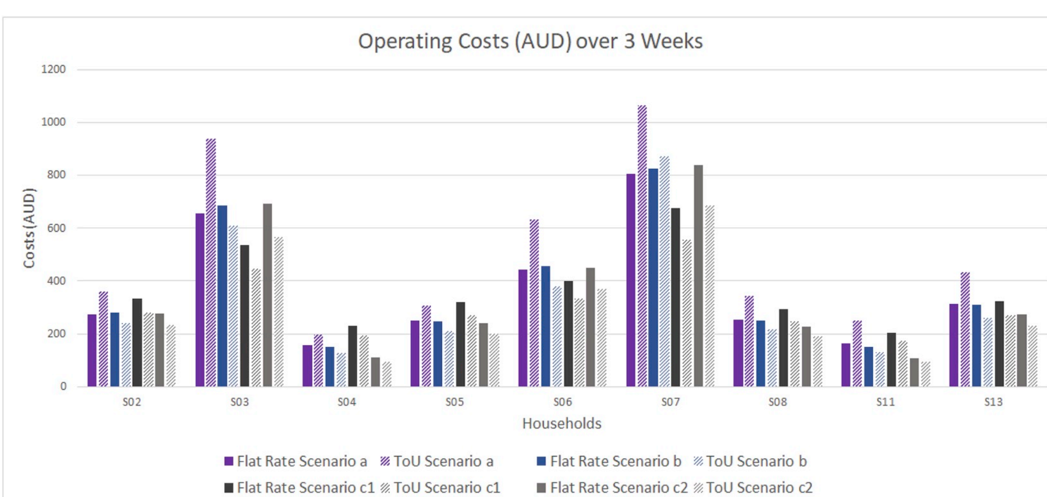

Fig. 11. Operating costs in Australian dollars over the three weeks period for the three scenarios and the two tariffs.

different viewpoints, both parties can reach an agreement that will benefit them both.

Finally, it is likely that the approach presented in this paper can also be used to assess the impact of different policies, such as those relating to tariff design. In this study, only two tariffs were used as proxies to the selection of battery control algorithms. It is possible to test other types of tariffs, as well as other types of incentives that influence the patterns of consumption using simple rules, such as those presented in Ref. [47]. These rules would represent exogenous types of control, being alternatives to centrally controlling batteries through their management system. The simulations could be run over larger areas, and, as new technologies are being taken up by individuals, parts of the networks might show very different behaviours than initially anticipated, leading to either an over or under-utilisation of their assets at different times of the day. This can have implications in terms of reliability of the network, if over-utilised, or revenue loss, if under-utilised. Testing incentives in such a way using simulations in MODAM could provide a good overview of their impact on the network.

5. Conclusion and future work

This paper presented the extension of MODAM, an existing ABM software, to perform simulations at the LV network level with the aim of assessing the benefits for both the customer and the DNSP when installing two types of battery settings, without centrally controlled management systems.

Information describing the configuration of the LV network in terms of network assets and its connected households, down to the household circuits, were added to the agent-based model definition. New behaviours were implemented such as those to represent the battery management systems and the demand over the household circuits. The ABM was validated by comparing recorded data at the household meter point to output of simulations under battery control algorithms with similar logic. Simulations were then run for three scenarios of battery system installations. Results showed that, in this case study, either individual or shared batteries would bring operational savings to the customers under the two tariffs considered. The assessment further showed that for this particular case, even without central control, the LV network did not see any major detriment to its assets. From the network viewpoint, these simulations allow them to understand the impact of new technology installation on their assets, as well as a way to engage with their customers who are planning on installing a battery. One crucial point when considering installing a common battery though is a fair distribution of the benefits amongst the users. Monitoring of the usage is important to ensure that users' requirements are met and benefits are shared equitably, to avoid unexpected detrimental behaviours and to reward people appropriately if it is to be successfully taken up.

Future work will involve running simulations over larger areas, looking at the impact of individual and shared storage resources at the MV level, as well as of virtual power plants over suburbs, using various tariffs and incentives to quantify the benefits for both the customers and the DNSP.

Declarations of interest

None.

Acknowledgments

The authors gratefully acknowledge the funding through an Australian Research Council Linkage grant [LP140100923], in partnership with Ergon Energy funding. We thank the diverse partners on this project, and especially Ergon Energy for "in-kind" support and for providing the data used in this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esr.2019.100372.

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