Probabilistic Assessment of PV-Battery System Impacts on LV Distribution Networks

Yiju Ma, Student Member, IEEE, Donald Azuatalam, Student Member, IEEE, Thomas Power, Student Member, IEEE, Gregor Verbič, Senior Member, IEEE and Archie C. Chapman, Member, IEEE

Abstract—The increasing uptake of residential batteries has led to suggestions that the prevalence of batteries on LV networks will serendipitously mitigate the technical problems induced by PV installations. However, in general, the effects of PV-battery systems on LV networks have not been well studied. Given this background, in this paper, we test the assertion that the uncoordinated operation of batteries improves network performance. In order to carry out this assessment, we develop a methodology for incorporating home energy management (HEM) operational decisions within a Monte Carlo (MC) power flow analysis comprising three parts. First, due to the unavailability of large number of load and PV traces required for MC analysis, we used a maximum a-posteriori Dirichlet process to generate statistically representative synthetic profiles. Second, a policy function approximation (PFA) that emulates the outputs of the HEM solver is implemented to provide battery scheduling policies for a pool of customers, making simulation of optimization-based HEM feasible within MC studies. Third, the resulting net loads are used in a MC power flow time series study. The efficacy of our method is shown on three typical LV feeders. Our assessment finds that uncoordinated PV-battery systems have little beneficial impact on LV networks.

Keywords—distributed energy resources, policy function approximation, battery energy storage, solar PV systems, home energy management

I. INTRODUCTION

Residential rooftop PV generation is becoming an indispensable energy supply resource. In Australia, the annual installed capacity of small-scale PV systems has grown from less than 200 MW in 2009 to 1.1 GW in 2017, with the average installation size rising from 1.5 kW to 5.5 kW [1]. Projections by the Australian Energy Market Operator (AEMO) see the total rooftop solar generation capacity to increase from 4.3 GW in 2017 to 19 GW in 2035 [1]. This is confirmed by the CSIRO and Energy Networks Australia (ENA), who see significant growth in PV penetration. In particular, this level is predicted to increase from 16% to 40%, and 19% to 44%, in Victoria and Western Australia, respectively [2].

In addition to the increasing rooftop PV generation, residential batteries are becoming more significant in managing energy use for residential customers to reduce electricity cost. This is crucial in the Australian context, which has high electricity prices and low feed-in tariffs [3]. In response to this, 12% of the 172,000 residential solar installations in 2017 included a battery, while this proportion was 5% in 2016. Given this, a total of 28,000 battery systems had been installed by the end of 2017 [4]. In addition, projections by AEMO see residential battery capacity reaching 6.6 GW by 2035, with 3.8 GW expected to be installed as part of PV-battery systems [5]. A key driver to this trend is their falling costs, which are predicted to drop by 50% from 2017 to 2037 [1].

Rising PV penetrations can impose numerous technical problems on networks including over-voltages, reverse power flows with congestion problems, and phase unbalance. It is widely believed that battery systems will largely mitigate these problems [6], [7]. However, the extent to which PV-battery systems can benefit the distribution networks with increasing PV penetration has not been thoroughly investigated.

In power flow studies, Monte Carlo (MC) analysis can effectively capture uncertainties in the input parameters. In our work, MC is used to consider three sources of uncertainty, namely, the location of loads, and size and location of distributed energy resources (DER). Failing to accommodate these uncertainties can lead to inaccurate outcomes. However, using MC to evaluate the impacts of PV-battery systems in a distribution network is challenging, for two main reasons. First, battery operation is under the control of a home energy management (HEM) system, which is typically modelled using the tools of optimization. However, forming and solving an optimization problem is relatively time-consuming, and therefore impractical within MC analysis. Second, a large number of residential demand and PV traces are required for MC analysis, but are generally not available, and hence need to be synthesized. Our work proposes a novel methodology that overcomes these challenges to assess the impact of PV-battery systems on distribution networks.

A. Literature Review

In this subsection we review existing methods for: (i) assessing the impacts of PV generation on distribution networks using MC, (ii) solving battery scheduling problems within a HEM system, and (iii) modeling customers’ solar generation and electrical demand.

1) Monte Carlo Approaches: MC has been employed in many studies to capture uncertainties in the location and size of DER when assessing their impacts on voltage profiles and peak loading in LV networks [8], [9], [10]. In particular, the authors in [8] applied a probabilistic approach to evaluate the impacts of distributed generation with different penetration levels on voltage profiles. This method was extended in [11] to probabilistically allocate PV, combined heat and power systems, electric heat pumps and electric vehicles, to investigate the prevalence of voltage problems on LV feeders with different penetration levels of these low carbon technologies. In addition, the study in [12] proposed a probabilistic approach...
using MC analysis to investigate the maximum PV penetration level that can be tolerated by an LV network without voltage problems. However, none of these studies include battery scheduling in their analysis, as solving the HEM problem inside MC simulations is impractical due to the excessive computational burden.

2) Home Energy Management: To formulate a HEM problem, methods such as stochastic integer linear programming [13], dynamic programming (DP) [14] and approximate dynamic programming (ADP) [15] have been applied to compute the optimal battery schedules. These studies focus on minimizing energy costs for residential customers, but do not consider the impact of batteries on distribution networks. This is because solving such an optimization problem for a large number of HEM systems is computationally intensive.

In contrast to the methods above, the authors in [16] proposed a policy function approximation (PFA) algorithm to solve the HEM problem. The algorithm uses the battery schedules calculated from ADP to train a recurrent neural network that maps demand and PV generation to battery scheduling output. Then, the recurrent neural network is used as a PFA to quickly provide battery scheduling policies. This step averts the need to solve the optimization problem within the MC sampling loop, and hence, improves the computational performance.

3) Solar and Demand Modeling: The PFA method proposed in [16] has prompted the need for synthesizing stochastic demand and PV profiles. To achieve this, Markov chains have been frequently used in numerous studies, to build stochastic demand profiles using a bottom-up approach starting at the appliance level. Specifically, a Markov chain is used to simulate building occupancy profiles for the purposes of generating lighting demand [17] and residential energy demand profiles [18]. However, such bottom-up approaches are computationally expensive, and it is difficult to model energy usage at the appliance level in a way that represents the diversity of customer behavior.

In light of this, the study in [19] and [20] proposed a methodology for generating residential demand and solar profiles using a Markov process specific to the features of the existing data. Instead of working up from the appliance level, the method generates the synthetic profiles by first clustering a set of observed profiles using a Dirichlet process, which is then used to generate the transition matrices used in the Markov process.

B. Contributions

Within this context, this work proposes a novel probabilistic impact assessment framework, which embeds the battery scheduling optimization problem in the MC analysis, to assess the effects of batteries on LV networks. MC analysis can effectively capture the uncertainties in probabilistic power flow studies. In order to incorporate battery scheduling in such analysis, two challenges need to be overcome, which have not been addressed in the existing literature: (i) the need to generate a large number of residential demand and PV traces (not available) for the MC analysis, and (ii) incorporating the HEM problem within the MC analysis, which is impractical due to the excessive computational burden. Given this, the contributions of this work are:

- We use a Markov chain approach to synthesize large numbers of statistically similar, but independent demand and PV profiles with only limited amount of available smart meter data; and,
- We incorporate battery scheduling optimization within the MC analysis by training a PFA using a recurrent neural network to estimate the near-optimal battery schedules for a large pool of customers.

In doing so, we overcome the shortcomings of existing approaches to using MC for probabilistic power flow studies, which fail to accommodate schedulable batteries. Thus, for the first time, we can efficiently include the DER scheduling used to manage a customer's behind-the-meter energy use within a MC framework. Furthermore, the proposed framework allows a MC load flow analysis with a paucity of load data.

The proposed MC framework evaluates network performance specific to over-voltage issues, transformer loading level and phase unbalance with respect to varying PV and battery penetrations. The efficacy of our method is shown on one UK and two Australian LV networks. The results indicate that the uncoordinated battery operation can reduce over-voltage and thermal loading levels, while the impact on phase unbalance is distinct only when the network is highly unbalanced and has large PV generation. Our methodology reduces the computational time required to solve the HEM problem by more than 95%, which makes it computationally feasible to include battery scheduling within a MC framework.

The remainder of the paper is organized as follows. Section II describes the module that synthesizes large pools of demand and PV profiles. Section III presents the HEM system used to compute the battery schedules for each customer from the large data pool. The probabilistic power flow studies via MC analysis is described in Section IV. The three modules described in Sections II, III and IV are used to form the probabilistic impact assessment framework, shown in Fig. 1. This framework is used to assess the impacts of battery scheduling under time-of-use tariffs and self consumption maximization on mitigating network issues, and the results are discussed in Section V. Section VI draws conclusions.

II. DEMAND AND PV TRACE MODELS

In order to assess the performance of distribution networks when only a few demand and PV traces are available, a larger number need to be synthesized. This is the purpose of Module 1 in Fig. 1 to use an existing dataset to generate a larger pool of demand and PV profiles (net load traces). Module 1 works by assigning Markov processes according to a Dirichlet distribution identified via clustering, as described in Algorithm 1 and explained in more detail below.

A. Data Preparation

This work extends the non-parametric Bayesian model introduced in [19] and [20] to generate net load traces that are
Module I: Demand and PV Synthesis Analysis

1. Cluster the features of observed customers \( n \in \mathcal{N} \) from the SGSC project
2. Apply Dir(\( \alpha, \beta \)) to assign the features to unobserved customers \( m \in \mathcal{M} \)
3. Synthesize net load traces using a Markov process

Module II: HEM Problem

4. Formulate a sequential optimization problem and solve it using DP
5. Use a RNN to implement a PFA with the results from step 4
6. Apply the net load traces to the PFA to estimate their battery scheduling profiles

Module III: MC Impact Analysis

7. Uniformly sample from net load traces for load allocation
8. Uniformly sample from \( D_{\text{load}} \) for PV-battery assignment specific to \( P_{PV} \) and \( P_b \)
9. Run power flow analysis to plot probabilistic curves regarding voltage, current and phase unbalance

![Fig. 1. Overview of the Methodology.](image)

statistically similar to historical demand and PV generation of observed customers. The observed data was collected during the Ausgrid Smart-Grid Smart-City (SGSC) project.

Let \( n \in \mathcal{N} \) and \( m \in \mathcal{M} \) denote the set of observed and unobserved customers, respectively. The module first applies a clustering technique, namely maximum a-posteriori Dirichlet process mixtures (MAP-DP), to cluster the \( n \in \mathcal{N} \) customers into representative sets, denoted \( s \in \mathcal{S} \) according to their features. The features of demand are the day types (weekday or weekend) and number of residents, while those for PV include the PV capacity, panel orientation and weather information. Clustering is important because (i) considering each customer as a single category is computationally expensive, and (ii) it provides generalizable statistical information as the demand and PV generation in each set are correlated with their features.

B. Estimating the Dirichlet Distribution

After clustering, we could compute the frequencies, \( \{P_s\}_{s \in \mathcal{S}} \), of each \( s \in \mathcal{S} \) in the the population \( \mathcal{N} \). These values can be interpreted as the probability of an unobserved customer having certain features. However, they are only an estimate across the observed customers, and directly using them to allocate features fails to properly consider the error in this estimate, which can be significant where the fraction of customers observed is small. Thus, a Bayesian estimation approach is employed.

Specifically, in step 2 of Module 1, the model uses the count of each \( s \in \mathcal{S} \) in the the observed \( \mathcal{N} \) as a hyperparameter of a Dirichlet distribution, which itself is sampled to yield a categorical probability distribution over the features for unobserved customers, \( m \in \mathcal{M} \). Formally, this is given by:

\[
\alpha \sim \text{Dir}(\mathcal{N})
\]

\[
S_m | \alpha \sim \text{Cat}(p)
\]

In more detail, \( \alpha \) is a vector of concentration hyperparameters given by the number (c.f. frequency) of observed customers within each \( s \in \mathcal{S} \). Sampling from \( \text{Dir}(\alpha) \) yields the parameters, \( p \) of a categorical probability distribution, \( \text{Cat}(p) \) over the features for unobserved customers, \( m \in \mathcal{M} \). Finally, \( S_m \) is the random variable assigning a cluster to each unobserved customer \( m \), which is drawn from \( \text{Cat}(p) \).

This Bayesian approach to assigning clusters to unobserved customers ensures that the error in the estimate previously discussed is probabilistically accounted for.

C. Markov Chain Process

Step 3 in Module 1 involves synthesizing a large number of net load traces based on the feature assignments, by (i) generating Markov transition matrices and then (ii) sampling a trace, as follows.

First, a time-inhomogeneous Markov process is identified by constructing a set of observed state transition matrices, \( \{T_{n,t}\} \forall n, t \), each of which is indexed by the states for one observed customer for one time step. Specifically, a matrix of transition frequencies for each \( T_{m,t} \) that records all observed state transitions is calculated from the observed data. An unobserved state transition matrix, denoted \( T_{m,t} \), is generated specific to each of these transition count matrices. Gaussian kernel density estimation is applied to each \( T_{m,t} \) to ensure that unobserved state transitions are attainable (i.e. all states communicate and the Markov chain is recurrent).

Second, each row of \( T_{m,t} \) then defines a categorical distribution, from which a state can be drawn. For each synthetic profile, an initial state is drawn from the first matrix. Specifically, this is done using the sum of each row of the transition count matrix. The initial state is then drawn from this categorical distribution. Given this, the subsequent state is drawn from the \( i^{th} \) row of the second matrix. This process is continued for each remaining time step to construct one net load trace for one year. The net load traces serve as the inputs to the HEM problem in Module 2 for fast battery scheduling estimation.

III. HOME ENERGY MANAGEMENT PROBLEM

The DP method from \[16\] is used in conjunction with PFA to form Module 2 of the framework. This Module first formulates
Algorithm 1 Demand and Generation Profile Synthesis

1: Cluster \( n \in N \) into representative sets, \( s \in S \), using MAP-DP.
2: Compute \( \{T_{ns}\}_{n \in N} \).
3: for \( m \in M \) do
4: Sample from \( \text{Dir}(\alpha, \beta) \) to form a multinomial distribution.
5: Draw \( n \in N \) from \( s \in S \) using the multinomial distribution.
6: Assignment is made at random to \( m \in M \).
7: Compute \( T_{ns} \).
8: for \( s \in T_{ns} \) do
9: Define a multinomial distribution, from which a state can be drawn.
10: end for
11: Complete one net load trace.
12: end for

| Attached PV size (kW) | 1-4 | 5-6 | 7-10 |
|-----------------------|-----|-----|------|
| Battery Capacity (kWh) | 6.5 | 9.8 | 14.0 |
| Battery Power (kW)    | 4.2 | 5.0 | 5.0  |
| Manufacturer          | LG  | LG  | Tesla|

a Markov decision process (MDP) for each of the observed customers, \( n \in N \). The objective is to minimize the energy costs for each customer, with costs and benefits given by time-of-use tariffs and feed-in-tariffs. The decision variables of this algorithm includes the optimal scheduling policies for each battery system over a year. Second, a recurrent neural network (RNN) is trained as a PFA algorithm. The RNN returns a solution to the battery scheduling problem, so that it can be applied to the net load traces generated in Module 1. The details of this module are discussed below.

A. Scheduling Problem

In our work, the battery size is decided based on the size of the PV system. In Australia, typically, 2 kWh of battery is used per 1 kW of PV installed. The batteries used are from LG and Tesla, which provide three battery sizes to match the PV size ranges. The detailed allocation is summarized in Table 1.

The general formulation of the scheduling problem for each HEM system follows \( [16] \). In brief, the battery scheduling problem for each customer is formulated as a MDP, in which the states are the grid power and battery state of charge (SOC) for one year with 30-minute resolution. Solving the MDP using DP for each customer for one year requires 3 hours. This is time-consuming, and therefore impractical within MC analysis.

B. Policy Function Approximation

The computation time for DP is too great to be used within a MC study, so instead a PFA is used. The PFA algorithm implemented in Step 5 in Module 2 uses the DP outputs (SOC) to train a RNN, and then the RNN is used in the MC studies. Specifically, the inputs to the RNN include historical demand, PV generation, the electricity tariff and the SOC from the previous time step, \( t-1 \). The SOC at the current time step, \( t \), is the output, as shown in Fig. 3. In this work, we use a RNN because it has been shown to provide close-to-optimal performance when executing battery schedules trained on similar data \( [16] \).

IV. Probabilistic Impact Assessment Framework

To probabilistically assess the impact of residential batteries on distribution networks, Module 3 incorporates the HEM problem within the MC analysis. The results provide insights regarding the probabilities for a technical issue to occur based on different PV and battery penetration levels, which define the percentage of customers that have a PV system alone, or a PV-battery system. The detailed MC power flow analysis is discussed in this section.

A. Sampling Process

In order to capture the uncertainties in the power flow study, we probabilistically sample from the pool of synthetic net load traces for random allocation of loads, PV and battery systems. Specifically, customers are uniformly sampled from the pool.
of synthetic net load traces and allocated to the network. We denote the set of selected traces as $D$. In this set, the PV and demand profiles are correlated with respect to each customer $m \in M$. The load buses considered in the sampling process are kept the same as the ones given by the test circuit. Each load assignment accounts for eleven levels of PV penetration, denoted $P_{PV}$, ranging from 0% to 100%. Specific to each $P_{PV}$, the load traces to install a PV system is uniformly sampled from $D_{load}$, denoted $D_{PV}$. Following this, three levels (0%, 50%, 100%) of battery penetration, denoted $P_b$, are implemented for each $P_{PV}$. The traces to install a battery system are uniformly drawn from $D_{PV}$, denoted $D_b$. This process covers both Steps 7 and 8 in Module 3.

### B. Power Flow Analysis

The sampled data are used to run yearly power flow simulations for all MC realization paths (Step 9 in Module 3). Yearly voltage profiles for each customer and feeder head loading are used to determine the probabilities of a technical problem, namely over-voltage and/or congestion problem, according to the specific metrics defined below.

1) **Voltage Problem**: The maximum and minimum phase voltage thresholds at each busbar are 241.5 V (1.05 pu) and 218.5 V (0.95 pu) phase-to-neutral, respectively. This provides room for voltage rise and drop when peak load or high PV penetration occurs. The daily voltage profile is calculated for each customer and checked for compliance with the following probabilistic standard. Specifically, if a customer experiences a voltage violation on more than 95% of days in a year, the customer is considered to have a voltage problem.

2) **Thermal Loading Problem**: The thermal loading level is defined by the ratio of the half-hourly maximum current to the transformer capacity. Specifically, if the ratio is greater than 1, the network has a thermal problem.

3) **Phase unbalance**: This study also investigates the effects of PV-battery systems on the voltage unbalance factor (VUF), which is a measure of the phase unbalance [21]. Specifically, it is the ratio between negative and positive sequence voltages.

### V. RESULTS AND EVALUATION

The probabilistic impact assessment framework is applied to two typical Australian LV networks and one UK LV network. The results are analyzed by running yearly power flow analysis. The magnitude of a technical problem (over-voltage, transformer loading level and phase unbalance) is recorded at different levels of $P_{PV}$ and $P_b$.

#### A. Computational Performance

The computational performance of the methodology is the key to highlight in this work. Specifically, in Module 1, we synthesized 3000 net load traces with 30-minute resolution. Solving the scheduling problem for each net load trace for one year requires 3 hours using DP, which is impractical because there are 3000 synthesized traces. We use the PFA algorithm that emulates the schedules to reduce this time significantly to 5 minutes for each customer, which is greater than 95% reduction in computation time.

In terms of the MC analysis, we consider demand, PV and battery traces as the random variables in each MC realization. Specifically, 100 load profile draws are taken for each time slot of a year to capture the uncertainties in customer behaviors. Each load assignment dedicates to 11 levels of $P_{PV}$ and 3 levels of $P_b$. As a result, a total of 3300 yearly power flow simulations were conducted for one LV test feeder.

Using the precomputed PFAs, the computation time taken to perform 3300 yearly power flow simulations with 30-minute resolution was 33 days. In contrast, directly including the battery scheduling optimization (as a DP) would require 58 weeks. Thus, the use of PFAs is essential to making the entire MC process computationally feasible.

### B. Test Networks

In order to evaluate the method, two LV test networks with different lengths are adopted from Electricity North West Limited (ENWL), a British network operator [23]. Typically, Australian LV networks are designed to have higher capacity than the UK ones, mainly due to much larger air-conditioning loads. To match this design, the UK test networks are transformed into Australian-type LV networks by tripling the transformer and line capacity. These test feeders are denoted as AUS 1 and AUS 2, respectively. Each feeder is supplied by a 2250 kVA 11 kV/0.4 kV 3-phase transformer. In addition, one of the selected UK feeders is supplied as the third test case, denoted UK, with a lower feeder head ampacity for comparison. The details of the test networks are summarized in Table I. We sample from the pool of net load traces synthesized in Module 1 of our method for allocation to load points.

#### TABLE I. LV TEST FEEDERS

| Feeder Name | Length (m) | No. of customers | Feeder head ampacity (A) |
|-------------|------------|------------------|--------------------------|
| AUS 1       | 10235      | 302              | 1155                     |
| AUS 2       | 5656       | 223              | 1200                     |
| UK          | 5656       | 223              | 400                      |

1. The power flow analysis is performed in OpenDSS [22].
2. For transformers, we reduced the impedance, while for transmission lines we only reduced the resistance. The reactance mainly depends on the distance between the conductors, so we left it unchanged.
Fig. 4. Percentage of customers with voltage problems (first row), transformer loading level (second row) and phase unbalance (third row). Pink, green and blue bars represent 0%, 50% and 100% battery penetration levels, respectively. Each bar from top to bottom shows the maximum value, 75 percentile, median value, 25 percentile and minimum values.

C. Benchmark: Self-Consumption Maximization

The self-consumption maximization (SCM) heuristic scheduling strategy is incorporated in the MC framework to serve as the benchmark. In this strategy, the energy from the solar PV is firstly used to meet the demand, and then any excess PV generation is used to charge the battery, or exported to the grid if the battery is full. For brevity, the SCM is applied only to AUS 2, and the results are compared with the HEM profiles under time-of-use (TOU) tariffs.

D. Voltage Problems

The frequency of voltage problems with respect to increasing $P_{PV}$ and $P_b$ on the LV feeders is shown in Fig. 4 row one. The percentage of customers with a voltage problem follows an increasing trend across all test feeders with respect to rising $P_{PV}$, especially from 30% to 100%, while the UK feeder presents more voltage problems due to higher line impedances. Voltage problems can be reduced by 10-20% across all test feeders using HEM under ToU (Fig. 4). This scheduling strategy encourages batteries to charge when electricity price is low, and discharge when the price is high (during peak hours). However, the timespan for high PV outputs can extend and even overlap with peak demand, especially in summer. This is illustrated for some specific case in Fig. 5 in which the peak demand occurs between 4 and 6pm, causing the battery to discharge during high PV output. This reduces the grid power supply ($p_g$), when compared to the case without the battery ($\hat{p}_g$). As a result, $p_g$ and $\hat{p}_g$ cross at around 4:30pm, where the voltages become the same (as highlighted in the black boxes). Furthermore, at 4:30pm, rising demand causes the battery to decrease its charging power at high PV output, which keeps the voltage at a high level. In these scenarios, HEM under TOU is less effective at reducing over-voltage problems.

In addition, longer feeders (AUS 1) experience larger voltage drops, and hence, the rate of increase in frequency of voltage problems with respect to $P_{PV}$ is lower when compared with the smaller feeders (AUS 2 and UK). This is illustrated in Fig. 4 where the voltage problems increase at a slower
rate towards high \( P_{PV} \) for AUS 1. More so, there is a greater chance for longer feeders (AUS 1) to concentrate PV installations in particular parts of the network. Consequently, there is a greater variability in the voltage metric at low \( P_{PV} \), as illustrated at 40\% \( P_{PV} \) for AUS 1.

Compared to the SCM benchmark, HEM under TOU is more effective in mitigating over-voltage problems (Fig. 7). The SCM forces batteries to charge with excess PV output to reach the battery’s full capacity, which usually occurs before the end of the high solar generation time period. Due to this, batteries fail to consistently reduce voltage problems across the entire PV generation period. This can be seen in Fig. 6 where the battery reaches its full capacity at 3pm (purple curve). As a result, all excess solar generation after 3pm is exported to the grid, as illustrated by the section where \( P_{E} \) overlaps \( P_{D} \), keeping the voltage at a high level between 3 and 6pm. On the other hand, the HEM under TOU considers the price of electricity which is an indication of the timely demand and PV generation. In this method (Fig. 5), the charging profile (blue curve in the bottom plot) is more evenly distributed throughout the PV generation period, hence a more consistent reduction of the problems is expected. Although the HEM with TOU helps reduce voltage problems, it is far from a panacea for voltage problems on distribution feeders.

### E. Thermal Problems

This subsection evaluates the occurrence of thermal problems across all test feeders. The transformer loading drops between 0\% and 40\% \( P_{PV} \) for all test feeders, as illustrated by Fig. 4 row two. Within this interval, all solar generation is consumed by demand. However, with greater \( P_{PV} \) (more than 40\%), excess solar generation is exported to the grid, accumulating at the feeder head and increasing the transformer loading level. All test feeders follow these trends with the turning point at roughly 40\%. Before this point, PV systems alone helps in transformer loading reduction. Additionally, the loading levels are higher for longer feeders (AUS 1), as well as the feeders with lower transformer capacity (UK).

Batteries reduce the transformer loading levels by charging with solar generation, and then discharge during peak periods. They become more effective as both PV and battery capacities increase after 40\% \( P_{PV} \). For example, in AUS 1 (Fig. 4 row two), a 5\% reduction in thermal loading is achieved at 40\% \( P_{PV} \), this proportion increases to 20\% at 100\% \( P_{PV} \). In contrast to the voltage problem reduction, HEM under TOU is
more effective on longer feeders (AUS 1) that have higher battery capacities for charging with excess PV generation. Compared to the benchmark, the HEM under TOU is more effective in thermal loading reduction, as seen in Fig. 7. This is because the SCM forces the battery to charge to its full capacity before the end of the PV generation period, as explained previously for voltage problem reduction.

F. Phase Unbalance

This subsection presents the impacts on the VUF, with the results shown in Fig. 4 row three. Increasing $P_{PV}$ can amplify phase unbalance. Using AUS 1 as an example, when $P_{PV}$ on the feeder is low, typically between 0% and 40%, solar generation alone helps reduce the phase unbalance. When $P_{PV}$ is greater than 40%, unused solar generation is exported to the grid, and hence, increasing the phase unbalance. In this case, the unbalance is improved by charging the battery with excess solar generation. Specifically, the VUF for AUS 1 is reduced from 1.6% to 1.2% at 100% $P_{PV}$. PV and battery systems are shown to mitigate cases of high unbalance, as on AUS 1; while the impacts are less pronounced for the other test feeders (AUS 2 and UK) as they are rather balanced to begin with. Overall, the improvement on phase unbalance for either the HEM under TOU or the SCM is limited.

VI. CONCLUSIONS

In this work, we proposed a novel methodology that can (i) explicitly incorporate battery scheduling in a MC analysis, and (ii) synthesize statistically representative demand and PV profiles when only limited smart meter (highly granular) consumption data are available. The framework first models a large pool of net load traces by sampling from an appropriately-identifed Markov process. Then, the corresponding battery schedules are computed from a PFA, which was itself trained on solutions to the set of battery scheduling problems of the original customer data. By using the PFA, it is feasible to incorporate the HEM problem in MC analysis. 100 simulations were carried out per penetration level to capture all uncertainties in the size and location of demand and PV-battery systems. The results show that the PFA reduces the time needed to compute battery schedules by greater than 95%. Thus, for the first time, we can efficiently include the DER scheduling for managing the customer’s energy use within a MC framework, given only limited smart meter data available. The efficacy of the proposed MC framework is shown on 3 typical LV feeders. The outcomes indicate that uncoordinated PV-battery systems have limited beneficial impact on LV networks, although the scheduling strategy using HEM under TOU is slightly more effective in reducing over-voltages and thermal loading levels than the SCM. Additionally, the improvement on phase unbalance is distinct only for highly unbalanced networks.

REFERENCES

[1] AEMO, “Retail electricity price history and projected trends,” Report, 2017.
[2] CSIRO and ENA, “Electricity network transformation roadmap, final report,” Report, 2017.
[3] AEMO, “Impact of community and distributed energy storage systems on unbalanced low voltage networks,” in 2017 Australasian Universities Power Engineering Conference (AUPEC). IEEE, 2017, pp. 1–6.
[4] P.-C. Chen, R. Salcedo, Q. Zhu, F. De Leon, D. Czarowski, Z.-P. Jiang, V. Spitsa, Z. Zabar, and R. E. Uosef, “Analysis of voltage profile problems due to the penetration of distributed generation in low-voltage secondary distribution networks,” IEEE Trans. Power Delivery, vol. 27, no. 4, pp. 2020–2028, 2012.
[5] A. Navarro-Espinosa and L. F. Ochoa, “Probabilistic impact assessment of low carbon technologies in LV distribution systems,” IEEE Trans. Power Systems, vol. 31, no. 3, pp. 2192–2203, 2016.