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A plug-and-play home energy management algorithm using optimization and machine learning techniques

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Abstract—A smart home is considered as an automated residential house that is provided with distributed energy resources and a home energy management system (HEMS). The distributed energy resources comprise PV solar panels and battery storage unit, in the smart homes in this study. In the literature, HEMSs apply optimization algorithms to efficiently plan and control the PV-storage, for the day ahead, to minimize daily electricity cost. This is a sequential stochastic decision making problem, which is computationally intensive. Thus, it is required to develop a computationally efficient approach. Here, we apply a recurrent neural network (RNN) to deal with the sequential decision-making problem. The RNN is trained offline, on the historical data of end-users’ demand, PV generation, time of use tariff and optimal state of charge of the battery storage. Here, optimal state of charge trace is generated by solving a mixed integer linear program, generated from the historical demand and PV traces and tariffs, with the aim of minimizing daily electricity cost. The trained RNN is called *policy function approximation* (PFA), and its output is filtered by a control policy, to derive efficient and feasible day-ahead state of charge. Furthermore, knowing that there are always new end-users installing PV-storage systems, that don’t have historical data of their own, we propose a computationally efficient and close-to-optimal plug-and-play planning and control algorithm for their HEMSs. Performance of the proposed algorithm is then evaluated in comparison with the optimal strategies, through numerical studies.

Index Terms—PV-Storage systems, plug-and-play, planning and control, recurrent neural network, mixed integer programming, policy function approximation, k-means clustering.

COMMON NOMENCLATURE IN THIS PAPER

DR	demand response
RNN	recurrent neural network
ToU	time of use
HEMS	home energy management system
SOC	state of charge
MILP	mixed integer linear programming
PCC	point of common coupling
PFA	policy function approximation
fPFA	feasible policy function approximation
DoD	depth of discharge
PP	perfect prediction
IP	imperfect prediction

I. INTRODUCTION

Residential areas are responsible for nearly 40% of the energy consumption in developed countries. These areas

are known to have significant potential for energy and cost savings, as well as load shifting and peak power reserves, compared to industry and transportation [1], [2]. *Demand response* (DR) has received increased attention in recent years since it can efficiently support reducing electricity consumption and cost [3]–[6] in residential areas. Sending electricity price incentives to the smart homes is one of the common ways to implement DR program. The smart home under study here is equipped with PV solar panels and battery storage unit. In order to maximise the benefits of PV-storage systems, the smart home is equipped with *home energy management system* (HEMS), to schedule and coordinate the energy use. The optimization problem, undertaken by a HEMS, is a sequential decision making process with different sources of uncertainties, due to the stochasticity of electrical demand and PV generation [7]. There are different optimization techniques such as dynamic programming [8], [9], approximate dynamic programming [10], particle swarm optimization [11] and mixed-integer linear programming (MILP) [12], [13], employed to solve those stochastic problems. One should note that the computational burden of solving those optimization problems are high, while the HEMS’s algorithms are to be integrated into an existing smart meter or a device with limited computational power. Thus, there have been efforts to develop *policy function approximation* (PFA) algorithms, using machine learning techniques and based on end-users’ historical data, to efficiently plan and control the energy systems [7], [14]. In this paper, we describe a PFA formulation and tuning, and also design a filter to compute feasible solutions out of the PFA’s outcome (called feasible PFA). The result is a *plug-and-play* algorithm built on our feasible PFA, and applicable to new end-users *without* historical data, as well as existing users. In more detail, the main contributions of this paper are:

- (i) Deriving a novel and computationally-efficient plug-and-play algorithm for HEMSs.
- (ii) Illustrating through numerical studies that the designed algorithm results in to a close to optimal solution under imperfect prediction of demand and PV generation.
- (iii) Showing through numerical studies that the performance of the algorithm has low sensitivity on the prediction accuracy.
- (iv) Validating of the proposed strategy with the real data provided by the *Smart Grid*, *Smart City* project, which was a commercial-scale project involving residential customers in Sydney, Australia [15].

The remainder of this paper is organized as follows. Some known results are reviewed in Section II, which will be

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useful in the subsequent sections. Section III describes the connections between different components of the system and their functionality. To efficiently plan and control a PV-storage systems, a feasible PFA strategy for HEMS is formulated in Section IV. We then propose a plug-and-play algorithm for the HEMS in Section V, which is built upon the formulated PFA. Section VI presents numerical results and investigates the performance of the proposed plug-and-play algorithm in comparison with optimal algorithms. Finally, Section VII provides conclusions and suggestions for future studies.

II. PRELIMINARIES

In this section, we recall the time-series prediction problem and a strong machine learning tool (recurrent neural networks) that will be useful in the subsequent sections.

A. Time-series prediction

Many classes of experimental time-series are analyzed within the framework of the dynamical systems approach [16]–[18]. In this approach, the aim is to predict the state (y) of the dynamical system in the next time step, in response to the next input to the system. For this purpose, a predictor returns the prediction of the state of the time-series at time $t+1$, as a function of the n previous states, n previous inputs of the system (u), and the next input $u(t+1)$. This prediction problem is derived as

$$\hat{y}_{t+1} = f(y_t, \dots, y_{t-n+1}, u_{t+1}, \dots, u_{t-n+1}), \quad (1)$$

where the function $f(\cdot)$ is the predictor. One can generalize this approach for the task of predicting a sequence of future states using only the states and inputs observed in the past, and the planned inputs for the future. Examples of this task, which is known as a multi-step ahead time-series prediction problem, include predicting the time-series of electrical power consumption. This problem of k -step ahead prediction is then derived as

$$\hat{y}_{t+k} = f(\hat{y}_{t+k-1}, \dots, \hat{y}_{t+1}, y_t, \dots, y_{t+k-n+1}, u_{t+k}, \dots, u_{t+k-n+1}), \quad (2)$$

where, prediction of one-step ahead is being used for predicting the next step, and etc.

B. Recurrent neural networks

Recurrent neural networks (RNN) is one of the strong machine learning tools, which has been successfully applied to noisy and non-stationary time-series prediction problems [19], [20]. RNN models the temporal relationship of the time-series, using feedback connections to the internal nodes (known as hidden units in the hidden layers). A RNN model is trained by presenting the past values of the time-series to the input layer of the back propagation network. The weights of the network are then adjusted based on the error between the true output and the predicted output of the network, until the algorithm converges. Before the network is trained, the user must specify the number of hidden layers in the network, number of nodes in each hidden layer, and the stopping criteria of the learning algorithm.

Figure 1: System architecture and communication infrastructure in a smart home.

III. SYSTEM ARCHITECTURE

As it is shown in Figure 1, we consider a smart home equipped with PV solar panels and a battery storage unit. Thus, the exchanged power between the smart home and the grid (P_g) at the point of common coupling (PCC) is forced by the end-user's demand (P_d), PV solar generation (P_s) and battery storage's power flow (P_b), and given by

$$P_g = P_d - P_s + P_b, \quad (3)$$

where, P_d and P_s always have non-negative values, P_b is considered positive (or negative) when the battery storage is charging (or discharging). In addition, P_g is considered positive (or negative) when the power is imported from (or exported to) the grid. Here, the traded P_g is based on time of use (ToU) tariff and feed-in tariff. This means that the imported electricity has different prices at different times of the day, and is determined by the ToU tariff, and the exported electricity is determined by the feed-in tariff (is fixed here). Thus, to operate the battery storage in such a way to minimize daily electricity cost, the smart home is provided by a HEMS. To this end, HEMS receives data related to the weather forecast and ToU tariff for the day ahead, and applies an algorithm to compute control signal (ctrl), to be sent to the battery storage to control its state of charge (SOC).

A. HEMS's Planning and control algorithms

There are different proposed planning and control algorithms in the literature, that can be applied by the HEMS to control SOC of the battery storage. Among different optimization algorithms, it is common in the literature to take advantage of the modeling capabilities of *mixed integer linear programming* (MILP) algorithm for SOC scheduling. To model the SOC scheduling problem as a MILP, here, the variations in electrical demand and PV generation are incorporated in the optimisation process as non-controllable inputs. Solving the MILP will then result into the optimal solution for SOC scheduling, if we consider *perfect prediction* (PP) of the demand and PV generation. One should note

that it is not realistic to consider perfect prediction in the online setting, because forecasts are always prone to error. In addition, increasing the number of controllable appliances in the MILP model (e.g., space heating system, domestic hot water, washing machine, EVs, and etc), exponentially increases the computational burden of solving the MILP problem [13]. Given these all, we develop a fast algorithm for efficient planning and control of SOC of the battery storage systems, which has a desirable performance (in terms of efficiently reducing the electricity cost) under *imperfect prediction* (IP) of demand and PV generation.

IV. PROBLEM FORMULATION AND METHODOLOGY

In this section, a HEMS's algorithm is proposed to make computationally fast and cost efficient solutions for the battery storage's coordination. To compute and send the ctrl signals to the battery storage, the HEMS should be able to predict the efficient SOC for the day ahead, which is a time-series prediction problem (see Section II-A). RNN has been successfully applied to deal with prediction problems (see Section II-B).

A. Policy function approximation tuning

The HEMS will receive and store historical data during some years. A recurrent neural network, which is called *policy function approximation* (PFA) here, is then trained, to generate efficient solutions for SOC, under uncertain prediction of P_d and P_s . The training process requires a training data set, which includes historical data of P_d , P_s , optimal SOC (s^*) and ToU tariff. Here, historical data of s^* is generated by solving the MILP problem over historical data of P_d , P_s and ToU tariff. A powerful computer could be used to compute historical data of s^* . Thus, the problem is formulated as

$$\begin{aligned} \hat{s}(t+1) = & f(\underbrace{s(t), \dots, s(t-n+1)}_{\text{past SOC}}, \\ & \underbrace{c(t+n), \dots, c(t+1)}_{\text{ToU tariff ahead}}, \underbrace{c(t), \dots, c(t-n+1)}_{\text{past ToU tariff}}, \\ & \underbrace{P_s(t+n), \dots, P_s(t+1)}_{\text{solar ahead}}, \underbrace{P_s(t), \dots, P_s(t-n+1)}_{\text{past solar}}, \\ & \underbrace{P_d(t+n), \dots, P_d(t+1)}_{\text{demand ahead}}, \underbrace{P_d(t), \dots, P_d(t-n+1)}_{\text{past demand}}) \end{aligned} \quad (4)$$

where, $\hat{s}(t+1)$ is an approximation of the efficient SOC for one time-step ahead. One should note that the RNN represented as the function $f(\cdot)$ is tuned in such a way that computed $\hat{s}(t+1)$ is close to $s^*(t+1)$, for all t . Note that, in the training stage, the $\hat{s}(t+1)$ is defined as a function of past n steps of SOC, ToU tariff, PV solar generation and demand, and n steps ahead of ToU tariff, PV solar generation and demand. Here, n is the number of time steps that we consider, to model the time-series dependencies, in the RNN structure.

B. Real time execution of tuned PFA

To compute and send the ctrl signals to the battery storage, the HEMS will apply the tuned PFA to predict the efficient SOC. Thus, the problem is formulated as

$$\begin{aligned} \hat{s}(t+1) = & f(\underbrace{s(t), \dots, s(t-n+1)}_{\text{past SOC}}, \\ & \underbrace{c(t+n), \dots, c(t+1)}_{\text{ToU tariff ahead}}, \underbrace{c(t), \dots, c(t-n+1)}_{\text{past ToU tariff}}, \\ & \underbrace{\tilde{P}_s(t+n), \dots, \tilde{P}_s(t+1)}_{\text{predicted solar ahead}}, \underbrace{P_s(t), \dots, P_s(t-n+1)}_{\text{past solar}}, \\ & \underbrace{\tilde{P}_d(t+n), \dots, \tilde{P}_d(t+1)}_{\text{predicted demand ahead}}, \underbrace{P_d(t), \dots, P_d(t-n+1)}_{\text{past demand}}) \end{aligned} \quad (5)$$

where, $\tilde{P}_s(t+i)$ and $\tilde{P}_d(t+i)$, for $i = 1, \dots, n$, are the predictions of PV generation and end-user's demand, respectively, for i^{th} time-step ahead.

1) $\tilde{P}_d$ computation: Taking into account the seasonality in the end-user's behavior, we consider predicted demand for the i^{th} time-step ahead to be given by the demand of seven days before, at the same time-step, which means $\tilde{P}_d(t+i) = P_d(t+i-7\text{days})$.

2) $\tilde{P}_s$ computation: we consider predicted PV generation for the i^{th} time-step ahead to be given by $\tilde{P}_s(t+i) = P_s(t+i) + \xi$, where ξ is the prediction error. In this study, we assume ξ to be a random variable with uniform distribution.

C. Control policy

Since the constraints on the battery operation are not considered in the PFA formulation, the computed $\hat{s}(t+1)$ might violate some of these constraints. Thus, a control strategy is employed to make sure that this violation will not happen. This strategy simply applies a filter on the $\hat{s}(t+1)$, to make sure the computed SOC for the time-step ahead is feasible. This filter take into account the constraints on the battery storage's operation, such as maximum rate of charge or discharge (Δs), batteries capacity (C_b) and maximum depth of discharge ($\overline{DoD}$). Applying the filter on $\hat{s}(t+1)$ will result in $\tilde{s}(t+1)$, which is a feasible and efficient solution for the one-step ahead of SOC. One should note that $\tilde{s}(t+1) - \tilde{s}(t) = P_b(t+1)$. The overall policy is then called *fPFA*, since it results in to a feasible policy function approximation.

V. PLUG-AND-PLAY ALGORITHM

There are always new end-users starting using PV-storage systems with the need of having an efficient policy to plan and control their battery storage system. In addition, there are end-users who will upgrade their storage and/or their PV panels. Moreover, the occupancy of the homes might change, which will result into changes in their consumption patterns. Given these all, the plug-and-play algorithm 1 has been proposed for

Algorithm 1 Plug-and-play

- 1: - Find end-users with considerable historical data
 - 2: - Cluster them based on consumption pattern (see V-A)
 - 3: - Train PFA for each of those end-users (see IV-A)
 - 4: - Find the indicator PFA in each cluster (see V-B)
 - 5: - Assign new end-user into one of the clusters
 - 6: - Apply indicator PFA for that end-user (see IV-B)
 - 7: - Compute ctrl signal related to $\tilde{s}(t + 1)$ (see IV-C)
-

efficient planning and control of SOC of the battery storage systems, for the new end-users.

As it is mentioned in this algorithm, end-users with considerable (at least one year) historical data are chosen (step 1). These end-users are then clustered based on their consumption patterns (step 2).

A. Clustering End-users with historical data

In the literature, different consumption patterns have been considered for end-users. These patterns depend on their career type, daily habits, number of residents, and etc. For example, there are five generic load profiles described in [21], which include evening peak, day focus, night focus, double Peak and high day&evening peak. Here, end-users are clustered, based on their half an hourly average consumption pattern during one day, for one year, and by applying k-means clustering algorithm [22]. One should note that the generic load profiles are considered as the center of each cluster.

Then, a PFA will be trained for each of these end-users, and an indicator PFA will be selected for each cluster (steps 3-4).

B. Indicator PFA of each cluster

In each cluster, the trained PFA for each end-user is tested on other end-users of the same cluster. The PFA with the best performance (less prediction error) is selected as the indicator PFA of that cluster.

Here, new end-users are assigned into one of the consumption patten's clusters, based on survey being filled by them (step 5). Then, the indicator PFA and the mentioned control policy will be applied for sending ctrl signals to the new end-users (steps 6-7).

VI. STUDY CASE AND SIMULATION RESULTS

In this section we present numerical results and discuss performance of the proposed plug-and-play home energy management algorithm.

A. Historical data of demand, PV generation and s^*

Here, the demand and PV generation dataset is provided by the *Smart Grid, Smart City* project, which is a commercial-scale project involving residential customers in the Sydney region of Australia [15]. The dataset contains anomalous or incomplete demand and PV generation data for some end-users due to different reasons such as inverter failure. Thus,

a clean dataset, which is related to the 52 end-users has been extracted by Ratnam et.al [23], and are utilized in this paper. This dataset is related to three years of historical data of demand and PV generation, for the years 2011, 2012 and 2013. The size of the PV generation ranges 3.0 to 10.0 kW (in steps of 1.0 kW), with an average value of about 5 kW (which corresponds to the average PV size in Australia). Statistically, 9.5%, 29.0%, 38.5%, 8.0%, and 15.0% of the 52 customers have installed PV capacities of 3.0, 4.0, 5.0, 6.0, and 7.0-10.0 kW, respectively. The battery capacity of each end-user depends on the size of the installed PV solar panels. The PV-battery size combinations (see [24]) and batteries specifications are given in Table I and Table II, respectively.

Table I: PV-Battery Size Combinations

PV panel size (kW)	Battery capacity (kWh)
3 - 4	6.5 (LG Chem RESU 6.5)
5 - 6	9.8 (LG Chem RESU 10)
7 - 10	14 (Tesla Power Wall 2)

Table II: Batteries Specifications

Battery Type	C_b (kWh)	DoD (kWh)	Δs (kW)	efficiency (%)
LG Chem RESU 6.5	6.5	5.9	4.2	95
LG Chem RESU 10	9.8	8.8	5.0	95
Tesla Power Wall 2	14.0	13.5	5.0	90

B. Optimal and $fPFA$ policies performance in one day

Comparison of optimal and $fPFA$ policies performance, in one day of 2013, and for one of the end-users is discussed in this section, and the simulation results are shown in Figure 2. In the part *a*), the ToU tariff and feed-in tariffs are shown, which are related to the buying/selling electricity from/to the grid (P_g is positive/negative).

Part *b*) illustrates the real demand P_d^R and real PV generation P_s^R for that day, which are employed by the optimal policy MILP_{PP} (solving MILP considering perfect prediction). One should note that the predicted demand and PV generation, which are used in the $fPFA_{IP}$ policy (feasible PFA with imperfect prediction) are computed as it is described in IV-B, and ξ is assumed to have a uniform distribution causing predicted PV generation to deviate at most 10% from the P_s^R . The computed SOC based on MILP_{PP} and $fPFA_{IP}$ policies are shown in the part *c*).

Part *d*) of the figure compares the forced P_g , based on MILP_{PP} and $fPFA_{IP}$ policies, at the PCC. Note that the $fPFA$ has been trained for the fifth end-user among 52, employing the first 300 days of the year 2013 as the training dataset. It has been then tested to compute efficient SOC for the 320th day of that year, in this example. Having trained RNNs with different number of hidden layers and different number of nodes in each layer (see II-B), and considering the trade-off between complexity of the network and accuracy in prediction, an RNN with one hidden layer and 20 nodes in that layer has been chosen here. The number of time-steps from the past and ahead (see eq. (4) and eq. (5)) are both equal, and we have $n = 48$. This means, $fPFA$ policy takes

Figure 2: Example of $fPFA$ policy performance in comparison with the optimal policy for the 320th day of the year 2013: a) ToU tariff and feed-in tariff, b) real demand P_d^R and real PV generation P_s^R , c) Comparison of computed SOC based on MILP_{PP} and $fPFA_{IP}$ policies, which are the computed SOC based on the optimal policy considering perfect prediction of demand and PV generation, and $fPFA$ policy with imperfect prediction, respectively, and d) Comparison of exchanged power with the grid P_g , based on the MILP_{PP} and $fPFA_{IP}$ policies, at the PCC.

into account 48 past time-steps (past 24 hours since the data is half an hourly) of the data, and also prediction of the 48 time-steps ahead. In this example, if there is no battery (NB) in the place, which means P_g is force by demand and PV generation only, electricity cost is 7.1\$. Considering battery in the place and applying optimal and $fPFA$ policies for scheduling and control of the battery, will result in to the price of 5.8\$ and 6.2\$, respectively.

C. Yearly economical assessments of plug-and-play policy

It will not be fair to compare the price of different HEMS strategies, for only one day, since the SOC for the beginning and end of the days, are set differently by those strategies. To validate performance of the mentioned scheduling policies in a fair manner, and also investigate the proposed plug-and-play algorithm, annual (year 2013) electricity cost of different end-users are discussed, for different policies. Since the evening peak generic profile cluster (see V-A) is the one with more end-users among the others (20 out of 52 end-users), it is under our consideration here (fulfilling steps 1-2 of Algorithm 1). Following the steps 3-4 of the algorithm, the trained PFA on the historical data of 2013 of the 8th end-user has been selected as the indicator PFA of the evening peak generic profile cluster. Figure 3 illustrates performance of the $fPFA$

Figure 3: Comparison of annual cost of electricity for 20 end-users, with evening peak generic profile (see V-A), for MILP_{PP}, MILP_{IP}, $fPFA_{PP}$, $fPFA_{IP}$ and NB cases, which are scheduling and controlling of the storage system based on MILP with perfect prediction (optimal solution), MILP with imperfect prediction, $fPFA$ with perfect prediction, $fPFA$ with imperfect prediction, and the case that that no battery is installed (NB), respectively.

policy considering perfect and imperfect predictions ($fPFA_{PP}$ and $fPFA_{IP}$, respectively), in comparison with optimal policy considering perfect and imperfect predictions (MILP_{PP} and MILP_{IP}), and also with the case of no battery (NB) in the place. As it is shown in this plot in yellow, if the end-users are having no battery (NB) in the place, their annual electricity cost is at the highest, with the average of 641\$.

In the case of being equipped with battery, scheduling of SOC by applying the MILP_{PP}, gives the lowest cost for all the 20 end-users. One should not that the end-users are sorted in this figure from the lowest to the highest cost given by MILP_{PP} strategy. The average electricity cost among these end-users, when applying MILP_{PP}, is annually 352\$, which is 45% less than the NB case. The scheduling of SOC, by applying the MILP_{IP} and $fPFA_{IP}$, result in to close annual cost in all the end-users, which means that the proposed plug-and-play strategy performs close to the optimization algorithms with imperfect prediction, while it has much less computational burden. The average annual cost for MILP_{IP} and $fPFA_{IP}$, are 453\$ and 477\$, respectively, which are 29% and 26% less average annual costs than the NB case.

One should note that applying the $fPFA_{PP}$ strategy gives slightly lower cost than $fPFA_{IP}$, in some of the end-users. This means the plug-and-play strategy with imperfect prediction of demand and PV generation, performs close to the case of having perfect prediction. The average annual cost for MILP_{PP} is 469\$, which is 27% less than the NB case. It is important to mention that the data in this figure, shown by square markers, are discrete. The reason that the markers are connected by the dashed lines is to help the readers for easier comparison of different policies. For example, to easily see that the NB and the MILP_{PP} cases are representing the upper

and lower bounds for annual costs, respectively.

VII. CONCLUSION

In this study, we have proposed a plug-and-play algorithm for HEMSs, to efficiently plan and control PV-storage systems, with the aim of minimizing annual electricity cost. Here, RNN has been employed to deal with the underlying sequential decision-making problem. The RNN is trained on the historical data of end-users demand, PV generation, ToU tariff and optimal state of charge of the battery storage. The trained RNN here is called policy function approximation (PFA), and its output is filtered by a control policy, to derive efficient and feasible day-ahead state of charge. In addition, knowing that there are always new end-users installing PV-storage systems (they don't have historical data), we propose a computationally efficient and close to optimal plug-and-play planning and control algorithm for their HEMSs. Performance of the proposed algorithm is evaluated in comparison with the optimal strategies. It is shown that, considering imperfect prediction of day-ahead demand and PV generation, the proposed plug-and-play strategy performs close to the optimization algorithms. In addition, the plug-and-play strategy with imperfect prediction, performs close to the case of having perfect prediction, which means there is no need to have sophisticated and accurate prediction algorithm. As a future step, one can investigate the performance of the proposed algorithm for other generic profile clusters.

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