Probabilistic Impact Assessment of Network Tariffs in Low Voltage Distribution Networks

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Abstract—In this paper, we present a probabilistic framework to assess the impacts of different network tariffs on the consumption pattern of electricity consumers with distributed energy resources such as thermostatically controlled loads and battery storage; and the resultant effects on the distribution network. A mixed integer linear programming-based home energy management system with implicit modeling of peak demand charge is used to schedule the controllable devices of residential customers connected to a low voltage network in order to analyze the impacts of energy- and demand-based tariffs on network performance. The simulation results show that flat tariffs with a peak demand component perform best in terms of electricity cost reduction for the customer, as well as in mitigating the level of binding network constraints. This is beneficial for distribution network service providers where there is high PV-battery penetration.

Index Terms—distributed energy resources, thermostatically controlled loads, battery energy storage systems, solar PV, home energy management systems

NOMENCLATURE

| Symbol | Description |
|--------|-------------|
| $D$    | Set of days, $d \in D$ in a year (1-365) |
| $H$    | Set of time-slots, $h \in H$ in a day (1-48) |
| $M$    | Set of months, $m \in M$ in a year (1-12) |
| $p_a$  | Appliance/base load power (inflexible) |
| $p_{pv/d}$ | Solar PV power/total customer demand |
| $p^{\pm}$ | Power flowing from/to grid |
| $p^g$  | Maximum power taken from/to grid |
| $\hat{p}$ | Maximum value of $p^g$ over a decision horizon |
| $d^g$  | Direction of grid power flow (binary) |
| $T_{in}$ | Electric water heater (EWH) internal temperature |
| $u_{th}$ | EWH operational status (binary) |
| $\eta_{th/i}$ | EWH/Inverter efficiency |
| $e^{b/s}_{+/\pm}$ | Battery state of charge/charging status (binary) |
| $p^{b/+/-}$  | Battery charging/discharging power |
| $\eta^{b/+/-}$ | Battery charging/discharging efficiency |
| $\bar{e}^{b}_{+/\pm}$ | Battery maximum charging/discharging power |
| $e^{b/\bar{e}}$ | Battery minimum/maximum state of charge |
| $T_{fit/toff}$ | Flat/time-of-use energy charge |
| $T_{fix/fit}$ | Fixed daily charge/feed-in-tariff (FiT) |
| $T^{pk}/p^{pk}$ | Peak demand charge/monthly peak demand |

I. INTRODUCTION

The average household electricity price in OECD countries (using purchasing power parity) increased by over 33% between 2006 and 2017 (a rise from 13.16 to 17.52 US c/kWh). In Australia and Germany particularly, figures currently stand at about 20.4 and 39.17 US c/kWh respectively, which is an increase from roughly 12.52 US c/kWh (in Australia) and 20.83 US c/kWh (in Germany) from the year 2006. These are countries that from the outset had supportive green energy policies and generous FiT rates and with a steady decline in the cost of distributed energy resources (DER) and, the PV-battery penetration levels are also relatively high.

In Germany, the subsidies that supported investment in renewable generation are now appearing in the residential energy bills. Similarly, although renewable subsidies account for less than 10% of the electricity bill in Australia, the rise in the network tariff were often incurred in order to host greater penetrations of rooftop PV and meet forecasted demand growth. The network tariff in Australia accounts for over 50% of the retail bill, and it is projected to increase in the near future. Presently, with the reduction of FiT rates in these countries, these price hikes have driven prosumers to increase their levels of self-consumption, while distribution network service providers (DNSPs) simultaneously raise tariffs to compensate for the resultant revenue loss. This introduces a death spiral in electricity prices as DNSPs need to cover revenue shortfalls regardless of falling consumption rates.

In order to forestall electricity price increases due to rising network tariffs, it is essential for DNSPs to design and implement more cost-reflective tariffs such that consumers are charged according to the extent to which they contribute to network peak demand and other long-run network cost drivers. In light of this, demand-based tariffs have been proposed by network companies as an interim solution to inequitable pricing and cross-subsidies (between consumers and prosumers) existing as a result of purely volumetric tariffs, and are currently being implemented in some parts of Australia. However, the impacts of these new tariffs on a consumer’s energy usage pattern and on network performance have not been well investigated. This motivates the work presented here.

Within this context, recent studies have considered the economic impacts of energy- and demand-based tariffs on residential customers and on utilities’ revenue. Simshauer in showed demand-based tariffs to be effective at resolving network price instability and reducing cross-subsidies between consumers without DER and prosumers, and in, the authors showed how it could be used to ensure a stable revenue for DNSPs. In, the authors suggested that a peak demand tariff based on a customer’s yearly peak demand should be considered by DNSPs, as it performed best in terms of cost-
reflectivity and predictability amongst other tariff types. On the contrary, [10] tested demand-based tariffs proposed by the Australian Energy Regulator (AER) on households in Sydney and concluded that without due adjustments made, these tariffs show low cost-reflectivity. From these, 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 [11].

Despite these efforts, very little research has considered the technical impacts of network tariffs on the distribution network. This is paramount because the aggregate network peak demand and energy losses are the long-run network cost drivers. It was shown in [12] that time-of-use (ToU) tariffs alone can increase peak loading on networks with deep DER penetration levels. In view of this, authors in [13] showed that demand-based tariffs could be used to mitigate transformer loading at medium voltage (MV) substations. More so, the results in [14] demonstrated the effectiveness of demand-based tariffs in alleviating peak demand whilst considering demand response from customers’ controllable appliances. In [14], however, customers were exposed to spot market prices and the effects of PV-battery systems were not considered.

Given this background, in this paper, we examine residential customers’ response to energy- and demand-based network tariffs. A mixed integer linear programming (MILP)-based home energy management system (HEMS) framework, which minimizes electricity cost, is used to assess the effects of this response on typical low voltage (LV) distribution networks. Ample studies into the area of home energy management have used different optimization approaches in the HEMS formulation [15][16], but incorporating demand charges in these can be challenging. Whilst modeling demand-based tariffs, if the demand charge is included explicitly in the optimization model as a constraint, the problem can become intractable because a min-max problem results even with a MILP formulation. To overcome this, we implicitly model the peak demand charge as a linear term in the objective function, with an additional inequality constraint which limits the monthly demand according to the set demand charge [17]. In this way, we achieve same results as with the explicit modeling of the peak demand constraint but with lesser computational burden. Building on our earlier work in [17], we include electric water heaters (EWH) as part of the HEMS formulation since they account for a considerable portion of energy consumption in the Australian context and can affect peak loading.

The optimization-based simulation is run for a year to account for seasonal variations in demand and solar PV output and specific to each of 332 customers. Furthermore, three scenarios are considered based on customer DER ownership, namely, EWH only, EWH+PV, and EWH+PV+Battery; and simulation is performed for four different network tariff types. The output of the optimization which reflects customer response to the tariff types is then used to carry out probabilistic power flow studies. In summary, the analysis in this paper extends the preliminary results in our earlier conference paper [17] in the following ways:

- With limited data available, we derive a solar PV/demand and EWH statistical model to generate sufficient net load traces and hot water draws required to carry out power flow studies for customers with EWH and/or PV-battery systems.
- We propose a framework for assessing customer response to different network tariffs whilst incorporating detailed battery and EWH appliance models. With this, we carry out statistical economic impact analysis of these tariff types on LV customers.
- We demonstrate the effects of energy- and demand-based network tariffs on typical LV distribution networks. Specifically, we examine impacts on annual feeder head loading and customer voltage profiles for different PV-battery penetration levels.

The remainder of this paper is structured as follows: In the next section, we present an overview of the tariff assessment framework. This is followed by detailed household DER modeling including PV/demand and EWH hot water draw statistical models in Section III. Section IV details the optimization model of the network tariff types. In Section V, we perform annual electricity calculations and in Section VI, we describe the power flow analysis framework. The results of our case studies are discussed in Section VII and we conclude the paper in Section VIII.

II. METHODOLOGY

A summary of the probabilistic assessment framework is detailed in Figure 1. In Module I, using yearly historical data, we generate a pool of net load traces and corresponding hot water draw profiles by applying the PV/demand and EWH hot water draw statistical models described in Section III. In Module II, the output of the statistical models are fed as input to the MILP-based HEMS to solve the yearly optimization problem for the different tariff types and results are saved for each customer. With the assumption that these customers are part of a LV network, the optimization results and output data from Module I are used to perform time-series yearly Monte Carlo (MC) power flow studies on LV distribution networks using OpenDSS [18]. 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 customer voltage profile and feeder head loading at different PV-battery penetration levels. We describe the steps needed to achieve this in the following sections.

A. Low Voltage Networks

The low voltage network data used in this work were obtained from the Low Voltage Network Solutions Project [19]. Table I summarizes the main features of the three networks used as case studies in this work. These are residential LV networks of different lengths and number 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 networks are more robust with higher load capacity when compared to that from the UK. Therefore, we have increased the transformer capacity by a factor of three and decreased...
the line impedances by a factor of three since the average consumption in Australia is roughly three times that in the UK. However, the overall structure of LV networks in both countries are similar.

B. Network Model

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

C. Network Tariffs and Retail Charges

A typical residential customer retail bill consists of network (distribution and transmission) charges, generation costs for energy, retailer’s charge and other related costs. We have sourced the network tariff data from Essential Energy\[1\]. These are assumed fixed and known in advance. In Table III the residential electricity prices for customers in the Essential energy distribution zone for retailer, Origin Energy\[2\] is shown. These prices include the actual cost of electricity, retailer’s service fee, and the network charge. The different network tariffs (energy, Flat and ToU, and demand-based, FlatD and ToUD) are described below:

- **LV Residential Anytime (Flat)**: Includes a fixed daily charge and a flat usage charge.
- **LV Residential Time-of-use (ToU)**: Includes a fixed daily charge and a ToU usage charge.
- **Small Residential - Opt in Demand Anytime (FlatD)**: Includes a fixed daily charge, a flat usage charge and a peak demand charge.
- **Small Residential - Opt in Demand (ToUD)**: Includes a fixed daily charge, a ToU usage charge and a peak demand charge.

D. Customer Demand and DER Data

We sourced the demand and solar PV generation data from the Ausgrid (DNSP in NSW) Smart Grid, Smart City (SGSC)\[3\] data set. These are three years of half-hourly resolution smart meter data for the period between July 2010 to June 2013. The most recent data (financial year, July 2012 to June 2013) is used in this study because it is complete and of higher quality, compared to the previous years in the data set. We selected 123 customers from the data set who possess complete hot water usage, solar PV and uncontrolled demand data.

Since the average PV size of these customers is roughly 1.5 kW, we applied a heuristic 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, depending on the needs of the household. For

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\[1\] Essential Energy Network Price List and Explanatory Notes. Available at [https://www.essentialenergy.com.au](https://www.essentialenergy.com.au)

\[2\] Origin Energy NSW Residential Energy Price Fact Sheet for Essential Energy Distribution Zone. Available at [https://www.originenergy.com.au](https://www.originenergy.com.au)

\[3\] Peak period: 7am to 9am, 5pm to 8pm; shoulder period: 9am to 5pm, 8pm to 10pm; off-peak period: 10pm to 7am.

\[4\] SGSC is a commercial-scale trial project involving up to 300 residential customers in Sydney, Australia. Data is available at [https://www.data.gov.au](https://www.data.gov.au)
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. This assumption is made in this work. Table III shows the PV-battery size combinations.

### III. HOUSEHOLD DER MODELING

For each customer, \( c \in C \) possessing a set of appliances, \( A := \{1, 2, ..., |A|\} \), let \( a \in \{1, ..., M\} \) denote customer’s \( c \) appliance type, wherefore \( A_a \subseteq A \). In this work, we consider just 3 appliance types (\( M = 3 \)): Type 1 set includes energy storage devices, particularly batteries; Type 2 set includes thermostatically-controlled devices, particularly electric water heaters (EWH); Type 3 appliances constitute the base load and includes all must-run and uncontrollable devices.

#### A. Battery Energy Storage System (BESS) Modeling

The BESS operational model is linearized so that it fits the MILP optimization framework. Battery sizes utilized in this study range from 6 to 12 kWh and are obtained from ZEN Energy [20]. Table IV shows the battery parameters used for simulation. For all \( a \in A_1, h \in H \):

\[
e^{b}_{a,h} = e^{b}_{a,h-1} + \Delta h \left(\frac{p_{a}^{b+}}{\eta_{a}^{h+}} p^{a+}_{a,h-1} - \left(1/\eta_{a}^{h-}\right) p^{a-}_{a,h-1}\right) \quad (1)
\]

\[
p_{a}^{b+} \leq \bar{p}^{b+} s^{a+}_{a,h} \quad (2)
\]

\[
p_{a}^{b-} \leq \bar{p}^{b-} (1 - s^{a-}_{a,h}) \quad (3)
\]

\[
0 \leq p^{a+}_{a,h} \leq \bar{p}^{b+} \quad (4)
\]

\[
0 \leq p^{a-}_{a,h} \leq \bar{p}^{b-} \quad (5)
\]

\[
e^{b}_{a,h} \leq e^{b}_{a,h} \quad (6)
\]

#### B. Electric Water Heater (EWH) Modeling

The EWH operational model is given by a set of difference equations in order to fit them into an optimization model. We consider single-element EWH tanks from Rheem with parameters given in Table V. For all \( a \in A_2, h \in H \):

\[
p_{a,h} = \eta_{a}^{h} \tau_{a,h}^{th} Q_{a} \quad (7)
\]

| **TABLE III** | PV-BATTERY SIZE COMBINATIONS |
|----------------|-----------------------------|
| 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                 |

| **TABLE IV** | BATTERY PARAMETERS |
|---------------|-------------------|
| Minimum SOC (\( \theta^{h}_{b} \)) kWh | Maximum SOC (\( \theta^{b}_{h} \)) kWh | Round-trip efficiency (\( \eta^{h+} \)) % | Maximum charging rate (\( \bar{p}^{h+} \)) kW |
| 0.6           | 6                  | 90                 | 2.5                |
| 0.8           | 8                  | 90                 | 2.5                |
| 1.0           | 10                 | 90                 | 2.5                |
| 1.2           | 12                 | 90                 | 2.5                |

#### C. PV and Demand Statistical Model

In this section, we extend the non-parametric Bayesian model introduced in [21] to generate a pool of demand and PV profiles needed to perform power flow studies. To accomplish this, we first cluster historical data sourced from the SGSC program into representative clusters, using the MAP-DP (maximum a-posteriori Dirichlet process mixtures) 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 \( \text{Dir}(\alpha) \).

To assign a cluster to an unobserved customer, we use a random variable drawn from a categorical distribution \( \text{Cat}(\gamma) \) over the features of the particular cluster, where the parameters \( \gamma \) are obtained by sampling from \( \text{Dir}(\alpha) \). We then generate a pool of net load traces specific to assigned features based on a Markov chain process. More details on the PV and demand statistical model can be found in [22].

#### D. Hot Water Draw Statistical Model

The hot water statistical model is defined for aggregated intervals of time slots during the day. It comprises a location process over the features of the particular cluster, where the parameters \( \alpha \) are obtained by sampling from \( \text{Dir}(\alpha) \). We then generate a pool of net load traces specific to assigned features based on a Markov chain process. More details on the PV and demand statistical model can be found in [22].

where: \( C = \rho V c; A \approx 6V^{2/3}; \psi_{a} = \Delta h / C; \lambda_{a} = UA\Delta h / C; \phi_{a} = \rho W_{d}; W_{d} = \text{EWH water draw in liters.} \)
TABLE VI

| HW MODEL INTERVALS, WITH TIME SLOTS INDICATED BY THEIR START TIME. |
|------------------|------------------|------------------|------------------|
| Begin | End   | Begin | End   |
| 23:00 | 1:30   | 11:00 | 13:30 |
| 2:00  | 4:30   | 14:00 | 16:30 |
| 5:00  | 7:30   | 17:00 | 19:30 |
| 8:00  | 10:30  | 20:00 | 22:30 |

modeled as following a Weibull distribution $Wei(\kappa, \sigma)$, given by:

$$f(x|\kappa, \sigma) = \begin{cases} \frac{\sigma}{\bar{x}} \left( \frac{x}{\bar{x}} \right)^{\sigma-1} \exp\left( -\left( \frac{x}{\bar{x}} \right)^\sigma \right) & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$ (11)

where $\kappa > 0$ is a scale parameter and $\sigma > 0$ is a shape parameter.

Sampling from this model involves one additional element. Specifically, once the models are estimated and values of $\mu$, $\kappa$ and $\sigma$ computed, the full sampling process for an interval involves: (i) sampling a number of draws in an interval according to $Poi(\mu)$ (ii) allocating these draws to time slots over the interval’s time slots according to a uniform distribution and (iii) sampling draw sizes for each draw according to $Wei(\kappa, \sigma)$.

We emphasize that in order to sample time slots for hot water draws, each interval first has a number of draws sampled from the estimated Poisson distribution, and then that number of locations are allocated to draws in the interval according to a uniform distribution (with replacement) over time slots, as is the standard approach for sampling from Poisson processes.

IV. OPTIMIZATION MODEL

In this section, the optimization model for all tariff types considering customers with EWH and PV-battery installation is described. Each problem is solved for a year, using a rolling horizon approach and a monthly decision horizon. Each problem is solved for a year, considering customers with EWH and PV-battery installed.

A. Model for Energy-based Tariffs

For customers facing an energy-based tariff (Flat or ToU), the daily optimization model is given in (12) to (19) for all $h \in \mathcal{H}$:

$$\begin{align*}
\min_{p_{h}^{+}, p_{h}^{-}, d_{h}, e_{h}, T_{h}^{p}} & \left[ \sum_{h \in \mathcal{H}} T_{d}^{fit/toU} p_{h}^{+} - T_{d}^{fit} p_{h}^{-} \right] \\
\text{subject to } & \text{eqs. (1) to (9), (13)} \\
p_{h}^{+} - p_{h}^{-} & = \eta \left( \eta^{b} p_{h}^{b} - \left(1/\eta^{b}\right) p_{h}^{b} - p_{h}^{pv} \right) + p_{h}^{d} \\
p_{h}^{d} & = p_{h}^{base} + \sum_{a \in \mathcal{A}_{2}} p_{a,h} \\
p_{h}^{+} & \leq \bar{p}^{+}d_{h} \\
p_{h}^{-} & \leq \bar{p}^{+} \left(1 - d_{h}\right) \\
0 & \leq p_{h}^{+} \leq \bar{p}^{+} \\
0 & \leq p_{h}^{-} \leq \bar{p}^{-}
\end{align*}$$ (12) to (19)

B. Model for Demand-based Tariffs

For customers facing a demand-based tariff (FlatD or ToUD), an additional constraint (20) is used to limit the grid import according to the demand charge component, $T_{d}^{p} \hat{p}$ in (20). The daily optimization model is given below for all $h \in \mathcal{H}$:

$$\begin{align*}
\min_{p_{h}^{+}, p_{h}^{-}, d_{h}, e_{h}, T_{h}^{p}} & \left[ \sum_{h \in \mathcal{H}} T_{d}^{fit/toU} p_{h}^{+} - T_{d}^{fit} p_{h}^{-} \right] + \sum_{h \in \mathcal{H}} T_{d}^{p} \hat{p} \\
\text{subject to } & \text{eqs. (13) to (19)} \\
p_{h}^{+} & \leq \hat{p} \\
\end{align*}$$ (20) to (22)

C. Optimization Scenarios

The optimization models described above are solved for three scenarios based on customer DER ownership. Scenario I is the base case where all customers possess just EWH. Then we progressively add DER to form the other two scenarios, following (14). Where $p_{h}^{b} = p_{h}^{base} + p_{h}^{ewh}$, then the following scenarios hold:

1) Scenario I: All customers with EWH only - The energy balance equation is:

$$p_{h}^{+} = p_{h}^{d}$$ (23)

2) Scenario II: All customers with EWH and solar PV - The energy balance equation is:

$$p_{h}^{+} - p_{h}^{-} = \eta p_{h}^{pv} + p_{h}^{d}$$ (24)

3) Scenario III: All customers with EWH, solar PV and batteries - The energy balance equation is:

$$p_{h}^{+} - p_{h}^{-} = \eta^{b} p_{h}^{b} - \left(1/\eta^{b}\right) p_{h}^{b} - p_{h}^{pv} + p_{h}^{d}$$ (25)

V. ANNUAL ELECTRICITY COST CALCULATIONS

The annual electricity cost for customers with PV or PV-battery (Scenarios I and II) are calculated for each Tariff type as in (26) to (29) using $p_{h}^{+}$ and $p_{h}^{-}$ obtained as output variables from the optimization. For customers without DER (Scen. I), the calculations are done without the power export component ($T_{d}^{fit} p_{h}^{-}$).

$$\begin{align*}
\text{C(Flat)} & = \sum_{d \in \mathcal{D}} \left[ T_{d}^{fx} + \sum_{h \in \mathcal{H}} \left( T_{d}^{fit} p_{d,h}^{+} - T_{d}^{fit} p_{d,h}^{-} \right) \Delta h \right] \\
\text{C(ToU)} & = \sum_{d \in \mathcal{D}} \left[ T_{d}^{fx} + \sum_{h \in \mathcal{H}} \left( T_{d}^{fit} p_{d,h}^{+} - T_{d}^{fit} p_{d,h}^{-} \right) \Delta h \right] \\
\text{C(FlatD)} & = \sum_{d \in \mathcal{D}} \left[ T_{d}^{fx} + \sum_{h \in \mathcal{H}} \left( T_{d}^{fit} p_{d,h}^{+} - T_{d}^{fit} p_{d,h}^{-} \right) \Delta h \right] \\
& + \sum_{m \in \mathcal{M}} \left( T_{d}^{p} \hat{p} \right) \\
\text{C(ToUD)} & = \sum_{d \in \mathcal{D}} \left[ T_{d}^{fx} + \sum_{h \in \mathcal{H}} \left( T_{d}^{fit} p_{d,h}^{+} - T_{d}^{fit} p_{d,h}^{-} \right) \Delta h \right] \\
& + \sum_{m \in \mathcal{M}} \left( T_{d}^{p} \hat{p} \right)
\end{align*}$$ (26) to (29)
Algorithm 1 Monte Carlo Power Flow Algorithm

\[P\]: set of PV penetration levels, \(P := \{0, 25, 50, 75\}\)

\[B\]: set of Battery penetration levels, \(B := \{0, 40, 80\}\)

\[C\]: set of customers in a LV network, \(C := \{1, 2, \ldots, |C|\}\)

1: for each \(p \in P\) do
2: Read yearly load and PV profile
3: if \(p = 0\) then
4: Read \(p_{d,c}^\text{Sc}\) \(\forall c \in C, d \in D\), for Sc.I
5: for \(k = 1\) to 100 step 1 do \(\triangleright 100\ MC\ simulations\)
6: Sample uniformly from \(p_{d,c}^\text{Sc}\) for allocation to load points.
7: Run yearly power flow
8: Return \(v_{d,c}^{\text{head},k}\) and \(v_{d,c}^k\) \(\forall c \in C, d \in D\)
9: end for
10: else
11: for each \(b \in B\) do
12: Read \(p_{d,c}^b\) \(\forall c \in C, d \in D\), for Sc. I, II and III.
13: for \(k = 1\) to 100 step 1 do \(\triangleright 100\ MC\ simulations\)
14: \(p_{d,c}^\text{Sc.I} := (100 - p)\%\ of \ p_{d,c}^\text{Sc.I} + p\%\cdot(100 - b)\%\ of \ p_{d,c}^\text{Sc.II}\)
15: \(p_{d,c}^\text{Sc.II} := p\%\cdot b\%\ of \ p_{d,c}^\text{Sc.III}\)
16: Repeat Lines 6 to 8
17: end for
18: end for
19: end if
20: end for

The value \(p_{d,c}^{\text{peak}}\) 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, the demand-based tariffs each has two variants based on the calculation of the monthly peak demand.

VI. Power Flow Analysis

The net grid power exchange \((p_d^g = p_d^{\text{up}} - p_d^{\text{down}})\) resulting from the HEMS optimization solution and the data generated from the statistical models (see Module III, Step 5 in Figure [1]) are fed as input to a distribution network model to perform MC power flow analysis, using Algorithm [1]. We then carry out a probabilistic assessment of yearly voltage profiles \((v_{d,c})\) for each customer and feeder head loading \((v_{d,c}^{\text{head}})\) 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:

- A customer is said to have a voltage problem if his phase-to-neutral voltage goes outside the range \(0.95\ \text{pu} \leq v_{d,c} \leq 1.05\ \text{pu}\) for 95% of days in a year.
- There is a thermal loading problem if the current flowing through line \(i_{d,c}^{\text{head}}\) (feeder head) exceeds its thermal rating.

VII. Results

In this section, the results from the optimization and network power flows are analyzed and discussed. For the annual electricity cost calculations, 332 customers have been chosen from the generated pool of customers, since the largest feeder used as case study comprises 302 customers.

A. Monthly Peak Demand

To calculate customers’ monthly peak demand under the tariff types, we find the maximum grid import power for each month from the optimization results. Figure 2 illustrates the monthly peak demand for 332 customers in Scenarios I-III. These results show that solar PV alone (Scen. II) is not sufficient to significantly reduce the peak demand recorded in the base case (Scen. I). With solar PV and batteries (Scen. III), the monthly peak demand even increased with energy-based tariffs, but was lowered with demand-based tariffs as compared with Scenario II. We can also deduce that ToU-based tariffs perform worst as DER is progressively added compared with flat tariffs (Flat and FlatD). This is due to the creation of new peaks when all batteries charge off-peak times to minimize customers’ electricity costs. Generally, using demand-based tariffs results in a lower monthly peak demand compared to energy-based tariffs due to the additional demand charge to penalize grid power import.

B. Annual Electricity Cost

In this section, we analyze the annual electricity costs for all scenarios using results from Section V as plotted...
in Figure 3. Overall, customers pay less for electricity as DER is progressively added. While demand-based tariffs result in a lower electricity cost compared to energy-based tariffs in Scenario I, this slightly levels off in Scenarios II and III. This is because when prosumers’ grid power import is clipped due to demand charges, they compensate for this by exporting more power to the grid. Nevertheless, the FiT rates are small compared to the retail rates so the net savings are minimal. With PV and batteries (Scenario III), however, large power export pays off with ToU 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 costs values are quite close.

C. Effects of Network Tariffs on Line Loading

In this section, we analyze the feeder head loading for the different PV-battery penetration levels (Figure 4). The loading levels are generally high because we have shown the phases with the highest loading (other phases follow similar pattern) for each feeder and also examined the maximum feeder head loading over the year for each MC simulation. The results show that ToU perform worst as the battery penetration level increases, which is in conformity with the results in [12]. 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 line loading due to large grid imports at 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, line loading increased with higher battery penetration with ToU, while it reduced with ToUD. Contrarily, Flat results in lower line loading for all feeders. And including a demand charge to the flat tariff (FlatD), line loading is reduced even further as seen in all three feeders. This works well with increasing battery penetration in both fairly balanced (Feeders 1 and 2) and unbalanced LV networks (Feeder 3) since there are no incentives for large grid power exports as with ToU tariffs.

D. Effects of Network Tariffs on Customer Voltage Level

In terms of customer voltage profiles, Figure 5 shows that ToU results in higher voltage problems in all three feeders compared to the 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). Here, batteries are beneficial in reducing voltage problems. Energy-based flat tariff (Flat) 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 (FlatD), there is a slight improvement in the customer voltage profiles as can be observed in all feeders, but more evident in Feeder 1.

VIII. CONCLUSIONS AND FURTHER WORK

In this research, we have shown that in the presence of DER, adding a peak demand charge to either a Flat or ToU
tariff is effectively reduces peak demand and subsequently line loading. Generally, flat tariffs perform better than ToU tariffs for mitigating voltage and alleviating line congestion problems. We conclude that flat tariffs with a peak demand charge will be most beneficial for DNSPs. With regards to customer economic benefits, the best tariff depends on the amount of DER a customer possesses. But, the cost savings achieved by switching to another tariff type is marginal. More so, with reference to our previous work (all customers without EWH) [17], we can also conclude 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 study, 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 established principles in economic theory rather than using already published tariffs from DNSPs.

Fig. 5. Percentage of customers with voltage problems.

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