Optimization based Real-Time Home Energy Management in the Presence of Renewable Energy and Battery Energy Storage

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***Abstract*—This paper introduces a new Home Energy Management System (HEMS) to reduce the daily household energy costs, Maximize the PV self-consumption and increase customer benefits through managing the operation of a Home Energy Storage System (HESS) in an economic way. The proposed HEMS uses an optimization-based rolling horizon technique to determine the optimal settings of the HESS based on real-time measurements. The optimization process is executed every two minutes to update the settings for the HESS. The results obtained show the capability of the HEMS to reduce household utility bills and achieve an overall reduction in peak energy demand.**

Keywords—Home energy management system, Smart home, Convex optimization, Rolling Horizon, Autoregression forecasting.

NOMENCLATURE

C_{Home}	Daily household electricity cost (£).
C_{Home_buy}	Daily cost of the electrical energy purchased from the main distribution grid (£).
$C_{Micro_{sell}}$	Daily income from the exported electrical energy to the main distribution grid (£).
ΔT	Sampling time (h) (i.e. 2 minutes/60).
$TR_{buy}(t)$	Electricity purchase tariff at a time interval t (£/kWh).
$TR_{sell}(t)$	Electricity sale tariff at a time interval t (£/kWh).
$TR_{OP\&M}$	Operating and maintenance price of the HESS (£/kWh).
$P_{Utility}(t)$	Electrical power drawn by the home from the main distribution grid at a time interval t (kW), where a +ve value means that the home imports power from the main distribution grid, and a -ve value means that the home exports power to the main distribution grid.
$P_{load}(t)$	Electrical load demand of the home at a time interval t (kW).
$P_{PV}(t)$	Electrical power generated by the PV system located at the home at a time interval t (kW).
$P_{bat}(t)$	Electrical power discharge/Charge by the battery at a time interval t (kW), where a +ve value denotes battery discharging, and a -ve value denotes charging.
$P_{HESS}(t)$	Net electrical power discharged/charged by the HESS (battery +converter) located at the home at a time interval t (kW), where a +ve value means that the HESS discharges, and a -ve value means that the HESS charges.
$E(t)$	Stored energy in the HESS at a time interval t (kWh).
$E(t-1)$	Stored energy in the HESS at a time interval t-1 (kWh).
η_d, η_c	Efficiencies of the battery discharging and charging respectively (%).
$B_{Capacity}$	Battery capacity (kWh).
η_{Conv}	Power converter efficiency (%).
$SOC(t)$	State of charge of the battery at a time interval t (%).
P_{con_const}	Constant power losses in the power converter (kW).
$P_{HESS\,max}$	Maximum discharge/charge power that can be produced by the HESS at time interval "t" (kW).
SOC_{max}	Maximum state of charge limit of the HESS (%).
SOC_{min}	Minimum state of charge limit of the HESS (%).

I. INTRODUCTION

a) Motivation and Background

With the increasing penetration of domestic solar panels and the impending move to electric vehicles and the electrification of heating, there is a real need to understand how Home Energy Management Systems (HEMS) and Home Energy Storage Systems (HESS) can be used to defer network re-enforcement costs [1].

A HEMS can reduces household utility bills and ensures an overall reduction in peak energy demand as demonstrated in [2]. A HEMS can also play an important role in encouraging local consumption of the energy generated by renewable energy resources (such as PV systems) in homes rather than exporting the surplus electric energy to the main distribution grid. This can be achieved by moving loads in time (Demand Side Management (DSM)) or by incorporating Home Energy Storage Systems (HESS) into homes to capture excess PV or off-peak (low cost) grid energy and use it at peak times [3],[4].

b) Relevant Literature

In recent years there has been much research into exploiting energy market real-time-pricing schemes to develop and enhance the use of HEMS to manage home electricity consumption economically [5], [6]. For example in [7], an optimal energy management model to minimize fuel and battery wear costs is presented which finds the optimal power flow, taking into account the available photovoltaic power. Another energy management scheme which integrates wind energy is proposed in [8]. In [9], an optimization strategy is developed to effectively consider price based demand response techniques. The authors in [10] introduced a smart HEMS to support the grid. The system uses renewable energy resources such as PV as an alternate power source which helps in reducing the dependence of the home on the grid. In [11], [12] the authors presented forecasting algorithms for home consumption demand for one day ahead using a short sampling time. The results suffer from a poor mean absolute percentage error.

c) Contributions and Organization

This paper introduces a HEMS to minimize the daily household electricity costs through managing the operation of the HESS. The proposed methodology depends on using an optimization based rolling horizon technique to determine the optimal settings for the HESS which ensures the best economic daily operation of the home.

The main contribution of this work can be summarized as follows:

- The proposed HEMS uses a real-time interactive algorithm to determine accurate settings for home-based HESS.
- The hierarchy of the proposed HEMS is built to be able to capture every tiny change in the system and respond to it. This is achieved through scanning input data and generating battery settings in a short sample time (i.e. 2 minutes); comparing this to similar research published, most techniques use a long sample time (i.e. ranging from 15 minutes up to 2 hours).
- The proposed HEMS can deal with any pricing policies available in the energy market and ensures that the most economic cost reduction is achieved.
- The proposed methodology has only minimal dependence on communication technologies, which increases its reliability and reduces the possibility of failure due to loss or delay of data.
- The proposed HEMS depends on real-time energy forecasting for the loads and local generation each sample time (i.e. 2 minutes). Real-time energy forecasting ensures that the forecasted values are accurate as they are updated automatically if unexpected changes occur.

The paper is organized as follows: Section II focuses on introducing the proposed HEMS including system modelling and formulation of the optimization problem, as well as the optimization technique used to solve the proposed optimization problem. Section III shows the integrated real-time auto-regression forecasting algorithm. In section IV, the results obtained are presented.

II. Convex Optimization-Based Rolling Horizon Energy Management

The proposed methodology depends on using an optimization based rolling horizon technique to determine the optimal settings for the HESS which ensures the best daily economic operation of the home. Every sample time, the forecasted daily profiles for load demand and PV generation are updated using the real-time measurements of the consumption and the PV generation, an optimization process is performed, and optimal settings for the HESS are obtained. The optimization process is performed for a time frame from t=0 to t=24 h and repeated every 2 minutes. The HESS behaviour is optimized for the next time slots (from t=t+1 to t=24h). However, the optimized setting for the next time slot only (t+1) is delivered to the HESS. Fig 1 shows the detailed steps of the HEMS algorithm.

In this paper, Minimizing the daily household electricity costs can be formulated as a convex optimization problem [13], [14]. Since linear functions are convex, so linear programming problems are convex problems. Convex optimization is a subfield of optimization that studies the problem of minimizing convex functions over convex sets [15]. The mathematical formulation of the convex problem is expressed as follows:

minimize objective function $\quad f_0(x)$

subject to constraints $\quad g_i(x) \leq b_i$, i=1,…, m

$\quad h_i(\mathrm{x}) = 0$, i=1,…., p

where $x \in R^n$, the functions $f_0(x)$ *and* $g_i(x)$ must be convex, and the function $h_i(x)$ must be "affine"

The objective function is the cost function formulated at A which minimizes the daily household electricity costs. While the constraints are equations 5, 9 and 10. The Interior-point method is used to solve the convex optimization problem since it shows excellent results in practice [13]. The main advantage of using the convex optimization technique in this research is the processing time: it needs only 5 seconds to perform the optimization process and determine the best reference values.

A. Cost function formulation

The cost function is formulated to minimize the daily household electricity costs "C_{Home}". This cost can be developed in terms of payments and incomes [16]. The payments include the cost of purchased electricity from the main distribution grid, and the daily operating and maintenance cost of the HESS; incomes consider the revenue of the energy sold to the main grid (i.e. the excess electricity produced by the PV generation after satisfying the home demands and charging the home-based HESS). The daily household electricity costs can be formulated as follows:

$$\mathrm{C}_{Home} = \mathrm{C}_{Home\_buy} + C_{Home\_sell} + \mathrm{C}_{HESS_{op\&mc}} \tag{1}$$

$$\mathrm{C}_{Home\_buy} = \begin{cases} \sum_{to}^{\mathrm{T}} \Delta\mathrm{T} \times \mathrm{TR_{buy}(t)} \times \mathrm{P_{Utility}}(t) & , \mathrm{P_{Utility}}(t) > 0 \\ 0 & , \mathrm{P_{Utility}}(t) \leq 0 \end{cases} \tag{2}$$

$$C_{Home\_sell} = \begin{cases} \sum_{to}^{\mathrm{T}} \Delta\mathrm{T} \times \mathrm{TR_{sell}(t)} \times \mathrm{P_{Utility}}(t) & , \mathrm{P_{Utility}}(t) < 0 \\ 0 & , \mathrm{P_{Utility}}(t) \geq 0 \end{cases} \tag{3}$$

$$\mathrm{C}_{HESS_{op\&mc}} = \Delta\mathrm{T} \times \mathrm{TR_{OP\&M}} \times \sum_{to}^{\mathrm{T}} |\mathrm{P_{HESS}(t)}| \tag{4}$$

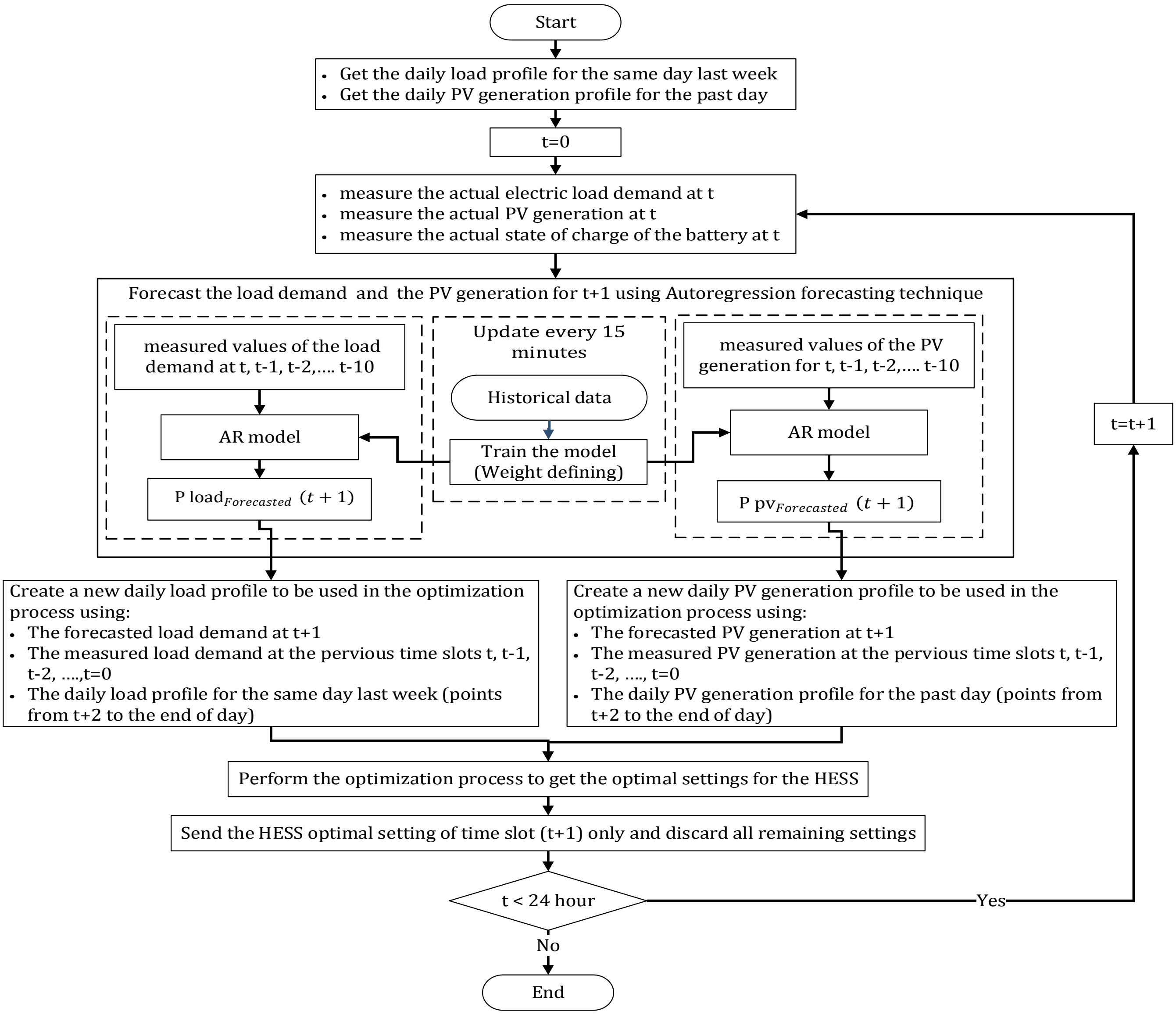

Fig. 1. The detailed steps of the Home Energy Management Control algorithm

B. System description, modeling and constraints

The case study system used in this paper is for UK based home which includes distributed (rooftop) Photovoltaic (PV) generation system and a HESS. The home is also connected to the main distribution grid to import any additional energy. Fig. 2 shows the architecture of the home used in this study.

The model and the constraints of the system under study can be represented by the following equations:

The balance equation of the total active power in the home is formulated as follows:

$$P_{\text{Utility}}(t) + P_{\text{HESS}}(t) = P_{home\_load}(t) - P_{\text{PV\_gen}}(t) \quad (5)$$

The model of the HESS used in this research is represented by the following equations:

$$E(t) = \begin{cases} E(t-1) - \dfrac{\Delta T \times P_{\text{bat}}(t)}{\eta_{\text{d}}} & , P_{\text{bat}}(t) \geq 0 \\ E(t-1) - \Delta T \times \eta_{\text{c}} \times P_{\text{bat}} & , P_{\text{bat}}(t) < 0 \end{cases} \quad (6)$$

$$\text{SOC}(t) = \frac{E(t)}{B_{\text{Capacity}}} \quad (7)$$

Also, a power converter is used to control the HESS and acts as an interface between the HESS and the HEMS. The following equation represents the power converter model:

$$P_{\text{HESS}}(t) = \begin{cases} P_{\text{bat}}(t) \times \eta_{\text{Conv}} - P_{\text{con}_{\text{const}}} & , P_{\text{bat}}(t) > 0 \\ \dfrac{P_{\text{bat}}(t)}{\eta_{\text{Conv}}} + P_{\text{con}_{\text{const}}} & , P_{\text{bat}}(t) \leq 0 \end{cases} \quad (8)$$

There are constraints associated with the operation of the HESS: power output constraints, and State of Charge (SOC) constraints.

HESS power output constraints: This constraint reflects the maximum power that can be charged/discharged by the HESS over a fixed time interval. This constraint reflects the operating limits of the HESS.

$$-P_{\text{HESS max}} \leq P_{\text{HESS}}(t) \leq P_{\text{HESS max}} \quad (9)$$

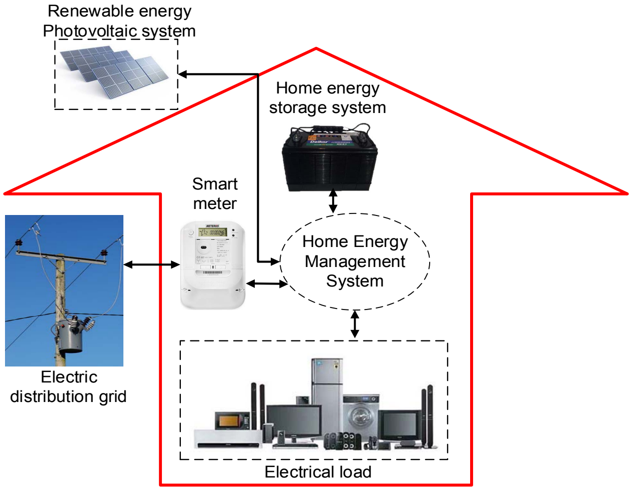

Fig. 2. Home architecture

HESS SOC constraint: This constraint defines the maximum and the minimum SOC level of the HESS. This constraint is important to the BESS operation and is set following the recommendation of the IEEE [17]. Maximum and minimum SOC level constraints avoid overcharging or deep discharge of the BESS to maximise the lifetime of the BESS. Overcharging and deep discharging of the BESS significantly reduce battery lifetime [18].

$$\mathrm{SOC}_{\min} \leq \mathrm{SOC}(t) \leq SOC_{\max} \tag{10}$$

III. Integration of the Adaptive Autoregression Forecasting Algorithm and the HEMS

The HEMS depends on the forecasted load demand and PV generation for the next sample time to calculate the correct HESS settings. Therefore, selecting an accurate forecasting algorithm to forecast the required inputs for the HEMS with high accuracy is essential.

Forecasting of the load demand and PV generation for the next minute or minutes is called very short term energy forecasting (VSTEF). An Autoregression (AR) algorithm is one of the most popular algorithms in VSTEF [19]. In this paper, an Adaptive AR algorithm is used to forecast the home demands and the home-based PV generation for the next sample time (i.e. 2 minutes) with high accuracy. AR is a simple method that can be used to obtain accurate forecasts for time series problems. Energy forecasting using the AR model is based on using a time series model that depends on stochastic calculations in which the future values are predicted based on the past values. Adaptive AR forecasting is used in this paper as it is a simple method, has a fast calculation time (only 1 second for forecasting the next point), is adaptive and can be trained easily for the time series used.

The AR model used in this research is defined by the following equation:

$$\mathrm{y_t} = \Phi + \psi_1 \mathrm{y_{t-1}} + \psi_2 \mathrm{y_{t-2}} + \cdots + \psi_p \mathrm{y_{t-p}} + \mathrm{A_t} \tag{11}$$

where $\mathrm{y_t}$ is the forecasted value, $\psi_1, \psi_2, \ldots \psi_p$ and Φ are coefficients found by optimizing the model on training data, $\mathrm{y_{t-1}}, \mathrm{y_{t-2}}, \ldots . \mathrm{y_{t-p}}$ are the past series values (lags), P is the order of the AR model and $\mathrm{A_t}$ is white noise, is assumed zero in this paper.

IV. Results

In this section, the simulation results for the HEMS are shown. The simulation process is performed using MATLAB software. The system parameters and tariff values used in the simulation are shown in Table I [20], [21], [22].

TABLE I. SYSTEM PARAMETERS AND TARIFF VALUES

Parameter	Value	Parameter	Value
Sample time	2 minutes	$\mathrm{P_{C\_conv}}$	10 W
Battery capacity	12 kWh	η_{Conv}	95 %
$\mathrm{SOC_{min}}$	20 %	$\mathrm{P_{BESS\ max}}$	±2.5 kW
$SOC_{\max}$	90 %	$\eta_{\mathrm{d}}, \eta_{\mathrm{c}}$	90 %
$\mathrm{TR_{sell}}$ (fixed all day)	4.85 pence /kWh	$\mathrm{TR_{OP\&M}}$	2 pence /kWh
TOU purchasing tariff (Off peak)	5 pence/kWh From 12 am to 7 am		
TOU purchasing tariff (Mid-peak)	12 pence/kWh From 7 am to 4 pm and From 8 pm to 12 am		
TOU purchasing tariff (Peak)	25 pence/kWh From 4 pm to 8 pm		

Fig. 3a shows the actual daily load and PV generation profiles for the home used in this simulation. Fig. 3b and Fig. 3c show a comparison between the $P_{Utility}(t)$ in case of not using HEMS or battery storage and in case of using the proposed HEMS respectively. Fig. 4 shows the real settings delivered to the HESS and also the actual SOC of the HESS through the day.

It is obvious from Fig. 3c that the HEMS managed to consume the energy generated by renewable energy resources (such as PV systems) locally in the home rather than exporting the surplus electrical energy to the main distribution grid. The HEMS managed to feed the home demands at the peak-time hours (from 16:00 to 20:00) using the HESS rather than importing energy from the main distribution grid during the peak tariff period (i.e. 25 pence/kWh). The HEMS imports more energy from the main distribution grid during the off-peak tariff time (from 00:00 am to 07:00 am) at a low price (i.e. 5 pence/ kWh) to feed the home demands and also charge the HESS. The HESS is charged from the imported energy from the main distribution grid at off-peak tariff time and also from the surplus PV generation which is obvious from Fig. 4b.

From Fig. 3c, the uncaptured export power at a time interval (12:00 to 15:00) results from being the HESS fully charged at this interval; can be observed from Fig. 4b, hence the HEMS exported the excess power to the utility. The observed spikes in Fig. 3c result from inaccurate forecasted values for the load demand or PV generation at some points, which therefore affects the HESS settings leads to these spikes. These spikes do not actually affect the daily household energy cost as it lasts for a very short sample time (less than 30 seconds).

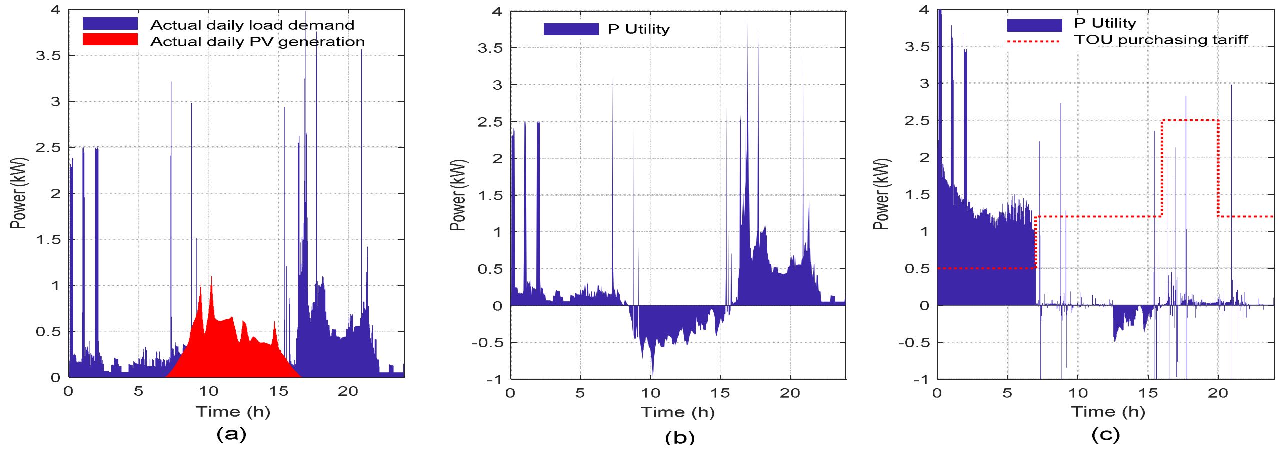

Fig. 3. (a) the actual daily load demand and PV generation for the home, (b) the actual $P_{Utility}$ without using HEMS or HESS, (c) the actual $P_{Utility}$ after using HEMS.

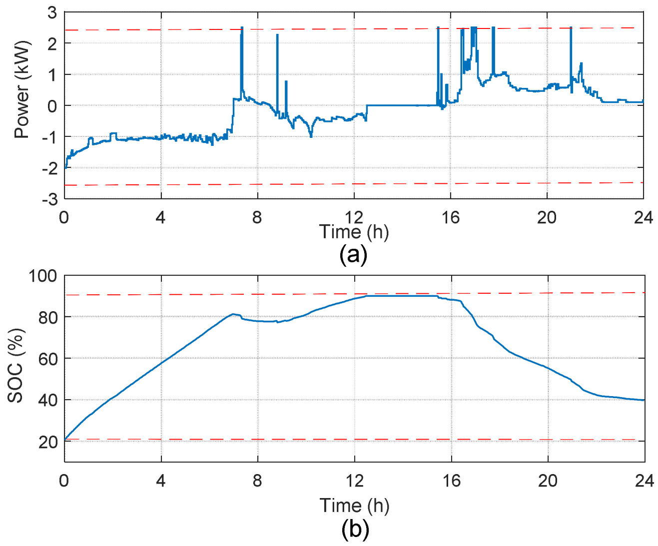

Fig. 4. (a) the HESS optimal settings obtained from the HEMS, (b) the actual state of charge (SOC) of the HESS through the day

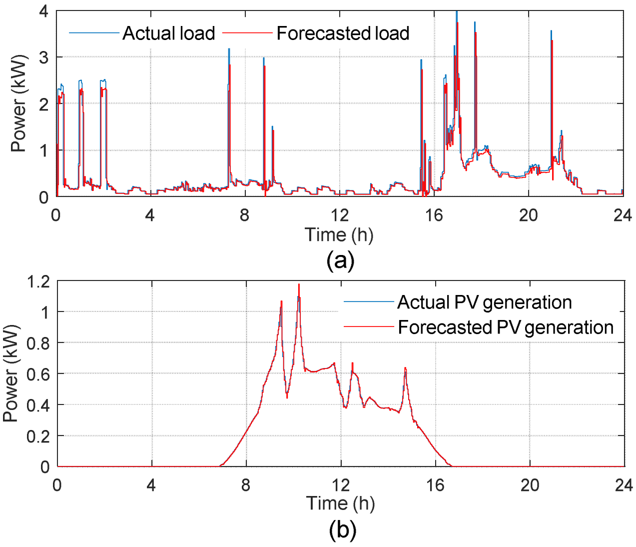

Fig. 5. (a) the forecasted and the actual daily load for the home, (b) the forecasted and the actual PV generation for the home.

TABLE II. A COMPARISON BETWEEN THE PROPOSED HEMS AND OTHER CASES

Case		Household energy costs (£)	Saving*(%)	PV self-consumption (%) **	MAPE of the forecasted load (%)	MAPE of the forecasted PV (%)
1	Without using HEMS or HESS	576.63	–	39.22 %	–	–
2	HEMS + day ahead forecasting	431.19	25.28 %	72.35 %	48.2 %	36.7 %
3	The proposed HEMS	393.85	31.69 %	87.98 %	18 %	13 %
4	Ideal case (perfect forecasting)	352.68	38.83 %	96 %	0 %	0 %

*Yearly saving percentage is compared to the case where no HEMS or HESS are used.
**Yearly PV self-consumption percent = yearly generated PV energy consumed by the home *100 /total yearly generated PV energy.
Case 2: This case represents HEMS using conventional forecasting algorithm as in [11], [12]. The day ahead forecasted profiles for load demand and PV generation used in this case are assumed to be the real profiles with Gaussian white noise to represent the forecasting errors.
Case 3: This case represents the proposed HEMS in this paper.

Using HESS settings of a short sample time (i.e. 2 minutes) enables the HEMS to capture every tiny change in the system and respond to it in real time: this is obvious in Fig. 4a. It is obvious from Fig. 4b that the optimization strategy takes into consideration the HESS modelling and constraints, and manages to keep the SOC of the HESS and all other constraints associated with it within limits (SOC between 20 and 90 %, maximum charging/discharging power 2.5 kW).

Fig. 5a shows both the forecasted and the actual daily load profiles for the home. Fig. 5b shows both the forecasted and the actual PV generation profiles for the home. It is obvious from the figures that the Adaptive AR forecasting algorithm succeeded in forecasting accurately the load demand of the home as well as the PV generation using the rolling horizon technique. The mean absolute percentage error (MAPE) of the forecasted load is 8%. This value is acceptable for this type of domestic loads (i.e. home loads which are characterized by sharp changes in a short sample time), comparing to using other forecasting methods [11], [12]. The MAPE for the forecasted PV profile is 11%.

The economic results obtained show that the proposed strategy succeeded in minimizing the daily cost of the energy drawn from the main grid. The daily household energy cost reduced from £1.37 /day to £1.079/day - a daily reduction of 21 percent. Table II shows a comparison between the effect of using the proposed HEMS comparing to other cases on the yearly household energy cost saving, the yearly PV self-consumption, and the yearly Mean Absolute Percentage Error (MAPE) of the forecasted load demand and the PV generation.

V. CONCLUSION.

The proposed HEMS significantly reduces the daily household electricity cost and also reduces the imported energy by the household at peak times, providing benefit for both householder and utility operator. A complete model for the home system has been built, taking into account all the constraints that affect the daily operation. The economic results of the proposed HEMS demonstrate the capability of the proposed methodology to achieve a yearly household payment reduction up to 32 percent, and a yearly PV self-consumption of up to 87 percent. Using a short sample time of 2 minutes enables the proposed HEMS to observe and respond to the small changes in the load and generation throughout the day, which achieves better performance for the end user.

ACKNOWLEDGMENT

This work is supported by the Egyptian Government-ministry of higher education (cultural affairs and missions sector) and the British Council through Newton-Mosharafa fund.

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