Probabilistic Assessment of Impact of Flexible Loads Under Network Tariffs in Low-voltage Distribution Networks

Donald Azuatalam, *Graduate Student Member, IEEE*, Archie C. Chapman, *Member, IEEE*, and Gregor Verbič, *Senior Member, IEEE*

***Abstract*—Given the historically static nature of low-voltage networks, distribution network companies do not possess the tools for dealing with an increasingly variable demand due to the high penetration of distributed energy resources (DERs). Within this context, this paper proposes a probabilistic framework for tariff design that minimises the impact of DER on network performance, stabilises the revenue of network company, and improves the equity of network cost allocation. To deal with the lack of customers' response, we also show how DER-specific tariffs can be complemented with an automated home energy management system (HEMS) that reduces peak demand while retaining the desired comfort level. The proposed framework comprises a nonparametric Bayesian model which statistically generates synthetic load and PV traces, a hot-water-use statistical model, a novel HEMS to schedule customers' controllable devices, and a probabilistic power flow model. Test cases using both energy- and demand-based network tariffs show that flat tariffs with a peak demand component reduce the customers' cost, and alleviate network constraints. This demonstrates, firstly, the efficacy of the proposed tool for the development of tariffs that are beneficial for the networks with a high penetration of DERs, and secondly, how customers' HEM systems can be part of the solution.**

***Index Terms*—Battery energy storage system, demand-based tariff, distributed energy resource (DER), home energy management system (HEMS), low-voltage network, solar photovoltaic (PV), thermostatically controlled load.**

Nomenclature

A. Sets

$\mathcal{A}$ Set of appliances ($a \in \mathcal{A}$, $\mathcal{A}=\{1,2,...,|\mathcal{A}|\}$)

$\mathcal{B}$ Set of battery penetration levels ($b \in \mathcal{B}$, $\mathcal{B}=\{1,2,...,|\mathcal{B}|\}$)

$\mathcal{C}$ Set of customers ($c \in \mathcal{C}$, $\mathcal{C}=\{1,2,...,|\mathcal{C}|\}$)

$\mathcal{D}$ Set of days in a year ($d \in \mathcal{D}$, $\mathcal{D}=\{1,2,...,365\}$)

$\mathcal{D}'$ Set of days in a month ($d' \in \mathcal{D}'$, $\mathcal{D}' \subset \mathcal{D}$)

$\mathcal{E}$ Set of edges

$\mathcal{H}$ Set of half-hour time-slots in a day ($h \in \mathcal{H}$, $\mathcal{H}=\{1,2,...,48\}$)

$\mathcal{M}$ Set of months in a year ($m \in \mathcal{M}$, $\mathcal{M}=\{1,2,...,12\}$)

$\mathcal{N}$, $\mathcal{N}_c$ Set of total nodes and subset of nodes connected to load buses

$\mathcal{P}$ Set of PV penetration levels ($p \in \mathcal{P}$, $\mathcal{P}=\{1,2,...,|\mathcal{P}|\}$)

B. Variables

C Annual electricity cost

$\hat{p}$ Dummy variable for modelling demand-based tariffs

d^g Direction of power flow (0: demand to power grid, 1: power grid to demand)

e^b State of charge of battery

$p_{a,h}$ Power of electric water heater (EWH)

$p^{b+/-}$ Charging/discharging power of battery

$p^{g+/-}$ Power flowing from/to power grid

s^b Charging status of battery (0: discharging; 1: charging)

T^{in} Internal temperature of EWH

T^{out} Outlet temperature of EWH

T^{inlet} Inlet temperature of EWH

u_a^{th} ON/OFF status of EWH (thermostatically controlled load) (0: OFF; 1: ON)

C. Parameters

α Appliance type of customer c

$\eta^{b+/-}$ Charging/discharging efficiency of battery

η^i Inverter efficiency

η_a^{th} Efficiency of EWH (thermostatically controlled load)

κ Scale parameter

μ Rate of draw events during the interval

ρ Density of water

σ Shape parameter

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D. Azuatalam (corresponding author), A. C. Chapman, and G. Verbič are with the School of Electrical and Information Engineering, The University of Sydney, Sydney, New South Wales, Australia (e-mail: donald.azuatalam@sydney.edu.au; archie.chapman@sydney.edu.au; gregor.verbic@sydney.edu.au).

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A Cross-sectional area of EWH

$\underline{e}^b$ The minimum state of charge of battery

$\bar{e}^b$ The maximum state of charge of battery

Δh Half hourly time step

M Number of appliance types

i_d^{head} Feeder head loading current

$\hat{p}$ Implicit peak demand constraint

$\bar{p}^{b+/-}$ The maximum charging/discharging power of battery

p^{base} Base load of customer

p^d Total demand of customer

p^{ewh} Power of electric water heater

$\bar{p}^g$ The maximum power taken from/to power grid

$p_{d,c}^{g,Sc1}$, $p_{d,c}^{g,Sc2}$, $p_{d,c}^{g,Sc3}$ Power taken from/to power grid in Scenarios 1-3

p^{pv} Power from solar PV

p^{res} Net residual demand

Q_a Power rating of EWH

s Specific heat

U Conductance

V Size (in volume) of EWH

v_0 Substation voltage

v_c Voltage at each (customer) load point

$v_{d,c}$ Yearly voltage profile

W_d Water use of EWH

D. Tariffs

p^{pk} Monthly peak

T^{fit} Feed-in tariff

T^{fix} Fixed daily charge

T^{flt} Flat energy charge

T^{pk} Monthly peak demand charge

T^{tou} Time-of-use energy charge

I. Introduction

THE investment in customer-owned photovoltaic (PV)-battery systems is growing rapidly across the globe, as they become cost-effective in certain jurisdictions. For example, the total installed capacity of residential PV-battery systems in Australia is projected to increase from 5 GW in 2017 to 19.7 GW in 2037 [1], [2]. In Germany, the total installed capacity of PV-battery systems alone currently stands at 43 GW, and is projected to increase to 150 GW by 2050 [3], [4]. The battery storage systems are expected to follow suit, with currently 100000 installations (approximately 6 GWh) and projections to double within the next two years [5].

The trend towards more residential PV-battery systems is being driven by two major factors. On one hand, the average household electricity prices in the Organisation for Economic Cooperation and Development (OECD) countries increased by over 33% from 2006 to 2017 (using purchasing power parity). In particular, in Australia and Germany, prices have risen to about 20.4 and 39.17 US cent/kWh, respectively, from roughly 12.52 US cent/kWh (in Australia) and 20.83 US cent/kWh (in Germany) in 2006 [6]. The feed-in-tariff (FiT) rates for PV generation have been reduced simultaneously in these countries. On the other hand, the costs of PV and battery systems have seen precipitous falls in recent times. These energy price hikes and reductions in the asset cost are driving customers to increase their levels of self-consumption by investing in energy storage technology to complement rooftop PV-battery systems.

This presents a dilemma to distribution nework service providers (DNSPs) and vertically-integrated electricity utilities, i.e., how to design tariffs that reflect the long-term marginal cost of electricity network assets, so that all consumers receive a price signal indicating the extent to which they each contribute to network peak demand, while ① not encouraging customers with distributed energy resources (DERs) to defect from the power grid, and ② without unfairly apportioning network costs on customers without PV or other DERs. This is proven to be a difficult task in the literature [7]-[10].

To this end, this paper proposes a probabilistic framework to enable DNSPs to test the cost-reflectivity of various network tariffs. The framework considers various DER including rooftop PV, battery storage and flexible loads. It integrates statistical models of PV generation, electricity demand, and electric hot water use, a novel formulation of home energy management system (HEMS) that explicitly models peak demand charge, and a Monte Carlo (MC) power flow model to assess the technical and economic impacts of network tariffs on distribution networks. This paper thus fills an important gap in the existing research, which has so far considered either only technical or only economic aspects of the problem using deterministic tools.

In more detail, recent studies have considered the economic impacts of energy- and demand-based tariffs on the revenues of residential customers and utilities. Demand-based tariffs can effectively resolve the instability of network price and reduce cross-subsidies between consumers without DERs or prosumers [11], and also ensure a stable revenue for DNSPs [12]. From the perspective of customers, [13] uses a peak coincidence network charge coupled with a fixed charge to reduce the energy cost for price-responsive customers. This slightly outperforms a peak demand charge, but leads to a reduction in the overall system cost compared with traditional volumetric tariffs.

Reference [14] suggests that a peak demand tariff based on a customer's yearly peak demand should be considered by DNSPs, as it performs the best in terms of cost-reflectivity and predictability among other tariff types. On the contrary, demand-based tariffs proposed by the Australian Energy Regulator (AER) has been tested on households in Sydney. Without due adjustments made, these tariffs show low cost-reflectivity [15]. It is evident that the suitability of network tariffs in terms of cost-reflectivity is dependent on the assumptions made in the actual design and on how customers respond to these tariffs [16].

Despite these efforts, very little research has considered the technical impacts and consequences of network tariff designs on the use of distribution networks. This is paramount because the aggregate network peak demand and energy losses are the long-term network cost drivers. In [17], the time-of-use (ToU) tariffs alone can increase peak loading on networks with high penetration levels of DERs, where customers seek to maximise their cost savings. In view of this, [18] shows that demand-based tariffs could be used to mitigate transformer loading at medium-voltage (MV) substations. Similarly, the results in [19] demonstrates the effectiveness of demand-based tariffs in alleviating peak demand considering demand response from controllable appliances of customers. In [19], however, customers are exposed to spot market prices (dynamic prices), and the effects of PV-battery systems are not considered.

Given this background, this paper extends our preliminary results [20] to address two main problems.

1) DNSPs currently do not possess tools to assess the impact of network tariffs on peak demand. Thus, we propose a probabilistic framework that supports the design of DER-specific cost-reflective tariffs.

2) Even when appropriate tariffs exist, they might not be effective due to the lack of customers' response. Therefore, we also show how DER-specific tariffs can be complemented with an automated HEMS that allows customers to shift the demand while retaining the desired comfort level.

The proposed framework first generates synthetic traces of PV generation, electricity demand, and electric hot water use, which are fed into an HEMS optimisation model that determines the optimal DER schedule given the network tariff. The HEMS optimisation is then run for 332 customers for a year to account for seasonal variations in demand and solar PV output. Three scenarios are considered based on customer DER ownership, namely, electric water heater (EWH) only, EWH+PV, and EWH+PV+battery. Simulations are performed for four different network tariff types. The output of the HEMS optimisation model, which determines the shape of the electric demand profile, is used in probabilistic power flow to examine the impact of the tariff types on typical low-voltage (LV) distribution networks.

The objective of the HEMS optimisation model based on mixed-integer linear programming (MILP) is to minimise customers' electricity cost under energy- and demand-based network tariffs, subject to device constraints and grid connection limits. For modelling demand-based tariffs, we include the peak demand charge as a linear term in the objective function corresponding to an additional peak demand variable multiplied by the set demand charge. It is incorporated into the model using an inequality constraint that sets the peak demand variable equal to the maximum monthly demand. In this way, we retain the computational efficiency of the MILP approach by avoiding the computationally expensive min-max formulation [19] that models the peak demand explicitly. We have built on our earlier work in [20] by including EWHs as part of the HEMS formulation, since they account for a considerable portion of energy consumption in Australia and can affect peak loading [21].

In summary, the proposed framework is underpinned by: ① a novel home energy management formulation that explicitly considers peak demand charges while retaining the computational efficiency of the conventional MILP formulation; ② a principled statistical solar PV and demand model to synthesise a pool of residential load traces; ③ a principled statistical model of electric hot water use to synthesise a pool of residential electric hot water use profiles.

To validate the methodology, we demonstrate the impacts of energy- and demand-based network tariffs on typical LV distribution networks. Specifically, we investigate the effects of these network tariffs on annual feeder head loading and customer voltage profiles at different penetration levels of PV-batteries.

The remainder of this paper is organised as follows. Section II presents an overview of the tariff assessment framework. Section III describes the steps to derive the statistical models of solar PV/demand and electric hot water use. Section IV outlines the modelling of household DER. Section V details the optimisation model of the network tariff types and steps taken to calculate the annual electricity cost. Section VI describes the framework of power flow analysis. The case study is described in Section VII while the simulation results are presented and discussed in Section VIII. Section IX concludes the paper and suggests further work.

II. Methodology Overview

To evaluate the impact of network tariffs on customer response and the resultant effects on an LV distribution network, it is imperative to model the HEMS of each customer individually. Figure 1 shows the weekday net demand profiles for a set of ten customers at 80% penetration level of PV and the aggregate net demand of the same ten customers.

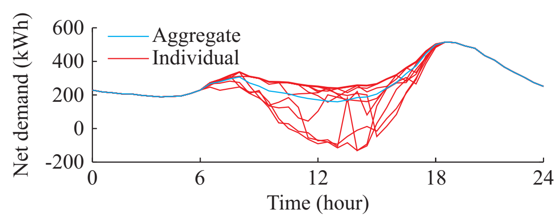

Fig. 1. Weekday net demand profiles for a set of ten customers at 80% penetration level of PV and aggregate net demand of the same ten customers.

It is observed from Fig. 1 that while the net demand of individual customers can be negative, which implies power export to the grid, the aggregate profile is always positive. This shows that an aggregate demand model can be misleading. In contrast, we model each customer individually. The statistically generated demand profiles are then randomly assigned to different locations in the network using an MC approach, which serves as an input for probabilistic load flow analysis.

An overview of the methodology for the probabilistic assessment framework is detailed in Fig. 2. In Module 1, using yearly historical data, a pool of net load traces and the corresponding electric hot water use profiles are generated by applying the statistical models of PV generation, electricity demand, and electric hot water use, which will be described in Section III. In Module 2, the outputs of the statistical models are fed as inputs to the MILP-based HEMS to solve the yearly optimisation problem for different tariff types, and the results are saved for each customer. The MILP-based HEMS is described in Sections IV and V. Firstly, Section IV describes the detailed models of battery energy storage system (BESS) and the electric hot water system, which can be reused under different tariff designs and incentive structures. Secondly, Section V outlines the optimisation model, whose objective is to minimise the electricity cost of customers under energy- and demand-based tariffs. Section V also details the optimisation model for three scenarios based on DER ownership, and the cost implications of different tariff types. Based on this, the economic impacts of the network tariffs are analysed and discussed in Section VIII-A.

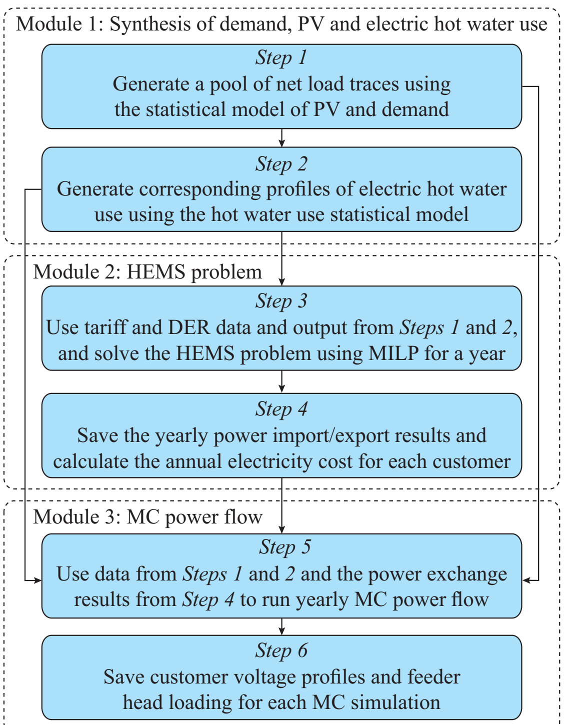

Fig. 2. Overview of methodology.

To assess the technical impacts of the network tariffs on the distribution network, we assume that the residential customers, with individually modelled HEMS and price response, all form part of an LV distribution network. Hence, the optimisation results and output data from Module 1 are used to perform time-series yearly MC power flow studies on three representative LV distribution networks using OpenDSS [22] as described in Section VI. MC simulation is employed to cater for the uncertainties in customer location and the size of DER. Therefore, 100 MC power flow simulations are performed to investigate the impacts of the network tariff types on the voltage profile of customers and feeder head loading at different penetration levels of PV-battery.

III. Statistical Models of Demand, Solar PV, and Electric Hot Water Use

In order to perform a probabilistic assessment of the impact of flexible loads in LV distribution networks under various network tariffs, a large pool of PV, demand, and EWH profiles are required. To this end, we provide the models to generate representative profiles using principled statistical approaches.

A. Statistical Models of Demand and Solar PV

In this section, we extend the nonparametric Bayesian model introduced in [23] to generate a pool of demand and PV profiles needed to perform probabilistic power flow studies. To accomplish this, we firstly cluster historical data sourced from the solar home electricity data of Ausgrid into representative clusters using the maximum a-posteriori Dirichlet process mixtures (MAP-DP) technique. Next, we employ the Bayesian estimation method to estimate the probability that an unobserved customer possesses certain features identified in particular clusters. The number of occurrence of these features (count) is used as a hyperparameter of a Dirichlet distribution $Dir(\alpha)$.

To assign a cluster to an unobserved customer, we use a random variable drawn from a categorical distribution $Cat(\gamma)$ over the features of the particular cluster, where the parameters γ are obtained by sampling from $Dir(\alpha)$. We then generate a pool of net load traces specific to assigned features based on a Markov chain process. More details on the statistical models of demand and solar PV can be found in [24].

The demand and solar PV statistical models are cross-validated in [24], using the smart-grid smart-city (SGSC) data set. As an illustration, the comparison between 1000 synthetic demand profiles and the aggregate demand profile of the 1000 customers to generate the synthetic data are presented in Fig. 3. A very good match can be observed with the mean absolute error of 9.80% in this case.

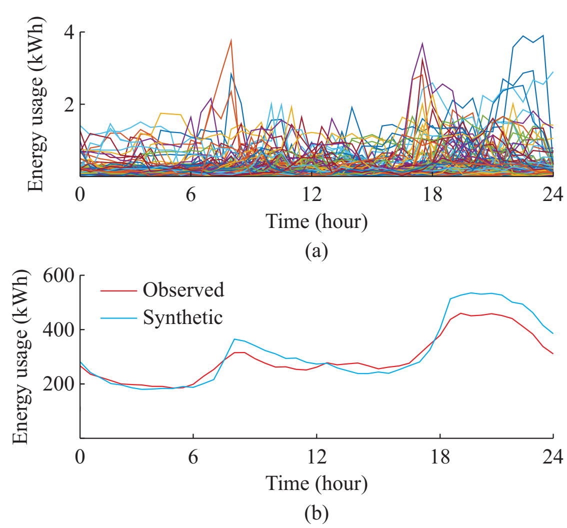

Fig. 3. Demand profiles. (a) 1000 synthetic demand profiles. (b) Aggregate observed and synthetic weekday demand profiles.

B. Statistical Model of Electric Hot Water Use

The statistical model of electric hot water is defined for the aggregate intervals of time slots during the day. It comprises a location distribution within an interval and a magnitude distribution for each time slot. The model is estimated following three steps. Firstly, the data is broken into the intervals of the day, comprised of sets of contiguous time slots. The specific intervals used in this paper are given in Table I.

TABLE I
INTERVALS IN ELECTRIC HOT WATER MODEL WITH TIME SLOTS INDICATED BY BEGINNING TIME AND ENDING TIME

Beginning time	Ending time	Beginning time	Ending time
23:00	01:30	11:00	13:30
02:00	04:30	14:00	16:30
05:00	07:30	17:00	19:30
08:00	10:30	20:00	22:30

Secondly, a location process is estimated for each interval. This consists of a distribution over the number of the draws in an interval, and is given by a homogeneous Poisson distribution $Poi(\mu)$ with a probability given by:

$$P(k \text{ draws in interval}) = \exp\left(-\mu\right)\frac{\mu^k}{k!} \tag{1}$$

Thirdly, a magnitude distribution is estimated for the size of the draws in each interval. The magnitude of the draws is modeled as following a Weibull distribution $Wei(\kappa, \sigma)$ with a probability density function given by:

$$f(x|\kappa,\sigma) = \begin{cases} \dfrac{\sigma}{\kappa}\left(\dfrac{x}{\kappa}\right)^{\sigma-1}\exp\left[-\left(\dfrac{x}{\kappa}\right)^{\sigma}\right] & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{2}$$

Sampling from this model involves one additional element. Specifically, once the model is estimated and the values of μ, κ, and σ are computed, the full sampling process for an interval involves: ① sampling a number of draws in an interval according to $Poi(\mu)$; ② allocating these draws to the time slots over the interval according to a uniform distribution; ③ sampling the draw size for each draw according to $Wei(\kappa, \sigma)$.

It is emphasized that each interval firstly has a number of draws sampled from the estimated Poisson distribution, and then that number of locations are allocated to the draws in the interval according to a uniform distribution (with replacement) over time slots, which is as the standard approach for sampling from the Poisson processes. Different from the demand and PV traces, the cross-validation for EWH traces is not possible due to the lack of empirical ToU data of electric hot water use.

IV. MODELLING OF HOUSEHOLD DER

For each customer $c \in \mathcal{C}$ who possesses a set of appliances $\mathcal{A} := \{1, 2, ..., |\mathcal{A}|\}$, let $\alpha \in \{1, 2, ..., M\}$ denote the appliance type of customer c, wherefore $\mathcal{A}_\alpha \subseteq \mathcal{A}$. In this work, only three appliance types are considered ($M = 3$). Type 1 set includes energy storage devices, particularly batteries. Type 2 set includes thermostatically-controlled devices, particularly EWHs. Type 3 appliances constitute the base load and include all must-run and uncontrollable devices.

A. Modelling of BESS

The operation model of BESS is linearised so that it fits the MILP optimisation framework. The battery sizes used in this paper range from 6 to 12 kWh and are obtained from ZEN Energy [25]. We have assumed the minimum/maximum battery SOC of 10%/100% nominal capacity and a round-trip efficiency of 90% for all battery sizes. For all $a \in \mathcal{A}_1, h \in \mathcal{H}$:

$$e^b_{a,h} = e^b_{a,h-1} + \Delta h\left[\eta^{b+}_a p^{b+}_{a,h-1} - (1/\eta^{b-}_a)p^{b-}_{a,h-1}\right] \tag{3}$$

$$p^{b+}_{a,h} \leq \bar{p}^{b+} s^b_{a,h} \tag{4}$$

$$p^{b-}_{a,h} \leq \bar{p}^{b-}(1 - s^b_{a,h}) \tag{5}$$

$$0 \leq p^{b+}_{a,h} \leq \bar{p}^{b+} \tag{6}$$

$$0 \leq p^{b-}_{a,h} \leq \bar{p}^{b-} \tag{7}$$

$$\underline{e}^b \leq e^b_{a,h} \leq \bar{e}^b \tag{8}$$

B. Modelling of EWH

The operation model of EWH is given by a set of difference equations in order to fit them into an optimisation model [26], [27]. We consider single-element EWH tanks from Rheem Electric Storage Water Heaters Specification Sheet, and estimate the EWH sizes for the 123 selected customers using their electric hot water profiles. Some of the simulation parameters of EWH are presented in Table II. For all $a \in \mathcal{A}_2, h \in \mathcal{H}$:

$$p_{a,h} = \eta^{th}_a u^{th}_{a,h} Q_a \tag{9}$$

$$T^{in}_{a,h} = T^{in}_{a,h-1} + \psi_a p_{a,h} + \lambda_a(T^{out}_{a,h-1} - T^{in}_{a,h-1}) + \phi_a(T^{inlet}_{a,h-1} - T^{in}_{a,h-1}) \tag{10}$$

$$T^{in,\min}_{a,h} \leq T^{in}_{a,h} \leq T^{in,\max}_{a,h} \tag{11}$$

where $A \approx 6V^{2/3}$; $\psi_a = \dfrac{\Delta h}{C}$; $\lambda_a = \dfrac{UA\Delta h}{C}$; $C = \rho V s$; $\phi_a = \rho W_d$; $\rho =$ 1000 kg/m^3; $s = 4.18$ kJ/kg $\cdot$ °C; $T_{in} \in [60, 82]$°C; and $U = 1.00$ W/m^2 $\cdot$ °C.

TABLE II
SOME PARAMETERS OF EWH

Percentage of customers (%)	V (L)	Q_a (kW)	A (m^2)
2.44	80	1.8	1.114
8.94	125	3.6	1.500
86.99	160	3.6	1.768
1.63	250	4.8	2.381

The second term at the right-hand side (RHS) in (10) represents the energy from the resistive element of the EWH. The third term represents the heat losses to the ambient, while the last term represents the energy required to heat the inlet cold water.

V. Optimisation Model and Calculations of Electricity Cost

In this section, the optimisation model for all tariff types considering customers with EWH and PV-battery is described. Each problem is solved for a year using a rolling horizon approach and a monthly decision horizon. For customers with just EWH and solar PV, the models are modified accordingly by removing the battery parameters as described in Section V-C. In Section V-D, we provide the formulas for computing the annual electricity cost for each tariff type.

A. Optimisation Model for Energy-based Tariffs

For customers facing an energy-based tariff (Flat or ToU, which will be explained in Section VII-B), the monthly optimisation model is given in (12) for all $h \in \mathcal{H}$, subject to (2)-(11), and (13)-(18).

$$\min_{\substack{p^{g+}_{d',h}, p^{g-}_{d',h}, p^{b+}_{d',h}, \\ p^{b-}_{d',h}, p^{d}_{d',h}, d^{g}_{d',h}, \\ s^{b}_{d',h}, e^{b}_{d',h}, u^{th}_{d',h}, \\ T^{in}_{d',h}}} \sum_{d' \in \mathcal{D}'} \left(\sum_{h \in \mathcal{H}} T^{flt/tou} p^{g+}_{d',h} - T^{fit} p^{g-}_{d',h} \right) \tag{12}$$

$$p^{g+}_{d',h} - p^{g-}_{d',h} = \eta^{i} (p^{b+}_{d',h} - p^{b-}_{d',h} - p^{pv}_{d',h}) + p^{d}_{d',h} \tag{13}$$

$$p^{d}_{d',h} = p^{base}_{h} + \sum_{a \in \mathcal{A}_2} p_{a,d',h} \tag{14}$$

$$p^{g+}_{d',h} \le \bar{p}^{g} d^{g}_{d',h} \tag{15}$$

$$p^{g-}_{d',h} \le \bar{p}^{g} (1 - d^{g}_{d',h}) \tag{16}$$

$$0 \le p^{g+}_{d',h} \le \bar{p}^{g} \tag{17}$$

$$0 \le p^{g-}_{d',h} \le \bar{p}^{g} \tag{18}$$

B. Optimisation Model for Demand-based Tariffs

For the customers facing a demand-based tariff (FlatD or ToUD, which will be explained in Section VII-B), an additional constraint (20) is used to limit the power import from the grid according to the demand charge component $T^{pk} \hat{p}$ in (19). This does not explicitly model the demand charge as in practice, but implicitly achieves the same objective of clipping the peak demand of a customer and subsequently reducing the annual electricity costs, which are shown in Figs. 4 and 5. Different tariffs including Flat, ToU, FlatD, and ToUD will be discussed in detail in Section VII-B. The monthly optimisation model is given in (19) for all $h \in \mathcal{H}$, subject to (3)-(11), (13)-(18), and (20).

$$\min_{\substack{p^{g+}_{d',h}, p^{g-}_{d',h}, p^{b+}_{d',h}, \\ p^{b-}_{d',h}, p^{d}_{d',h}, d^{g}_{d',h}, \\ s^{b}_{d',h}, e^{b}_{d',h}, u^{th}_{h}, \\ T^{in}_{d',h}, \hat{p}}} \left[T^{pk} \hat{p} + \sum_{d' \in \mathcal{D}'} \left(\sum_{h \in \mathcal{H}} T^{flt/tou} p^{g+}_{d',h} - T^{fit} p^{g-}_{d',h} \right) \right] \tag{19}$$

$$p^{g+}_{d',h} \le \hat{p} \tag{20}$$

C. Optimisation Scenarios

The optimisation models described above are solved for three scenarios based on the ownership of customer DER. Scenario 1 is the base case where all customers possess just EWH. DERs are then progressively added to form the other two scenarios following (13). $p^{d}_{h} = p^{base}_{h} + p^{ewh}_{h}$, then the following scenarios hold:

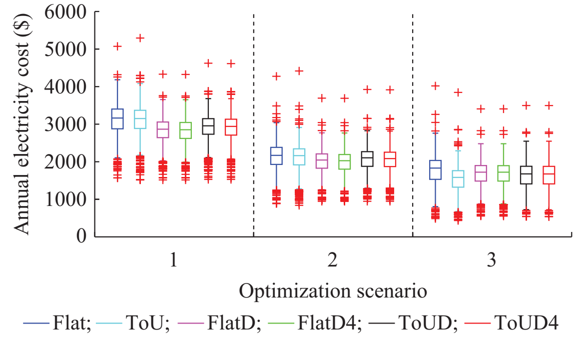

Fig. 4. Annual electricity cost for 332 customers in three scenarios.

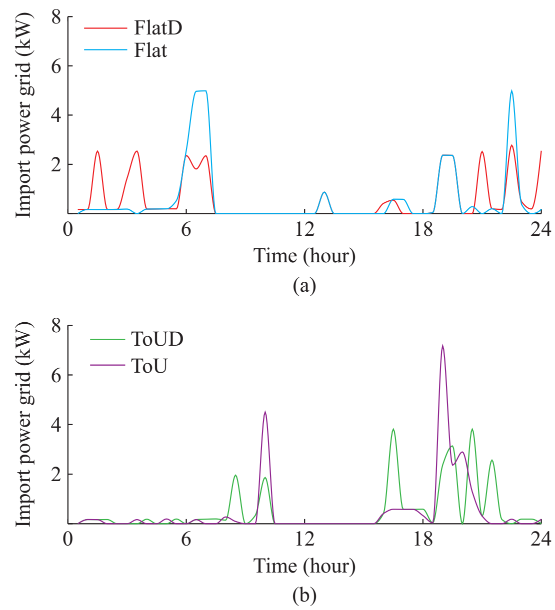

Fig. 5. Illustration of peak demand reduction due to $\hat{p}$ in optimisation problem (20). (a) Peak demand reduction achieved using demand charges with Flat tariff. (b) Peak demand reduction achieved using demand charges with ToU tariff.

1) Scenario 1: the energy balance equation for customers with EWH only is:

$$p^{g+}_{h} = p^{d}_{h} \tag{21}$$

2) Scenario 2: the energy balance equation for customers with EWH and solar PV is:

$$p^{g+}_{h} - p^{g-}_{h} = -\eta^{i} p^{pv}_{h} + p^{d}_{h} \tag{22}$$

3) Scenario 3: the energy balance equation for customers with EWH, solar PV and batteries is:

$$p^{g+}_{h} - p^{g-}_{h} = \eta^{i} (p^{b+}_{h} - p^{b-}_{h} - p^{pv}_{h}) + p^{d}_{h} \tag{23}$$

D. Calculations of Annual Electricity Cost

The annual electricity costs for the customers with PV or PV-battery (Scenarios 2 and 3) are calculated for each tariff type as in (24)-(27) using $p^{g+}_{d',h}$ and $p^{g-}_{d',h}$, which are obtained as the output variables from the optimisation. For the customers without DER (Scenario 1), the calculations are done without the power export component $T^{fit} p^{g-}_{d',h}$.

$$C(Flat) = \sum_{d \in \mathcal{D}} \left(T^{fx}_{d} + \sum_{h \in \mathcal{H}} (T^{flt} p^{g+}_{d,h} - T^{fit} p^{g-}_{d,h}) \Delta h \right) \tag{24}$$

$$C(ToU) = \sum_{d\in\mathcal{D}}\left(T_d^{fx} + \sum_{h\in\mathcal{H}}(T_h^{tou} p_{d,h}^{g+} - T^{fit} p_{d,h}^{g-})\Delta h\right) \tag{25}$$

$$C(FlatD) = \sum_{d\in\mathcal{D}}\left(T_d^{fx} + \sum_{h\in\mathcal{H}}(T^{flt} p_{d,h}^{g+} - T^{fit} p_{d,h}^{g-})\Delta h\right) + \sum_{m\in\mathcal{M}}(T^{pk} p_m^{pk}) \tag{26}$$

$$C(ToUD) = \sum_{d\in\mathcal{D}}\left(T_d^{fx} + \sum_{h\in\mathcal{H}}(T_h^{tou} p_{d,h}^{g+} - T^{fit} p_{d,h}^{g-})\Delta h\right) + \sum_{m\in\mathcal{M}}(T^{pk} p_m^{pk}) \tag{27}$$

where p_m^{pk} is calculated either based on the peak monthly demand (FlatD and ToUD) or on the average top four daily peak demand (FlatD4 and ToUD4) for each month. In essence, each of the demand-based tariffs has two variants based on the calculation of monthly peak demand.

VI. Power Flow Analysis

We consider an LV distribution network as a radial system denoted by $\mathcal{G}(\mathcal{N},\mathcal{E})$. This comprises $|\mathcal{N}|$ nodes in set $\mathcal{N} := \{0, 1, ..., N\}$ representing network buses and distribution lines denoted as a tuple (i, j), which connects the nodes and is represented by the set of edges $\mathcal{E} := \{(i, j)\} \subset \mathcal{N} \times \mathcal{N}$. Each customer $c \in \mathcal{C}$ in the network is connected to a load bus as a single-phase load point, where the load buses $\mathcal{N}_c$ is a subset of the total nodes in the network and $\mathcal{N}_c \subseteq \mathcal{N}$. Let $\boldsymbol{V} = [v_0, v_1, ..., v_N]$ be the voltage magnitudes at the nodes. The voltages at each (customer) load point v_c are monitored at every half-hour in the year to check for any voltage violations. More so, the current i^{head} is monitored to check for any thermal loading problems. We assume that each customer $c \in \mathcal{C}$ in the network utilises an HEMS to manage a set of appliances in order to minimise the electricity cost.

The net power exchange of the grid $p_d^g = p_d^{g+} - p_d^{g-}$ resulting from the HEMS optimisation solution and the data generated from statistical models (Module 3, *Step 5* in Fig. 2) are fed as the input to a distribution network model to perform MC power flow analysis using Algorithm 1.

We then carry out a probabilistic assessment of the yearly voltage profiles $v_{d,c}$ for each customer and feeder head loading i_d^{head} in order to ascertain the level of voltage and thermal loading problems associated with any particular network. The definitions of voltage and thermal loading problem are described below.

1) If a customer's voltage goes outside the range of 0.95 p.u. $\le v_{d,c} \le 1.05$ p.u. during 95% of days in a year, the customer is regarded to have a voltage problem [28].

2) If the current flowing through line i_d^{head} (feeder head) exceeds its thermal rating, there is a thermal loading problem in the network.

VII. Case Study

Necessary data are provided for the case study, which include the data for three representative LV distribution networks, the network tariff and retail charges, and the customer demand and DER data.

Algorithm 1: MC power flow algorithm

Set $\mathcal{P} := \{0, 25, 50, 75\}$, $\mathcal{B} := \{0, 40, 80\}$, and $\mathcal{C} := \{1, 2, ..., |\mathcal{C}|\}$

1: **for** each $p \in \mathcal{P}$ **do**
2:   Read yearly load and PV profile
3:   **if** $p = 0$ **then**
4:     **Read** $p_{d,c}^{g}, \forall c \in \mathcal{C}, d \in \mathcal{D}$, for Scenario 1 ▷ base case: 0% PV-battery
5:     **for** $k \leftarrow 1$ to 100 (*Step 1*) **do** ▷ 100 MC simulations
6:       **Sample** uniformly from $p_{d,c}^{g,Sc1}$ for allocation to load points
7:       **Run** yearly power flow
8:       **Return** $i_d^{head,k}$ and $v_{d,c}^{k}$, $\forall c \in \mathcal{C}, d \in \mathcal{D}$
9:     **end for**
10:   **else**
11:     **for** each $b \in \mathcal{B}$ **do**
12:       **Read** $p_{d,c}^{g}, \forall c \in \mathcal{C}, d \in \mathcal{D}$, for Scenarios 1-3
13:       **for** $k \leftarrow 1$ to 100 (*Step 1*) **do** ▷ 100 MC simulations
14:         $p_{d,c}^{g,Sc1} := (100-p)\% \cdot p_{d,c}^{g,Sc1} + p\% \cdot (100-b)\% \cdot p_{d,c}^{g,Sc2} + p\% \cdot b\% \cdot p_{d,c}^{g,Sc3}$
15:         **Repeat** lines 6-8
16:       **end for**
17:     **end for**
18:   **end if**
19: **end for**

Note: ▷ means comment.

A. LV Distribution Networks

The LV distribution network data used in this work are obtained from the LV distribution network solutions project [29]. Table III summarizes the main features of the three networks used as case studies in this paper.

TABLE III
Network Data

Feeder number	No. of customers	Total length of all lines (m)	Feeder head ampacity (A)
1	175	5206	1200
2	186	4197	1200
3	302	10235	1155

These are residential LV distribution networks of different lengths and numbers of load points. Feeders 1 and 2 are fairly balanced, while Feeder 3 is unbalanced. Given that these feeders are from the UK, we have modified them to suit the Australian context. Typical Australian LV distribution networks are more robust with higher load capacity compared with those from the UK. Therefore, the transformer capacity is increased by a factor of 3 and decreased the line impedances by a factor of 3 since the average consumption in Australia is roughly three times that in the UK. However, the overall structures of LV distribution networks in both countries are similar.

B. Network Tariffs and Retail Charges

A typical residential customer retail bill consists of network (distribution and transmission) charges, generation costs for energy, charge of retailer, and other related costs.

We have sourced the network tariff data as shown in Table IV from Essential Energy Network Price List and Explanatory Notes. These are assumed to be fixed and known in advance. The peak demand charge is for the monthly peak demand of a customer, or, alternatively, the average of the top four daily peak demands of a customer in a month. In Table V, the residential electricity prices for the customers in the essential energy distribution zone for the retailer, Origin Energy is shown. These prices comprise the actual cost of electricity, service fee of retailer, and the network charge. In this paper, we have assumed that the retailers pass on the DNSP tariff structure to the consumers. The different network tariffs, i. e., energy-based (Flat and ToU) and demand-based (FlatD and ToUD), are described below.

TABLE IV
NETWORK TARIFF DATA

Tariff type	Fixed charge ($/day)	Anytime energy (cent/kWh)	Off-peak energy (cent/kWh)	Shoulder energy (cent/kWh)	Peak energy (cent /kWh)	Demand charge ($/(kW·month))
Flat	0.8568	11.0321				
ToU	0.8568		4.6287	12.6922	13.9934	
FlatD	0.8568	3.2169				4.2112
ToUD	0.8568		2.1419	3.4771	4.0804	4.2112

TABLE V
RETAIL TARIFF DATA

Tariff type	Fixed charge ($/day)	Anytime energy (cent/kWh)	Off-peak energy (cent/kWh)	Shoulder energy (cent/kWh)	Peak energy (cent/kWh)	Demand charge ($/(kW·month))
Flat	1.5511	31.3170				9
ToU	1.5511		21.3400	37.1470	38.5880	9
FlatD	1.5511	23.5018				9
ToUD	1.5511		18.8532	27.9319	28.6750	9

1) LV residential anytime (Flat): includes a fixed daily charge and a flat usage charge.

2) LV residential ToU: includes a fixed daily charge and a ToU usage charge (peak period: 07:00 to 09:00, 17:00 to 20:00; shoulder period: 09:00 to 17:00, 20:00 to 22:00; off-peak period: 22:00 to 07:00).

3) Small residential opt-in demand anytime (FlatD): includes a fixed daily charge, a flat usage charge, and a peak demand charge.

4) Small residential opt-in demand ToU (ToUD): includes a fixed daily charge, a ToU usage charge, and a peak demand charge.

C. Customer Demand and DER Data

We have sourced the demand and solar PV generation data from the solar home electricity data of Ausgrid (DNSP in New South Wales) [30]. This dataset comprises three years of smart meter data with half-hourly resolution from July 2010 to June 2013, for 300 residential customers in the Sydney region of Australia. The most recent data (for financial year, July 2012 to June 2013) is used in this study, because it is complete and of higher quality compared with the previous years in the dataset. Given that the solar home electricity data do not contain electric hot water usage data of customers, we have selected 123 customers from the Ausgrid SGSC [31] dataset with complete electric hot water usage, solar PV, and uncontrolled demand data. Then, we randomly allocate these electric hot water profiles to the selected 123 customers from the solar home electricity data.

Since the average PV size of the customers in the solar home electricity data is roughly 1.5 kW, a heuristic is applied to update the PV sizes to reflect the current PV uptake rates and the average size of installed PV systems in Australia. The updated average PV size of these customers is roughly 4 kW, and the sizes range from 3 to 10 kWp depending on the needs of the household. For the customers with solar PV and batteries installed, the battery size of the customer depends on the size of the solar PV installed. In Australia, typically, 1.5-3 kWh of storage is used per 1 kW of PV installed [1]. This assumption is made in this paper. The efficiency of PV inverter has already been accounted for in the dataset, so the efficiency of PV inverter is assumed to be 1 in the simulations. Table VI presents the PV-battery size combinations for the selected 123 customers with updated PV sizes.

TABLE VI
PV-BATTERY SIZE COMBINATIONS

Percentage of customers (%)	Solar PV size (kW)	Battery size (kWh)
76.42	3-4	6
20.33	5-6	8
2.44	7-8	10
0.81	9-10	12

VIII. RESULTS AND DISCUSSION

In this section, the results from the optimisation and network power flows are analysed and discussed. Firstly, we show the economic implications of various network tariffs by carrying out annual electricity cost calculations in Section VIII-A. Therefore, 332 customers have been chosen from the generated pool of customers, since the largest feeder used as case study comprises 302 customers. Following this, the impact of network tariffs on the daily and monthly peak demand of customer is discussed in Section VIII-B. Finally, the technical impacts on the network, of the different tariffs, are analysed in Sections VIII-C and VIII-D.

A. Annual Electricity Cost

In this section, we analyse the annual electricity costs for all scenarios using the results from Section V-D, as illustrated in Fig. 4. Overall, customers pay less for electricity as DER is progressively added. While the demand-based tariffs result in a lower electricity cost compared with the energy-based ones in Scenario 1, this slightly levels off in Scenarios 2 and 3. This is because when the power import of prosumers is clipped due to the demand charges, they compensate for this by exporting more power to the grid (via FiT payments). Nevertheless, the FiT rates are smaller compared with the retail rates so the net savings are minimal. With PV and batteries (Scenario 3), however, large power export pays off with a ToU tariff, which results in the least annual electricity cost for consumers. But this might not be most beneficial for DNSPs. Generally, we can conclude that customers are likely to be indifferent between these tariff types, since the annual cost values are quite close.

B. Daily and Monthly Peak Demand

The peak-demand charge has an effect of clipping a daily and monthly power import of customer according to (20). Figure 5 illustrates the daily peak demand reduction of Customer 3 (a randomly selected customer) using demand-based tariffs (FlatD and ToUD). We also calculate the monthly peak demand of the customer under the tariff types by finding the maximum grid import power for each month from the optimisation results. Figure 6 shows the monthly peak demand of 332 customers in Scenarios 1-3.

Figure 7 shows the percentage changes in the median peak demand as PV alone (Scenario 2) and PV-batteries (Scenario 3) are added. Generally, using demand-based tariffs results in a lower monthly peak demand compared with energy-based tariffs due to the additional demand charge to penalize the grid power import.

The results also show that among all tariff types, solar PV alone (Scenario 2) is not sufficient to reduce the peak demand recorded in the base case significantly (Scenario 1). It is shown in Fig. 7 that solar PV is more effective in reducing the peak demand due to energy-based tariffs (up to 16% with Flat tariff in January) than with demand-based tariffs (up to 6% in October). However, with PV and batteries (Scenario 3), the monthly peak demand even increases nearly up to 10% in June with ToU tariff, but is lowered to 40% in February with demand-based tariffs compared with Scenario 1. The ToU-based tariffs perform the worst as DER is progressively added compared with flat tariffs (Flat and FlatD). This is due to the creation of the new peaks when all batteries are charged during off-peak times to minimise the electricity costs of customers.

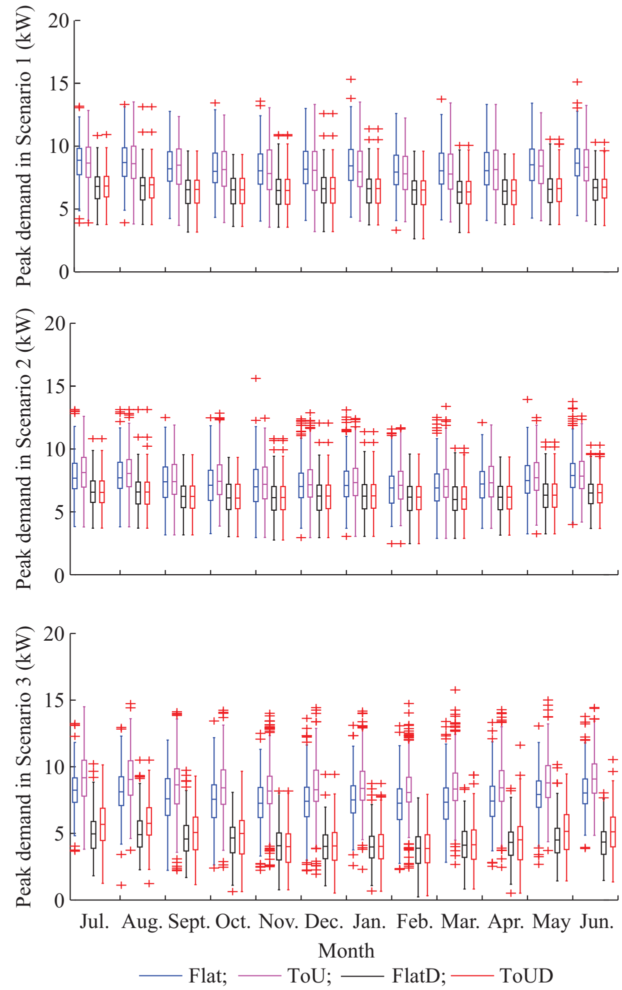

Fig. 6. Monthly peak demand of 332 customers in Scenarios 1-3.

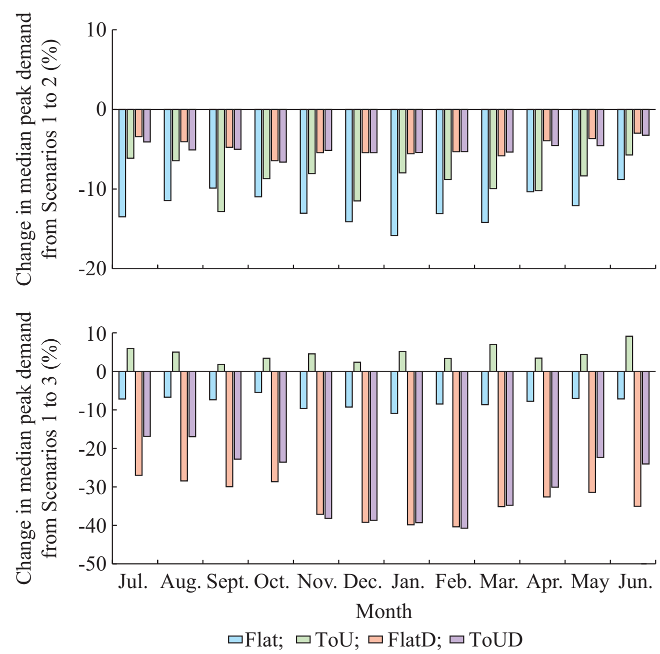

Fig. 7. Percentage change in median peak demand.

C. Effects of Network Tariffs on Line Loading

In this sub-section, we analyse the feeder head loading for the different penetration levels of PV-batteries, as shown in Fig. 8(a). The black dashed lines separate the battery ownership levels (of 0, 40 and 80% in order from left to right) at each penetration level of PV (25, 50 and 75%, separated by red dashed lines). There is no battery ownership at 0% penetration level of PV-batteries. The loading levels are generally high because we have shown the phases with the highest loading for each feeder (other phases follow similar pattern). Also, the maximum feeder head loading is examined over the year for each MC simulation.

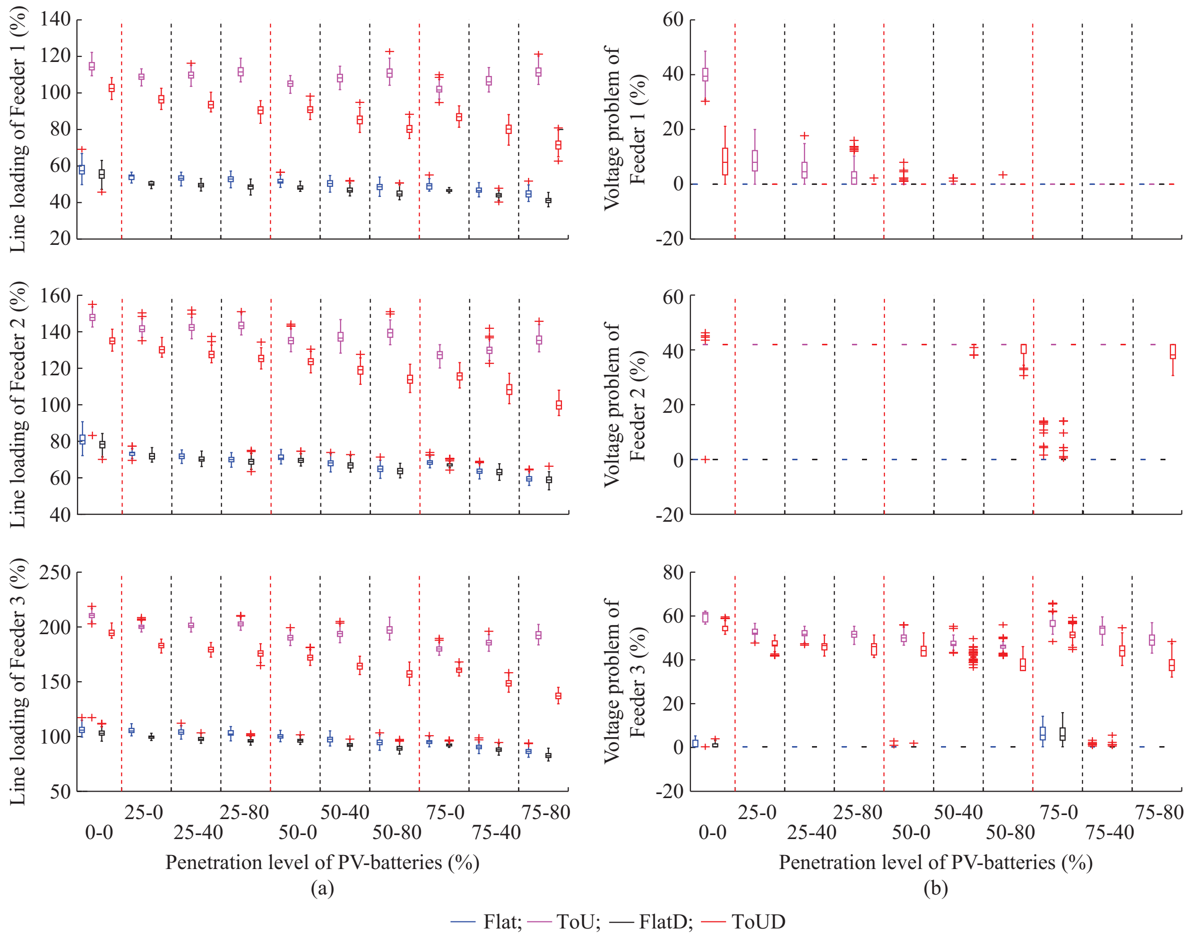

Fig. 8. Feeder head loading level and percentage of customers with voltage problems for Feeders 1-3. (a) Feeder head loading level. (b) Percentage of customers with voltage problems.

The results show that ToU tariff performs worst as the penetration level of batteries increases, which is in conformity with the results in [17]. This is due to the batteries' response to ToU pricing by charging at off-peak times, thereby creating new peaks. Furthermore, ToU-based tariffs (ToU and ToUD) can adversely affect the line loading due to large grid imports during off-peak times, and reverse power flows resulting from power export. This can be mitigated by adding a demand charge (ToUD) to at least clip the grid import levels with the aid of batteries. As observed in Fig. 8, the line loading increases with higher penetration level of batteries with ToU tariff, while it is reduced with ToUD tariff. Contrarily, Flat tariff results in lower line loading for all feeders. By including a demand charge to the flat tariff (FlatD), line loading is reduced even further as observed for all three feeders. This works well with increasing penetration of batteries in both fairly balanced (Feeders 1 and 2) and unbalanced LV distribution networks (Feeder 3), since there are no incentives for large grid power exports as with ToU tariffs.

D. Effects of Network Tariffs at Customer Voltage Level

In terms of customer voltage profiles, Fig. 8(b) shows that ToU tariff results in higher voltage problems in all three feeders compared with other tariffs. This is particularly obvious in the case of the unbalanced feeder (Feeder 3), but can be mitigated by adding a demand charge to the ToU tariff (ToUD). In this case, batteries are useful in reducing voltage problems. The Flat tariff, on the other hand, performs better than ToU-based tariffs in keeping customer voltage at the right levels. And again, by adding a demand charge to the flat tariff (FlatD), there is a slight improvement in the voltage profiles of customer.

IX. Conclusion and Further Work

In this paper, it is shown that in the presence of DER, adding a peak demand charge to either a Flat or ToU tariff effectively reduces the peak demand, and subsequently, the line loading.

To reduce the peak demand of customer, a computationally efficient optimisation formulation is proposed, which avoids the computationally expensive min-max formulation used in alternative approaches. It is demonstrated that the novel formulation, which can be seamlessly integrated into the HEMS of customer, can be used in conjunction with DER-specific tariffs to achieve better management of network and cost-reflective network charges.

Generally, flat tariffs perform better than ToU tariffs for mitigating voltage and alleviating line congestion problems. It is concluded that in the context of reducing network peaks, flat tariffs with a peak demand charge will be the most beneficial for DNSPs. With respect to the economic benefits of customer, the best tariff depends on the amount of DER possessed by customer. However, the cost savings achieved by switching to another tariff type is marginal. Moreover, with reference to our previous work where all customers are without EWH [20], it is also concluded that the EWH has equal impacts across all tariff types in terms of line loading. However, with EWH, the line loading is generally higher.

In this paper, we have not explicitly tested these tariffs for cost-reflectivity, although this is implicit in the results. In this regard, our next task will focus on the design of these tariffs using the established principles in economic theory rather than using the already published tariffs from DNSPs.

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Donald Azuatalam received the M.Sc. degree in sustainable energy systems from the University of Edinburgh, Edinburgh, U.K., in 2015, and the Ph.D. degree in electrical engineering from the University of Sydney, Sydney, Australia, in 2020. He is currently a Research Fellow with the Faculty of IT, Monash University, Melbourne, Australia. His research involves the application of optimization and artificial intelligence techniques for solving energy management and appliance scheduling problems in smart buildings, by efficiently controlling flexible loads and customer-owned flexible energy assets such as rooftop solar PV, and battery energy storage systems. Besides, he explores ways to ensure that these customer-oriented decisions do not deteriorate the performance of local electricity networks. His research interests include grid integration of renewable energy systems, energy management and control of distributed energy resources, distribution network cost allocation, and building energy modelling.

Archie C. Chapman received the B. A. degree in math and political science, and the B. Econ. degree (Hons.) from the University of Queensland, Brisbane, Australia, in 2003 and 2004, respectively, and the Ph.D. degree in computer science from the University of Southampton, Southampton, U.K., in 2009. He is currently a Senior Lecturer with the School of IT and Electrical Engineering, University of Queensland, St. Lucia, Australia. Prior to joining the University of Queensland, he was Research Fellow in Smart Grids at the University of Sydney, Sydney, Australia, from 2011-2019. His work focuses on the use of distributed energy resources such as batteries and flexible loads, to provide power network and system services, while making best use of legacy infrastructure. His research interests include optimization and control of large distributed systems using methods from game theory and artificial intelligence.

Gregor Verbič received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from the University of Ljubljana, Ljubljana, Slovenia, in 1995, 2000, and 2003, respectively. In 2005, he was an NATO-NSERC Postdoctoral Fellow with the University of Waterloo, Waterloo, Canada. Since 2010, he has been with the School of Electrical and Information Engineering, University of Sydney, Sydney, Australia. His expertise is in power system operation, stability and control, and electricity markets. His research interests include power grid and market integration of renewable energies and behind-the-meter distributed energy resources, with a particular focus on future power grid modelling and analysis, and demand response.