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PV and Demand Models for a Markov Decision Process Formulation of the Home Energy Management Problem

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***Abstract*—This paper proposes a hierarchical approach for estimating residential PV and electrical demand models using historical data. In brief, the method involves first clustering historical data into different day types, and then estimating PV and demand models using kernel regression. Clustering is done to capture intra-day variations in the PV and demand profiles, with the aim of capturing much of these intertemporal correlations in the day-type labels. This allows the draws from the kernel estimates within a day type to be done independently. This approach conforms with a Markov decision process construction of the smart home energy management system (SHEMS) problem, which is the ultimate target of the modelling procedure. Moreover, in practical applications, the SHEMS will need the type of a coming day in order to select a daily demand model, which can be done seamlessly using state identification methods. In comparison, forecasting a day's demand profile using time-series forecasting methods produces a prediction method that does not provide a probability structure that is directly incorporated into a Markov decision process scheduling model.**

***Index Terms*—Smart home energy management, residential PV model, demand model, kernel regression, clustering, Markov decision process, dynamic programming.**

NOMENCLATURE

k	Time-step
K	Total number of time-steps
i	Index of controllable devices
I	Total number of controllable devices
j	Index of stochastic variables
J	Total number of stochastic variables
$s_k^{\{i,j\}}$	State of i or j at time-step k
x_k^i	Decision of controllable device i at time-step k
ω_k^j	Variation of stochastic variable j at time-step k
$s^{i,\max}$	Maximum state of a controllable device
$s^{i,\min}$	Minimum state of a controllable device
μ^i	Efficiency of a controllable device [%]
l^i	Losses of a controllable device per time-step
C_k	Cost or reward at time-step k
π	Policy
V_k^π	Expected future cost/reward for following π from k

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I. INTRODUCTION

A SMART HOME is an automated residential building that uses distributed energy resources (DER) for managing energy consumption and providing suitable levels of comfort to its inhabitants. The number of smart homes with PV and battery storage systems has increased dramatically in Australia, New Zealand, some parts of USA and Europe, in response to rising electricity costs, government incentives, decreasing installation costs and growing concerns about climate change. For example, in June 2017, Australia reached 6.2 GW solar PV from residential and commercial users [1], while global solar PV had increased from 4 GW in 2003 to 128 GW in 2013 [2]. Residential batteries continue to reduce in cost, and are beginning to provide a financially feasible solution for storage for some usage profiles in residential buildings[1]. According to the Australian Energy Market Operator, the payback period for residential PV-storage systems is already below 15 years in South Australia, with other Australian states to follow suit in less than a decade [4]; while in the USA, residential customers with PV-storage systems have been forecast to reach grid parity within the next decade [5]. Indeed, in Australia, more than 20,000 residential energy storage systems were installed in 2017. This included approximately 12% of the 172,000 new PV installations that included a battery, bringing the total to 28,000 battery systems installed across Australia [6].

In order to maximize the benefits of PV-storage systems, residential energy users will use a *smart home energy management system* (SHEMS) to schedule their energy use. In particular, we assume that PV-storage systems will be widely adopted for the following three reasons. First, when a customer's PV generation is higher than its electrical demand, the extra electrical energy will be either stored or/and fed back to the electrical grid. However, in Australia, feed-in tariffs are set to reflect the average cost of offset generation in the wholesale spot energy market, which means that selling power back to the electrical grid is uneconomical since retail tariffs for imports also account for network costs. Coupled with ever-dropping PV costs, there is a strong incentive for PV owners to self-consume as much locally generated power as possible. The conjecture is that in the near future this may happen in other parts of the world too. Second, time-varying pricing methods, such as time-of-use tariffs means that the users will

[1]A comparison of price-competitive batteries in Australia can be found at [3].

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want to operate the battery in such a way that its state of charge is maximized at the beginning of time periods with peak price signals. Third, an automated SHEMS may also control the PV-battery system to achieve demand response [7]–[11] or direct load control [11], [12] for the financial benefit of customers but without human interaction.

Given this background, the underlying optimization problem undertaken by the SHEMS can be thought of a sequential decision making process under uncertainty. The problem contains two sets of stochastic variables, PV output and electrical demand. The variations in electrical demand are a result of customers' behaviour, which can be highly variable. However, there tends to be greater consistency or predictability in demand behaviour within appropriately labeled *day types*, where types can be determined by calendar events, seasons, weather, and so on. Similarly, the variations in PV output depend on the type of day (i.e. sunny, light cloud or dense cloud). Given this, a major step towards developing an effective SHEMS is to consider these stochastic variables using appropriate probability models, because better predictions of stochastic inputs should improve the SHEMS battery charge schedules, especially over those obtained from deterministic optimization methods using off-the-shelf solvers [13], [14].

Within this context, several methods have been proposed for solving the sequential stochastic optimization problem, each with their own benefits and drawbacks. They include stochastic *mixed-integer linear programming* (MILP) [13], [15]–[18], *particle swarm optimization* [14], [19], [20], *policy function approximations* using machine learning [21], *dynamic programming* (DP) [22], [23] and *approximate dynamic programming* (ADP) with temporal difference learning [24], [25]. In [24], [25], several of these methods were compared to assess their performance on a large number of test battery scheduling problems. These studies identified that although DP results in the best quality solutions, ADP comes a close second, with the benefit of much less computational effort. For this reason, the focus of this paper is probability models that are tailored to DP and ADP methods for solving the stochastic battery scheduling problem facing a SHEMS.

In more detail, in order to solve the SHEMS problem using ADP or DP, the sequential stochastic optimization problem is first cast as a *Markov decision process* (MDP). An MDP comprises: (i) a set of states, and for each state, (ii) an action set, (iii) a contribution (reward or cost) function for taking an action, and (iv) a transition function, which is a probability distribution over future states given the current state and the action is chosen. Importantly, the stochastic variable models used in the MDP have to conform to the MDP construction; and in particular, the transition functions must have the *Markov property*. This property is satisfied when the transition function depends only upon the present state, and is not conditioned on the sequence of states and actions that preceded it.

This key point motivates the modeling approach in this paper, and requires a detailed explanation. Specifically, if the transition function satisfies the Markov property, then the stochastic variable models must be conditional on a state representation that contains all the information regarding past realized values that is relevant to the next variable realization.

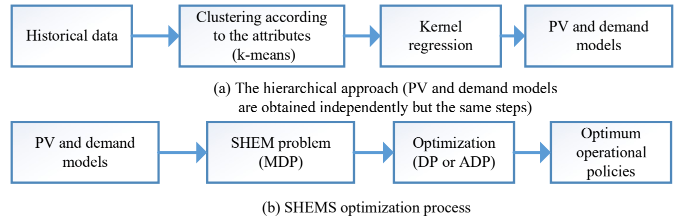

Fig. 1. (a) The steps of the proposed hierarchical approach used to obtain PV and demand models; and (b) SHEMS optimization process using the predicted PV and demand models. Note that PV and demand models are obtained independently using the same steps, except for the attributes used for clustering.

For example, some residential loads show strong short-term temporal anti-correlation, as many tasks within the home are completed at different times of the day on different days, but only once on any given day (e.g. clothes washing). This gives rise to a conditional structure on subsequent variable values (e.g. if the load has been high at 8am in the morning, it is less likely to be high at 9am). Given this correlation, the optimzation algorithm designer may choose to expand the state representation to incorporate such detailed conditional forecasts. However, this causes an explosion in the size of the state representation; and correspondingly, DP and ADP become computationally infeasible, as their complexity grows exponentially with state representation's size. As an alternative, we break this impasse by temporally aggregating the sequence of demand and PV realizations into day-types. This relieves the step-by-step realizations of these variables from the need to explicitly consider conditional inter-temporal correlations. In effect, enough intra-day conditional information is captured in day-type labels to significantly improve the MDP-based algorithms' performance, while maintaining a tractable state representation and computational burden.

Specifically, our paper proposes a hierarchical approach to estimate PV generation and electrical demand models using historical data, as depicted in Fig. 1(a). The method first clusters daily historical data according to a certain criteria, and then estimates probability distributions within each cluster using kernel regression. Note that this is not hierarchical clustering, rather it is a hierarchical probability model. The implication is that day-types provide improved PV output and demand predictions, corresponding to the statistical characteristics of the associated cluster. Future day types, such as sunny days with high demand, cloudy days with low demand, etc, can be identified using state identification methods, which themselves could be based on historical data, online monitoring of energy use patterns [26], [27], weather forecasts [28], or even by directly querying inhabitants about their daily plans. The design and evaluation of these methods is a separate problem as shown in Fig. 1(b).

The hierarchical approach is used as an input to the SHEMS optimization problem in the following way. To begin, day-types are assumed to be forecast accurately. Following this, demand and PV kernels are sampled independently for each time-step. Note that independent samples from the kernel-based demand and PV estimates conforms to the MDP construction (i.e. Markov property of the transition functions),

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which is needed to solve the problem using DP and ADP. For this type of stochastic optimization problem, the proposed method provides a tractable and sufficiently accurate estimator of demand and PV levels and their variability, as shown by the test cases. Specifically, the method is demonstrated on historical PV and demand data [29] collected during the recently completed *Smart Grid Smart City* (SGSC) project in New South Wales, Australia [30].

In the current literature, many proposed SHEMSs use estimates of PV output using weather forecasters and electrical demand using demand prediction algorithms [14], [22], [31]–[34]. In MDP-based energy management settings, many of these approaches have significant drawbacks including the following. To begin, the accuracy of their estimates depends on user inputs or the quality of the user behaviour prediction algorithm, with no explicit consideration of the variablity or distribution of loads. Although some aim to improve their accuracy by considering all home appliances separately, this introduces the additional complications of load disaggregation or device sub-metering, and household privacy concerns. Moreover, many of the methods are only suitable for certain scenarios, because predicting human behaviour is difficult in real life. For example, [31] is more appropriate for a family with a predictable lifestyle compared to students sharing a house. Finally, in most cases, the probability models associated with the PV output and demand are obtained based on prior knowledge or parametric assumptions. For example, in [14], an occupancy transition matrix with three occupancy states is used to incorporate uncertainty associated with the electrical demand. In other cases, Gaussian or skew-Laplace distributions are assumed, [22]; however, these distributions typically do not accurately represent a real demand and PV generation scenario.

In contrast to these approaches, the proposed model relies on non-parametric probability models and its estimation is entirely data-driven, requiring only mild assumptions to be made about the household's energy use patterns. On the other hand, our approach is restricted by the need to conform to the MDP formulation of the SHEM problem, in order to use DP or ADP. A range of other data-driven approaches for predicting PV and demand profiles are proposed in [35]–[37]. Consumption modeling based on Markov chains and Bayesian networks for a demand side management of isolated microgrids is proposed in [38] and grid-connected PV generation is predicted using a grey model and Markov chain in [39]. However, these methods are not suitable for our SHEMS problem because we have to estimate the entire day's demand and PV profile for the day-ahead optimization. Moreover, we are interested in the probability distributions of the PV and demand models for the stochastic optimization.

Paper structure: Section II states the stochastic energy management problem. This is followed by the main contribution of the paper, a hierarchical approach to estimate residential PV and demand models, in Section III. Section IV presents the simulation results and the discussion. Finally, note that preliminary versions of these models have been used in [24], [25], and this publication seeks to fully expand their derivation and evaluation.

II. Markov Decision Process (MDP) Problem

This section begins by describing the general formulation of the MDP problem. Then presents the formulation of the stochastic SHEMS problem as an MDP problem. Finally, presents stochastic MILP and DP used to solve the SHEMS problem. (*Note that this section is presented as a review for the sake of completeness, to help the reader understand the SHEMS problem and the stochastic PV and demand models that it requires. For more details, please refer to [25].*)

A. General MDP Problem

In general, an MDP comprises:

- a sequence of *time-steps*, $\mathcal{K} = \{1 \ldots k \ldots K\}$, where k and K denote a particular time-step and the total number of time-steps in the decision horizon, respectively;
- a set of *non-controllable inputs*, $\mathcal{J} = \{1 \ldots j \ldots J\}$, where each j is represented using:
  - a state variable, $s_k^j \in \mathcal{S}$;
  - a random variable, $\omega_k^j \in \Omega$, capturing exogenous information or perturbations;
- a set of *controllable devices*, $\mathcal{I} = \{1 \ldots i \ldots I\}$, where each i is represented using:
  - a *state variable*, $s_k^i \in \mathcal{S}$;
  - a *decision variable*, $x_k^i \in \mathcal{X}$, which is a control action;
  - *constraints* for the state and control variables;
  - a *transition function*, $s_{k+1}^i = \mathrm{s}^M\left(s_k^i, x_k^i, \omega_k^j\right)$, describing the evolution of a state from k to $k+1$, where $s^M(\cdot)$ is the system model consisting of device i's operational constraints such as power flow limits, efficiencies and losses, and;
- an *objective function:*

$$F = \mathbb{E}\left\{\sum_{k=1}^{K} C_k(\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\omega}_k)\right\}, \qquad (1)$$

  where $C_k(\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\omega}_k)$ is the contribution (i.e cost or reward of energy, or a discomfort penalty) incurred at time-step k, which accumulates over time.

Denote vectors of state, decision and random at time-step k by: $\mathbf{s}_k = [\ s_k^i \ldots s_k^I, s_k^j \ldots s_k^J\ ]^\mathsf{T}$, $\mathbf{x}_k = [\ x_k^i \ldots x_k^I\ ]^\mathsf{T}$, and $\boldsymbol{\omega}_k = [\ \omega_k^j \ldots \omega_k^J\ ]^\mathsf{T}$, respectively. The state variables, $\mathbf{s}_k$, contain the information that is necessary and sufficient to make the decisions and compute costs, rewards and transitions. Let a compact representation of the transition functions be given by: $\mathbf{s}_{k+1} = \mathbf{s}^M(\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\omega}_k)$. Note that the transition functions are only required for the controllable devices and ω_k (without a superscript) is the combined random variables vector of the non-controllable inputs.

B. Instantiation

The objective of the SHEMS is to minimize energy costs over a decision horizon. This paper presents the formulation of a system consisting of a PV unit and a battery, as depicted in Fig. 2. The problem is solved before the start of each day, using either a daily or a two-day decision horizon. The performance of a SHEMS is improved by incorporating random variation

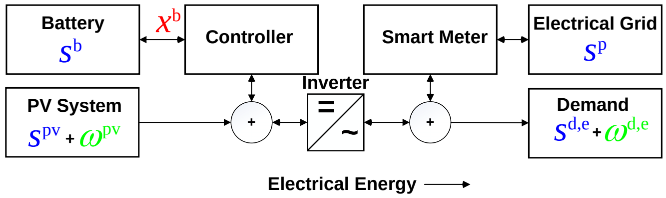

Fig. 2. Illustration of electrical energy flow in a smart home, and the state, decision and random variables use to formulate the problem.

in PV output and electrical demand of the home [14], [25]. In particular, in order to correctly formulate the SHEMS as an MDP, these variables are modeled using their mean as state variables while variation around the mean is encoded as random variables with zero mean. This allows the transition function to be separated into a deterministic term, using the mean, and a random term, using variation. Note that in this work we assume that the electricity prices are given by a fixed retail tariff, available before the start of the decision horizon, in the form of time-of-use price (ToUP). Accordingly, electricity prices are not treated as random variables, although this could in principle be done.

In more detail, SHEMS problem is instantiated as the MDP formulation in Section II-A as follows. The daily decision horizon is a 24 hour period, divided into $K = 48$ time-steps with a 30 minutes resolution. Note that the 30 minutes time resolution is chosen to match with typical dispatch time lines and also because the PV and demand data from the SGSC project [29] are only available at 30 minutes intervals.

The non-controllable inputs are the PV output, electrical demand, and electricity tariff, which are represented using:

- state variables for the mean PV output, s_k^{pv}, mean electrical demand, $s_k^{\text{d,e}}$, and electricity tariff, s_k^{p}.
- random variables for the variations in PV output, ω_k^{pv}, and variations in electrical demand, $\omega_k^{\text{d,e}}$.

Historical data are used to estimate the probability distributions associated with the uncertain variables using kernel regression as discussed in detail in Section III.

The controllable device is a battery, which is represented using:

- state variables for the battery SOC, s_k^{b}.
- control variables for charge and discharge rates of the battery, x_k^{b}.
- the energy balance constraint is given by:

$$s_k^{\text{d,e}} + \omega_k^{\text{d,e}} = \mu^{\text{i}} x_k^{\text{i}} + x_k^{\text{g}}, \tag{2}$$

  where x_k^{g} is the electrical grid power; μ^{i} is the efficiency of the inverter (note that the efficiency is $1/\mu^{\text{i}}$ when the inverter power is negative); and x_k^{i} is the inverter power at the DC side (positive value means power into the inverter), given by:

$$x_k^{\text{i}} = s_k^{\text{pv}} + \omega_k^{\text{pv}} - \mu^{\text{b}} x_k^{\text{b}}, \tag{3}$$

  where μ^{b} is the efficiency of the battery action corresponding to either charging ($1/\mu^{\text{b+}}$ as power flows into the battery) or discharging.
- transition functions governing how the battery SOC, $s_k^{\text{b}} \in [s^{\text{b,min}}, s_k^{\text{b,max}}]$, evolves over time, given by:

$$s_{k+1}^{\text{b}} = \left(1 - l^{\text{b}}(s_k^{\text{b}})\right)\left(s_k^{\text{b}} - x_k^{\text{b-}} + \mu^{\text{b+}} x_k^{\text{b+}}\right), \tag{4}$$

  where $l^{\text{b}}(s_k^{\text{b}})$ models the self-discharging process of the battery. Note that the battery SOC transition function is a non-linear function of a state.

Given this, denote $\mathbf{x}_k = x_k^{\text{b}}$, $\mathbf{s}_k = [s_k^{\text{b}}, s_k^{\text{d,e}}, s_k^{\text{pv}}, s_k^{\text{p}}]$, and $\boldsymbol{\omega}_k = [\omega_k^{\text{pv}}, \omega_k^{\text{d,e}}]$, for each time-step, k, in the decision horizon, as depicted in Fig. 2. In addition, the charge and discharge rates of the battery are constrained by $x_k^{\text{b+}} \le \gamma^c$ and $x_k^{\text{b}-} \le \gamma^d$, respectively, while SOC is constrained by $s^{\text{b,min}} \le s_k^{\text{b}} \le s^{\text{b,max}}$.

The characteristics of the devices that need to be defined are as follows: the discharge and charging efficiencies of the battery; efficiency of the inverter; the maximum possible charge rate with respect to the battery SOC; the maximum and minimum battery SOC; the maximum charge and discharge rates of the battery; and the losses of the battery.

The optimal policy, π^*, is a choice of action for each state $\pi : \mathcal{S} \to \mathcal{X}$, that minimizes the expected sum of future costs over the decision horizon; that is:

$$F^{\pi^*} = \min_{\pi} \quad \mathbb{E}\left\{\sum_{k=0}^{K} C_k(\mathbf{s}_k, \pi(\mathbf{s}_k), \boldsymbol{\omega}_k)\right\}, \tag{5}$$

where $C_k(\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\omega}_k)$ is the cost incurred at a given time-step, which is given by:

$$C_k(\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\omega}_k) = s_k^{\text{p}}\left(s_k^{\text{d,e}} + \omega_k^{\text{d,e}} - \mu^{\text{i}} x_k^{\text{i}}\right). \tag{6}$$

The problem is formulated as an optimization of the expected contribution because the contribution is generally a random variable due to the effect of $\boldsymbol{\omega}_k$. In SHEMSs, battery decisions x_k^{b}, are obtained depending on the state variables $\mathbf{s}_k = [s_k^{\text{b}}, s_k^{\text{d,e}}, s_k^{\text{pv}}, s_k^{\text{p}}]$, and realisations of random variables $\boldsymbol{\omega}_k = [\omega_k^{\text{pv}}, \omega_k^{\text{d,e}}]$ at each time-step. Here PV and electrical demand models are inputs to the SHEMS.

C. Existing solution techniques

This section briefly presents the existing solution techniques used to solve the SHEMS problem. The first method used is a scenario-based MILP approach, which is known as *stochastic* MILP in [23]. This technique requires us to linearize the constraints and transition functions mentioned in Section II-B. Here CPLEX is used to solve the SHEMS problem, however, all commercial solvers give similar quality solutions. The solutions of stochastic MILP are of lower quality because of the linear approximations made and the inability to incorporate all the probability distributions [23]. In response to these limitations, DP was proposed in [22] to improve the solution quality.

DP requires the problem to be modeled as an MDP. DP incorporates non-linear constraints and transition functions with no additional computational burden over using linear constraints and transition functions. In detail, the problem in (5) is easily cast as an MDP due to the separable objective function and Markov property of the transition functions. Given this, DP solves the MDP form of (5) by computing

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a value function $V^\pi(\mathbf{s}_k)$. This is the expected future cost of following a policy, π, starting in state, $\mathbf{s}_k$, given by:

$$V^\pi(\mathbf{s}_k) = \sum_{\mathbf{s}' \in \mathcal{S}} \mathbb{P}(\mathbf{s}'|\mathbf{s}_k, \pi(\mathbf{s}_k), \boldsymbol{\omega}_k) \left[C(\mathbf{s}_k, \pi(\mathbf{s}_k), \mathbf{s}') + V^\pi(\mathbf{s}') \right]. \tag{7}$$

An optimal policy, π^*, is one that minimizes (5), and which also satisfies Bellman's optimality condition:

$$V_k^{\pi^*}(\mathbf{s}_k) = \min_{\pi^*} \left(C_k(\mathbf{s}_k, \pi(\mathbf{s}_k)) + \mathbb{E}\left\{ V_{k+1}^{\pi^*}(\mathbf{s}')|\mathbf{s}_k \right\} \right). \tag{8}$$

The expression in (8) allows the optimal value function to be computed using backward induction, a procedure called *value iteration*. Given the optimal value function, an optimal policy is extracted by selecting an action leading to the lowest-value successive state from the current state. This is the key functional point of difference between DP and stochastic MILP. DP enables us to plan offline by generating value functions for every time-step. Once the value functions have been generated, faster online solutions can be made using (8). Note that a value function at a given time-step consists of the expected future cost from all the states. This process of mapping states and actions is not possible with stochastic MILP, which emphasizes the usefulness of DP, and also reinforces the need for good models of the problem's stochastic inputs. A comparison of stochastic MILP and DP is found in [25].

The next section explains the effects of stochastic variables on the SHEMS problem and presents the algorithm used to estimate their probabilistic models.

III. A HIERARCHICAL APPROACH TO ESTIMATE STOCHASTIC VARIABLE MODELS

In order to optimize performance, it is important for a SHEMS to incorporate variations in the PV output and electrical demand. This requires a stochastic optimization technique and benefits of this approach over a deterministic optimization are discussed in [24], [25]. Given this, SHEMSs require the mean PV output and the electrical demand with its appropriate probability distributions before the start of the decision horizon.

This section first discusses the stochastic variables and their effects on the SHEMS problem. It then presents a hierarchical approach based on clustering and kernel regression used to estimate the stochastic variables models. Note that the kernel estimator conforms to the MDP construction (i.e. Markov property of the transition functions), which is needed to solve the problem using DP or ADP.

A. Stochastic variables

The stochastic variables in the SHEMS problem considered in this paper are PV output and electrical demand. It is important to note that the below description is presented only for the sake of completeness because our proposed approach is purely a data-driven method. PV output depends on solar insolation, characteristics of the solar panels, orientation and cloud coverage. A forecast of the solar insolation and cloud coverage can be obtained before the horizon starts from weather forecasting services. The solar insolation can be obtained with a good accuracy as it only depends on the position of the sun, time of day in the year and geographic coordinates. However, cloud coverage is much harder to predict, especially for a particular location with a sufficient level of granularity (i.e. 1/2 hour). PV output is important to the SHEMS problem as it is a key source of energy and is expected to be closely coupled with the battery storage profile. Failing to accommodate the variation in PV generation can increase costs to the household as more power is imported from the grid.

The electrical demand of the household depends on the number of occupants and their behavioural patterns, which is difficult to predict in the real world. In the context of SHEMSs, electrical demand should be supplied from the DG units, storage units and the electrical grid. Failure to accommodate variations in electrical demand may result in additional costs to the household.

B. A hierarchical approach

This section first describes the PV model, and then explain the demand model with reference to the PV modeling approach, mutatis mutandis. The probability distributions of the PV output, which depends on the time and type-of-day (sunny, normal or cloudy days) are obtained in two steps. Note that this is similar to the procedure used to obtain the electrical demand models. First separate daily historical data into seasons and then cluster them using a *k*-means algorithm according to certain attributes to obtain clusters with different daily PV generations. Two attributes are compared: (i) total daily PV output so the clusters corresponds to sunny, partially sunny, normal, partially cloudy and cloudy days; and (ii) total morning and evening PV output so the clusters corresponds to sunny morning and cloudy evening etc. Here a *genetic algorithm* (GA) is used to optimize the time that separates morning and the evening. The objective of the GA is to minimize the *mean absolute error* (MAE) between the actual and estimated PV output profiles (more details are in the next section).

Second, for each time-step in the corresponding clusters, probability distributions of the PV output are estimated using an *Epanechnikov* kernel estimating technique. Details are found in [40]. The bandwidth of the PV generation kernel estimates are slightly increased from the default MATLAB values to obtain a smoother distribution in some residential buildings (more details are in the next section).

Note that when using these models for ADP or DP, the draws from the kernel estimates at each time-step within a day-type are independent so the Markov property of the transition functions is satisfied. However, the inter-daily transition probabilities are captured in the clustering process. The proposed approach does not require user inputs such as location, time, date or cloud coverage to estimate PV models.

The probability distributions of electrical demand are obtained in a similar way except the attributes of the *k*-means clustering algorithm are for different time intervals throughout the day. Six attribute sets for electrical demand are compared. Note that the 6^{th} attribute set has six time intervals, which is referred to as having six attributes. The rest of the attribute sets follow the same pattern. Similar to the PV output, these time intervals and the best number of clusters are optimized

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TABLE I
OPTIMISED TIME INTERVALS OF THE SIX ATTRIBUTE SETS USED FOR CLUSTERING ELECTRICAL DEMAND, AND NUMBER OF CLUSTERS AND MEAN ABSOLUTE ERROR FOR EACH.

6 attributes	*9 clusters*	*MAE = 0.1364*
• 00:00 to 3:00 and 20:00 to 00:00		
• 3:00 to 5:00	• 5:00 to 9:00	
• 9:00 to 12:00	• 12:00 to 14:30	
• 14:30 to 20:00		
5 attributes	*10 clusters*	*MAE = 0.1420*
• 00:00 to 2:30 and 21:00 to 00:00		
• 2:30 to 7:30	• 7:30 to 9:00	
• 9:00 to 14:00	• 14:00 to 21:00	
4 attributes	*7 clusters*	*MAE = 0.1386*
• 00:00 to 11:00 and 19:30 to 00:00		
• 11:00 to 12:00	• 12:00 to 15:30	
• 15:30 to 19:30		
3 attributes	*10 clusters*	*MAE = 0.1431*
• 00:00 to 8:30 and 19:30 to 00:00		
• 8:30 to 15:30	• 15:30 to 19:30	
2 attributes	*10 clusters*	*MAE = 0.1423*
• 00:00 to 10:00 and 13:30 to 00:00		
• 10:00 to 13:30		
1 attribute	*6 clusters*	*MAE = 0.1494*
• Entire day		

using a GA. As a result, the clusters are according to days with high, normal or low demand levels on different times of the day. It is worthwhile to note that before the start of the decision horizon, the SHEMS uses the predicted mean PV-output and the electrical demand to determine the type of day and hence the corresponding cluster.

IV. RESULTS AND DISCUSSION

This section discusses the results of the three steps used to generate and evaluate the PV output and electrical demand models; (i) cluster number and attribute selection, (ii) models estimation, and (iii) model evaluation. Specifically, Section IV-A describes how the number of clusters and the time intervals of their attributes are chosen for the PV output and electrical demand traces, using a GA. Then in Section IV-B, PV output and electrical demand models are estimated using the optimized number of clusters and their attributes, as well as a benchmark with no clustering. Measures of the goodness-of-fit of these models are reported, however, the purpose of the models is to improve the SHEMs optimization. As such, the estimated PV and demand models are used in stochastic MILP and DP based SHEMSs (Section IV-C), where the benefits of our hierarchical model are demonstrated by showing the reductions in cost they produce.

The estimation framework improves the optimization performance as shown by the year-long simulations in Section IV.C. The quality of daily stochastic variable models are illustrated using 8 scenarios (four days each for two residential buildings). Note that the two residential buildings are labeled A and B and the four days are labeled 1 to 4. For example residential building A day 1 is labeled Scenario A.1. The two residential buildings are as follows:

1) Central Coast, NSW, Australia based residential building with a 2.22 kWp PV system.
2) Sydney, NSW, Australia based residential building with a 3.78 kWp PV system.

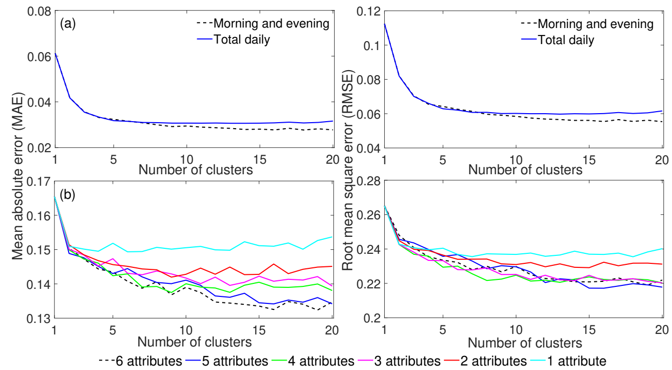

Fig. 3. MAE and RMSE vs. the number of clusters for (a) PV output and (b) electrical demand. The two attributes of the PV output are the total daily and total morning and evening PV outputs (separated at 12.30 pm) while the time intervals of the six attributes used for the electrical demand are in Table. I.

For each residential building, four scenarios corresponding to four different days are investigated: 15 July, 2012; 10 October, 2012; 5 January, 2013; and 15 April, 2013. These PV and electrical demand models are benchmarked using kernel estimates obtained without clustering. As mentioned earlier, the PV output and electrical demand data are available for three years, so the first two years of data are used for learning and the third year for validation.

A. Attributes and the number of clusters

The first task is to optimize and compare six attribute sets for the electrical demand and two attribute sets for the PV output. The GA is used to minimize the MAE of the predictions over a year and the maximum number of clusters is set to 10. Here GA is used as it is computationally intensive to find the exact solutions using other methods and a near optimal solution is enough for the given optimization problem.

The optimized time intervals of the six attribute sets for electrical demand are in Table I. Note that the 6th attribute set has six time intervals, which is referred to as having six attributes. The rest of the attribute sets follow the same pattern. Two attribute sets are used for the PV output: (i) the total daily PV output and (ii) the total morning and evening PV output. The time-step that separates morning and evening is 12.30 pm, which is optimized using GA. In Fig. 3, the optimized time intervals of the attributes are used to investigate the MAE and *root-mean-square error* (RMSE) with respect to the number of clusters that ranges between 1 to 20. Up to 20 clusters are investigated to see how RMSE and MAE behave as the number of clusters increases, however, a maximum of 10 clusters are believed to be a reasonable use in practical applications.

The exact number of clusters and attributes for electrical demand will vary depending on the inhabitants knowledge in practical applications so a range of suitable attributes and the corresponding number of clusters are presented in Table I. However, for the simulation purposes, six attributes and nine clusters are used as it results in the lowest MAE as depicted in Table I from GA results. In Fig. 3, the RMSE is similar for three to six attributes because the time intervals are optimized using the MAE. Even though six attributes are used in the

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TABLE II
TOTAL ACTUAL AND PREDICTED ELECTRICAL DEMAND AND PV OUTPUT WITH THEIR RMSE AND MAE FOR FOUR DAYS EACH FOR TWO RESIDENTIAL BUILDINGS. NOTE THAT * CORRESPONDS TO THE BENCHMARK SCENARIOS WITHOUT CLUSTERING.

Scenarios	PV output				Electrical demand			
	Actual (kWh)	Predicted (kWh)	RMSE	MAE	Actual (kWh)	Predicted (kWh)	RMSE	MAE
A.1	7.028	7.703	0.0284	0.0141	21.464	14.812	0.3387	0.2174
A.1*	7.028	7.934	0.0393	0.0189	21.464	9.170	0.5365	0.3453
A.2	11.978	13.34	0.06	0.0284	7.435	5.3230	0.1533	0.086
A.2*	11.978	10.52	0.0726	0.0441	7.435	6.2155	0.1555	0.0964
A.3	13.467	13.0915	0.0208	0.0107	5.521	5.352	0.0811	0.0526
A.3*	13.467	9.76	0.1245	0.0775	5.521	5.755	0.0596	0.0434
A.4	5.5533	6.274	0.1087	0.0567	9.35	5.8865	0.1511	0.0971
A.4*	5.5533	6.622	0.1050	0.0521	9.35	7.743	0.1343	0.0875
B.1	8.921	8.415	0.1679	0.0681	62.377	46.338	1.2595	0.822
B.1*	8.921	10.961	0.1657	0.0773	62.377	33.6235	1.3017	0.8005
B.2	26.772	25.055	0.1617	0.0931	18.022	8.9485	0.5502	0.2363
B.2*	26.772	19.373	0.3120	0.1825	18.022	17.7235	0.4914	0.2309
B.3	32.591	31.046	0.0641	0.0338	63.2270	54.733	0.7489	0.4743
B.3*	32.591	18.833	0.4397	0.2866	63.2270	18.376	1.3980	1.0089
B.4	16.034	14.7145	0.1501	0.0772	17.466	17.429	0.2252	0.1612
B.4*	16.034	9.3495	0.2939	0.1441	17.466	20.3295	0.3051	0.2050

simulations, results suggest that having two to six attributes and nine or ten clusters is a good estimate.

This paper uses five clusters for the PV output because the MAE and the RMSE of the PV output predictions decreases rapidly as the number of clusters increases up to five and then continues to decrease at a lesser rate as depicted in Fig. 3(a). Moreover, having a large number of clusters is not possible in practical applications as it requires a higher user interaction. The MAE and the RMSE of the PV output predictions using both of the attribute sets are approximately the same up to seven clusters and then having two attributes for morning and evening is slightly better. Given this, the number of attributes has little or no impact when five clusters are used.

B. PV and electrical demand models

The actual and the predicted values of the PV output and electrical demand obtained from the proposed hierarchical approach for different scenarios are shown in Fig.4. The example benchmark profile without clustering is labeled as Scenario A.1 (no clustering). The predicted values are the median, with the 10^{th} and 90^{th} percentiles shown as error bars, of the values in the corresponding cluster. The probability density functions (PDFs) of this variation are estimated using kernel regression.

There are several important observations of the derived PV and electrical demand models. The PDFs of the electrical demand is either a skewed unimodal or a bimodal distribution with smaller secondary peaks. These secondary peaks are because of the appliances with different power ratings are used at different times of the day. The kernel estimates of the electrical demand are right-skewed when the median values in the cluster underestimate the actual values, which means there is a higher probability of demand increasing than decreasing. This is mostly evident from Scenario A.1 with no clustering.

The PDFs of the PV output follows a skewed unimodal distribution. The RMSE and MAE of the PV output predictions are minimum for sunny days, such as the summer day on 5 January, 2013 for two residential buildings (A.3 and B.3), as depicted in Table II. This means that the PV profiles are smooth, as shown in Fig. 4. The converse is seen to be happening for cloudy days. In Scenario B.3 (residential building B on a summer day), PV panels generate the maximum output for approximately four hours between 12 pm to 4 pm. At these time periods, kernel estimates are skewed left and are limited at the peak, which means there is a probability of going cloudy but zero probability of increasing the PV output further as the generation capacity is reached. For some time-steps the PDFs discontinue after a certain point when there are no data points beyond that point in the corresponding cluster. For example, the 8 am PV output PDF in Scenario A.2 discontinues at 0.2 kW because the probability of having a high PV output early in the morning is zero.

The estimated models from the hierarchical approach are mostly better than the kernel estimates that are obtained without clustering, as shown in Table II. However, clustering has no benefits (sometimes slightly worse predictions) when the demand is very low with less variation throughout the day. These scenarios are extremely rare and the resulting prediction error is insignificant compared to the improvements from the other scenarios when clustering. The PDFs of the PV output can have bimodal distributions when the historical data are not clustered, as depicted by Scenario A.1 (no clustering). This can be overcome by increasing the bandwidth of the Epanechnikov kernel estimation technique. However, having a larger bandwidth means kernel estimates becomes less accurate. Also, the probability distributions are the same for every day in a particular season when the historical data are not clustered. This only works in situations where the user behaviour is very regular and predictable.

C. SHEMS solutions using the estimated PV and demand models

Here a PV-battery system is considered. The PV and electrical demand models are estimated using the proposed hierarchical approach. The yearly optimization results from stochastic and deterministic dynamic programming and stochastic MILP are given in Table III for the above two smart homes. In practical applications, the accuracy of the estimates depends

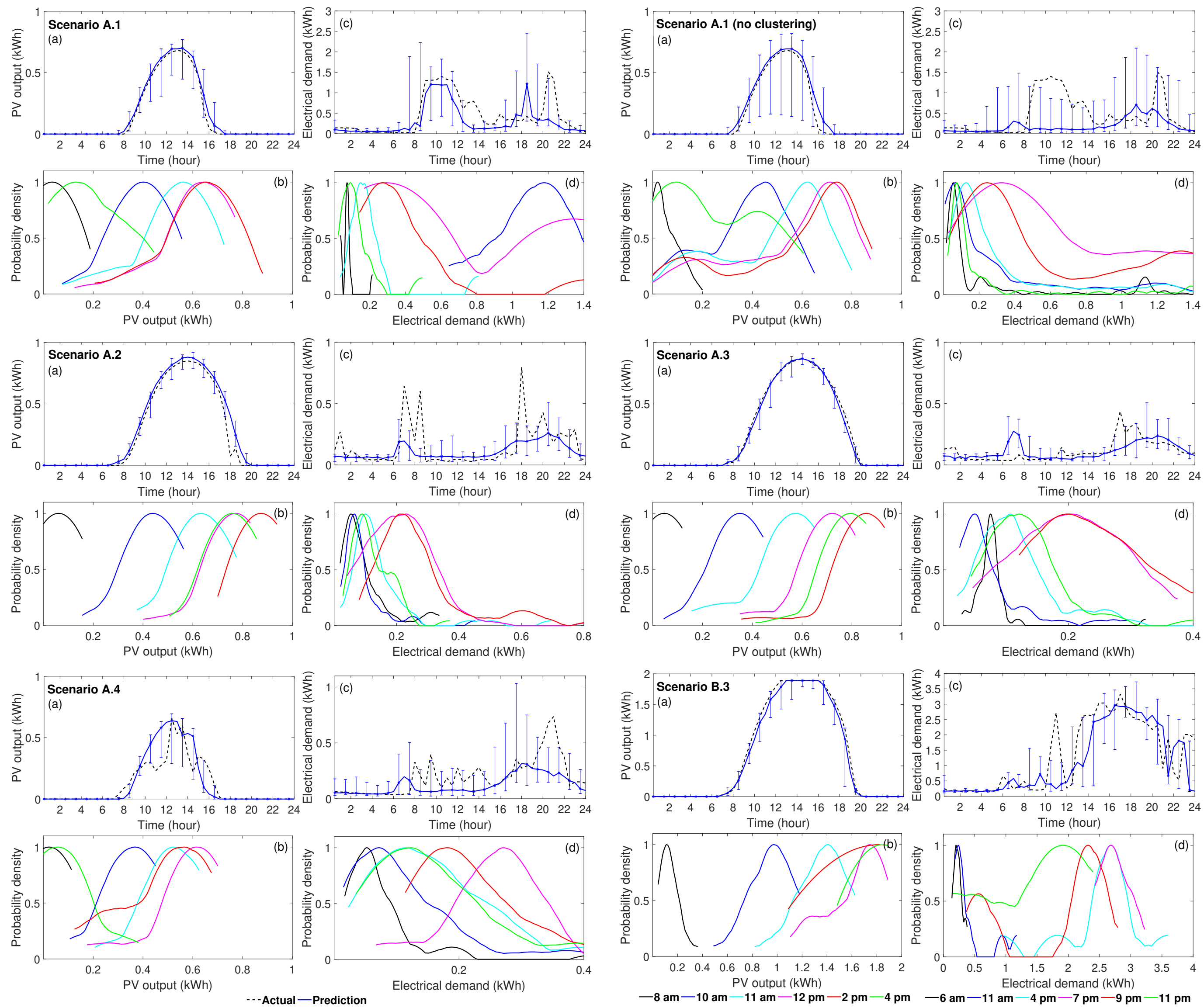

Fig. 4. Simulation results of Scenarios A.1 (Residential Building A, Day 1); A.1 (no clustering); A.2; A.3; A.4; and B.3 - (a) and (c) have the actual and predicted PV output and electrical demand, respectively; and (b) and (d) have the probability density functions of the PV and electrical demand models, respectively. The prediction is the median values of the cluster while its error bars are for the 10^{th} and 90^{th} percentiles. Note that the actual and prediction legend below the figure applies to plots (a) and (c) and the time legend applies to plots (b) and (d) of each scenario. Note that PV output and electrical demand are energy blocks within 30 minutes time slots.

on the user's (or the prediction algorithm's) ability to correctly determine the PV and electrical demand clusters. Given this, two sets of comparisons are given for: (i) reasonably good estimates (five PV clusters and nine electrical demand clusters with six attributes); and (ii) estimates with the minimum expected quality (three clusters for PV output and one cluster for electrical demand).

The results show that stochastic DP results in better quality solutions for all the cases followed by deterministic DP and then stochastic MILP. For lower quality estimates, stochastic DP will result in 5.13% and 3.37% improvement in electrical cost over deterministic DP for smart homes A and B respectively. The improvement is only 0.13% and 1.07% for Households A and B, respectively, when the estimates are accurate. In summary, a stochastic optimization approach is required because the estimates of the electrical demand and PV output are not always accurate as they depend on the user's ability to choose the correct cluster. However, the computational time of DP increases exponentially when looping over all the possible outcome spaces (i.e. on top of the computational burden from the deterministic DP). Given this, approximate dynamic programming has been proposed to implement computationally efficient SHEMSs with reasonably quality solutions [25]. Note that the focus in this section is only to present the applicability of the PV and demand model estimates from the proposed hierarchical approach in a SHEMS. An interested reader can refer to [25] for details on the solution techniques.

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TABLE III
YEAR-LONG SIMULATION RESULTS

Total yearly:	Household A	Household B
PV output (MWh)	2.91	5.99
Electrical demand (MWh)	4.29	9.82
Benchmark ($)	568.094	1208.3
PV (no storage) ($)	440.52	821.7
Stochastic DP (high quality estimates) ($)	253.62	546.86
Deterministic DP (high quality estimates) ($)	253.95	552.75
Stochastic DP (low quality estimates) ($)	258.59	588.76
Deterministic DP (low quality estimates) ($)	267.62	620.6
Stochastic MILP ($)	369.8	700.14

V. CONCLUSIONS

This paper has presented a hierarchical approach to estimate residential PV and demand models, which involves first clustering historical data into day types and second estimating probability distributions using kernel regression. The results showed that the accuracy of the estimates increases as the number of clusters and attributes increases for most of the scenarios. This is because the draws from the kernel estimations within a day type are independent so the clustering is needed to capture inter daily variations. These estimations conforms with the MDP construction so the SHEMS problem can be solved using DP or ADP. Moreover, in practical applications the user only needs to choose the correct day type instead of having to estimate the entire day's PV output and demand, which require intensive user interaction and may result in lower quality solutions.

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