Intelligent Short-Term Hybrid Forecasting Model Applied on a Community-based Home Energy Management System

Gerardo J. Osório
C-MAST, University of Beira Interior, Covilha, Portugal
gjosilva@gmail.com

Nuno Teixeira-Lopes
University of Porto
Porto, Portugal
up201604553@edu.fe.up.pt

Mohammad S. Javadi
INESC TEC
Porto, Portugal
mohammad.javadi@inesctec.pt

João P. S. Catalão
SYSTEC-ARISE
University of Porto
Porto, Portugal
catalao@fe.up.pt

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***Abstract*—With technological advancement and the urgency to decarbonize energy consumption habits, smart grids have gained special prominence in recent years, highlighting the importance of the massive integration of endogenous renewable sources and decision-making tools, like forecasting tools. The relevance and accuracy of the forecast make it possible to add a contribution to energy management tools in residential communities, from the point of view of end-users and the distribution network operator. This work presents the development of a short-term hybrid forecasting model, combining Long-Short Term Memory (LSTM) model forecast with the Holt-Winters forecast model, where the ability of the LSTM stands out in capturing the complex temporal patterns of historical time series, while Holt-Winters deals with trends and seasonality of historical data. Combining these models results in an intelligent hybrid system capable of efficiently dealing with the complexity inherent to renewable energy. Then, the forecasted results from load and solar generation are introduced on the home energy management model considering a small residential community, showing the relevance of accurate forecasted results tools to assist in the making decisions processes.**

***Keywords*—Energy community, Energy management system, Holt-Winters, Long short-term memory, Renewable production forecast**

NOMENCLATURE

Indexes

t, NT	Time index / Time slot set.
i, NA	Appliance index/ Set of appliances
j, NJ	Battery index/ Set of batteries
w	Scenario decision variable.

Parameters

α, γ, β	Holt-Winters smoother parameters.
$\sigma(\cdot)$	Sigmoid function.
n	Total number of observations.
NA	The total number of shiftable equipment.
NS	Total number of battery energy storage systems.
$P_i^{Ch,max}$,	Maximum power allowed in the battery energy storage system i to charge.
$P_i^{Dis,max}$	Maximum power allowed in the battery energy storage system i to discharge.
$\eta_i^{Ch}, \eta_i^{Dis}$	Efficiency of battery energy storage system i during the charging/discharging, respectively.
E_i^{min}, E_i^{max}	Minimum and maximum battery energy storage system capacity of unit i.
m	Holt-Winters seasonal period.
W_c, W_i, W_o, W_f	Long-short-term memory weights.
b_c, b_i, b_o, b_f	Long-short-term memory adjustment values.
S	Seasonality adjustment.
P_i	Nominal power of appliance i.
τ	Comfort index.

Variables

F_{t+m}	Period-ahead m forecast over the time t.
S_t, S_{t-s}	Current/Previous seasonality at time t.
l_t	Randomness at time t.
b_t	Tendency at time t.
$\tilde{c}_t$	Candidate memory at period t.
$\tanh(\cdot)$	Hyperbolic tangent function.
h_{t-1}	Previous output value.
x_t	Current input at period t.
i_t	Input gate at period t.
f_t	Evaluation gate at period t
c_t, c_{t-1}	Current/previous memory cell at period t, respectively.
o_t	Output gate at period t.
$\hat{Y}_t, Y_t, \bar{Y}_t$	Forecasted, real and average value at time t, respectively.
π_t^{G2H}, π_t^{H2G}	Time-of-use tariffs to buy or sell electricity to the grid, respectively.
$P_{w,t}^{G2H}, P_{w,t}^{H2G}$	Exchanged power from grid-to-home, and home-to-grid on scenario w, period t.
Δt	Time interval duration.
$STUP_{w,i,t}$	Startup of appliance i, at scenario w, time t.
$SHDN_{w,i,t}$	Shutdown of appliance i, at scenario w, time t.
C_i^{ST}, C_i^{SD}	Startup/Shutdown cost of appliance i, respectively.
$DI_{w,i}$	Discomfort index of appliance i, at scenario w.
$D_{w,t}^{Shift}, D_{w,t}^{fix}$	Amount of shiftable/fixed load at scenario w, time t, respectively.
$B_{w,i,t}, S_{w,i,t}$	Binary variables for the base and scheduled status of appliance i, at scenario w, time t.
$P_{w,t}^{PV}$	Solar production at scenario w, time t.
$P_{w,i,t}^{Ch}, P_{w,i,t}^{Dis}$	Charging and discharging power, from the battery energy storage system i, at scenario w, time t, respectively.

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$E_{w,i,t}$ Amount of energy stored on the battery energy storage system i, at scenario w, time t, respectively.

I. Introduction

From the different possibilities for the urgent decarbonization of the electricity sector and making it more environmentally friendly, resilient, profitable, and sustainable, the solution is to make the grid "smart". The Smart Grid (SG) definition could be resumed as an electrical network that uses a bidirectional flow of energy and information [1], including the role of the smart meter, whose capabilities include measuring and communicating users' energy consumption and providing additional data for operator monitoring and billing efficiently, signals from the electricity market, as well the smart energy management systems (EMS) in different strategic economic areas [2].

Considering the SG concept, demand-side management, and demand response programs play a crucial role as well in modeling the future of SG, covering the planning, implementation, and monitoring of public service activities, encouraging the use of electricity by customers, aiming to make desired changes in the utility load profile, helping to keep it as smooth as possible, adjusting the load and the demand during the operating period [3].

However, the tool for the decision-making process that manages the renewable generation, storage and distribution should be accurate and responsive enough to help the players act wisely, with robustness and quality, reducing the mismatch or discomfort to users. Here, the tools or models for optimal scheduling, shifting the loads, or managing the local generation or storage, i.e., the EMS systems have been gaining increased interest in the last years because of economic help and the needed flexibility in SG. [4].

Hence, considering SG there is also the concept of smart home (SH), and the home EMS considering electric vehicles, local endogenous electricity production (wind and/or solar), and/or storage, presented in models that consider the pear-to-pear interaction, or the massive integration of electric vehicles, increasing the interest of research [5]. For instance, in [6] the advantages of SH are highlighted, emphasizing the comfort. By programming routine actions, users have more freedom, making SH more attractive. Remote control and monitoring, whether through smartphones or computers and automation based on predefined configurations offer a more positive outlook.

Energy communities are defined as an extension of the SG concept, where agents assume the social control of energy resources shared through decentralization. Individual users, producers, and prosumers can develop independent initiatives, actively contributing to grid sustainability, where energy communities are legal entities focused on pooling resources, with the potential to reduce energy prices and load peaks [7].

Considering the integration of accurate tools for enhance the SG capabilities, decision tools used in the decision-making process are accurately needed to support and reinforce the signal decisions from other tools, which the hybrid intelligent forecasting models play an important role as the first stage of decision, especially when decisions are made in the short term [8].

The reason to consider intelligent hybrid models is that such forecasting models are more capable of better combining the best between two or more techniques, intending to reduce the forecast error, providing accurate information in useful time, with reduced resources, outperforming other models [9].

For instance, in [10] it was presented a hybrid method based on wavelet transform, Holt-Winters forecast and weighted nearest neighbor for the short-term load forecast, i.e., for the next 24 hours ahead, considering real cases from the day-ahead load data in the electricity markets of California and Spain. In [11] a full and orderly review of the direct forecasting of PV power generation was presented. It highlighted the meaning of the correlation of the input-output data and the preprocessing importance of forecasting models by considering an analysis of several solar power forecasting models, including hybrid forecast models, noticing the opportunities and challenges of the different approaches.

In [12] a hybrid model was presented for the ultra-short-term forecast of domestic electricity consumption based on the Holt-Winters method and extreme learning machine network, showing a significative forecast error reduction from the period analyzed. In [13] was presented the implication of considering some intelligent soft computing techniques to forecast renewable energy and load demand in different time horizons, helping to select the best technique to keep microgrids sustainable and reliable. In [14] was developed a hybrid model based on the Holt-Winters model and gated recurrent unit network model for short-term load-interval forecasting, to deal with the inherent complexity, volatility, and instability of power load, which is not trackable by point forecast models, as reported on "*Teddy Cup*" data mining challenge, from 2022, showing high-quality results.

Considering the previous aspects addressed, and the widespread information available considering hybrid intelligent forecast models this current work presents:

- The development of a short-term hybrid forecasting model, combining the predictive capabilities of the Long-Short Term Memory (LSTM) model with the Holt-Winters model.
- The hybrid forecasting model proposed will be applied to forecast the behavior of wind and solar production, and the load in the short-term, i.e., 24h, considering only the historical data.
- As an extension of this research, the forecasted results will be introduced on the home EMS like in [4], considering a small residential community, composed of 5 houses with smart features, including the inputs that resulted in a forecast of the load and PV generation.

The ability of the LSTM stands out in capturing the complex temporal patterns of historical time series, and Holt-Winters with smooth features, deals with trends, seasonality, and randomness of historical data.

With the combination of LSTM and Holt-Winters models, it is possible to present a forecast model capable of efficiently dealing with the inherent complexity of producing and exchanging renewable energy in small communities. Considering the contribution addressed, the current work will show as a goal the relevance of accurate forecasting results to assist in the making decisions process, like scheduling, shifting the load, or considering the users' high-level comfort indices as reported in [15] assisting the home EMS.

The remaining work is as follows: Section II shows the main mathematical information that models the hybrid forecasting tool and the main concept of the home EMS considered. Section III shows the study cases, main results, and respective analyses. Section IV shows the main conclusion and intentions for future works.

II. Mathematical Problem Information

A. Holt-Winters Model

Holt-Winters model is part of a class of exponential smoothing models originally designed to analyze the behavior of time series data, decomposing the historical data into trend, seasonality, and randomness components. Common ways include the additive or the multiplicative methods. In this work, the multiplicative method is used, where the trend and seasonality components are multiplied by the time series average value, generating the forecast profile. Mathematically it is described as [16]:

$$l_t = \alpha\left(\frac{Y_t}{S_{t-s}}\right) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{1}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{2}$$

$$S_t = \gamma\left(\frac{Y_t}{l_t}\right) + (1-\gamma)S_{t-s} \tag{3}$$

$$F_{t+m} = (l_t + b_t m)S_{t-s+m} \tag{4}$$

where Eq. (1) l_t represents the randomness of data Y_t at period t, and α denotes the randomness smoothing parameter. Eq. (2) denotes the trend b_t of data at period t, and β denotes the trend smoothing parameter. Eq. (3) shows the length of seasonality from the data Y_t at period t, where γ denotes the seasonality smoothing parameter. Finally, Eq. (4) constructs the forecast data m period ahead.

B. Long Short-Term Memory Network Model

Long Short-Term Memory (LSTM) model is an evolution of recurrent neural networks, developed to overcome the challenges that often occur with the use of gradients like in conventional networks. The LSTM innovation lies in the introduction of the state cell and gate structure, providing the ability to handle long-term dependencies, and mitigating the gradient risk [17], [18].

The fundamental concept of LSTM involves the state cell and three types of gates: *Input*, responsible for updating the state of the cell, and deciding what information to add. *Evaluation* determines which information will be ignored. and the *Output*, responsible for determining the output of the current cell. The conceptual model is presented in Fig.1. Each LSTM gate performs a specific function in each iteration [17].

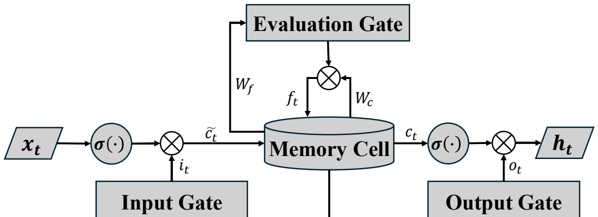

Fig. 1. Conceptual structure of LSTM model proposed.

- *Compute the Candidate's Memory* $(\tilde{c}_t)$, obtained by applying the hyperbolic tangent function (tanh) to the linear combination of the values of the previous output h_{t-1}, and the current input data x_t, weighted by W_c, increased by an adjustment value b_c:

$$\tilde{c}_t = \tanh(W_c \times [h_{t-1}, x_t] + b_c) \tag{5}$$

- *Compute the Input Gate* (i_t), by applying the sigmoid function $(\sigma(\cdot))$ to the linear combination of the previous output h_{t-1}, and the current input data x_t, weighted by W_i, increased by an adjustment value b_i:

$$i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \tag{6}$$

- *Compute the Evaluation Gate* (f_t), like the input gate, the sigmoid function $(\sigma(\cdot))$ is applied to the linear combination of the values of the previous output h_{t-1} and the current input data x_t, weighted by the weight W_f, and added by the adjustment value b_f:

$$f_t = \sigma(W_f \times [h_{t-1}, x_t] + b_f) \tag{7}$$

- *Memory Cell Update*, based on the results of the evaluation and input gates. The previous value of the memory cell c_{t-1} is multiplied by the result of the evaluation gate f_t, added to the product of the input gat i_t, and the candidate's memory c_t:

$$c_t = (f_t \times c_{t-1}) + (i_t \times \tilde{c}_t) \tag{8}$$

- *Compute the Output Gate*, where the sigmoid function $(\sigma(\cdot))$ is applied to the linear combination of the values of the previous output h_{t-1} and the current input data x_t, weighted W_o, added with an adjustment value b_o:

$$o_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \tag{9}$$

- Compute the LSTM Unit Output (h_t), is calculated by multiplying the output port result o_t by the hyperbolic tangent of the current memory cell c_t:

$$h_t = o_t \times \tanh(c_t) \tag{10}$$

C. Proposed Forecasting Model and Error Quantification

The proposed hybrid forecasting model considers the strategic combination of profile forecasting results, without consideration of exogenous data, from the LSTM model, and the Holt-Winters model, as shown in Fig.2. Initially, the historical data is normalized to facilitate LSTM training. Simultaneously, the Holt-Winters method is applied to the LSTM test data, incorporating the smoothing parameters, α, γ, β, from the Holt-Winters model.

The final step combines the results of the forecast models, considering the error minimization, which includes the Root Mean Square Error (RMSE) and the Mean Average Percentage Error (MAPE), with the test data in a feed-forward neural network, which is the best solution found will be the lower value or the best result after the number of epoch ~400 to 1000 epochs is reached considering the forecast profile data. Then, the results are converted to values with the same magnitude as the historical data, and the forecasted results are shown.

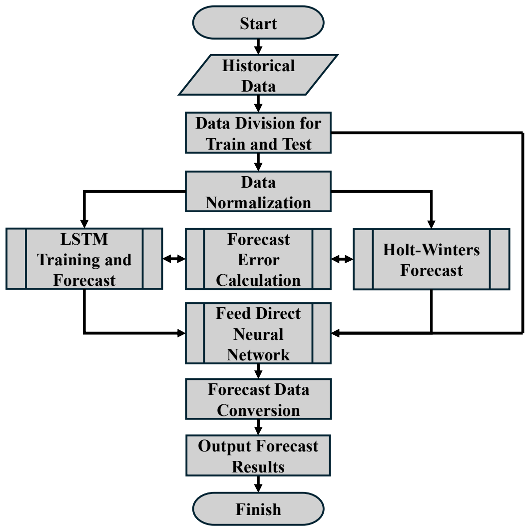

Fig. 2. Proposed hybrid forecast model.

The RMSE and MAPE are described as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t - \hat{Y}_t\right)^2} \tag{11}$$

$$\mathrm{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\frac{|Y_t - \hat{Y}_t|}{|\bar{Y}_t|} \times 100 \tag{12}$$

where T corresponds to the day-ahead forecast period, i.e., 24h, Y_t and $\hat{Y}_t$, correspond to the real and forecasted value, at time t, and $\bar{Y}_t$ is the mean value of Y_t to avoid the instability of the criterion when data is close to 0.

D. General Home Energy Management Model

The generalized mathematical formulation follows the mixed integer linear programming (MILP) model by following the concept developed in [4]. Here, the objective is to optimize energy management in a residential community, aiming to reduce users' daily expenses and considering penalties for discomfort associated with the changes in the operating hours of household appliances. The objective function is:

$$\begin{aligned} &Min\ Z \\ &= \left(\sum\nolimits_{w\in\Omega} p_w \left(\sum_{t=1}^{NT}\left[\pi_t^{G2H} p_{w,t}^{G2H}\Delta t - \pi_t^{H2G} p_{w,t}^{H2G}\Delta t\right]\right)\right) \\ &+ \left(\sum\nolimits_{w\in\Omega} p_w \left(\sum_{t=1}^{NT}\sum_{i=1}^{NA}\left[STUP_{w,i,t}C_i^{ST} + SHDN_{w,i,t}C_i^{SD}\right]\right)\right) \\ &- \left(\sum\nolimits_{i=1}^{NA}\left[C_i^{ST} + C_i^{SD}\right]\right) \\ &+ \left(\sum\nolimits_{w\in\Omega} p_w \left(\sum\nolimits_{i=1}^{NA}\tau\left[DI_{w,i}^{+} + DI_{w,i}^{-}\right]\right)\right) \end{aligned} \tag{13}$$

In Eq. (13), the *first term* describes the cost of energy transactions between the home and the grid, considering a Time-of-Use (TOU) price package mechanism, where electricity prices vary over time, weighting the costs in the objective function, associated with the purchase and sale of energy between the home and the grid. The *second term* describes the cost of starting/stopping appliances, allowing sustainable habits by penalizing frequent starting/stopping situations. The C_i^{ST} and C_i^{SD} parameters with high values represent the cost associated with these operations.

The *third term* describes the cost of discomfort by shift loads, indicating the total cost of startup/shutdown controllable appliances along the scheduling period. The *four terms* describe the total cost associated with discomfort, penalizing the independent shifting load from the scheduled period, influenced by the comfort index τ.

The lower of τ means that the user is with the peer-to-peer transaction even if comfort is reduced. The high value of τ means the opposite. In this work, it was assumed $\tau = 250$. The sensitivity analysis was performed in [15] discussing the impact of the discomfort index on optimal operation of SH.

The limitations inherent to the problem are associated with the technical and economic restrictions related to the load, the energy interaction between the home EMS and the electrical grid, and the use of the battery energy storage system (BESS), briefly described next. Eq. (14) describes the amount of dispatchable load in each time interval $D_{w,t}^{Shift}$, dependent on the device's nominal power, P_i, and its operational status, determined by the binary operational variable $S_{w,i,t}$.

$$D_{w,t}^{Shift} = \sum_{i=1}^{NA} S_{w,i,t}P_i \tag{14}$$

Eq. (15) limits unnecessary appliances' occurrences outside of the normal cycle, described through startup $STUP_{w,i,t}$ and shutdown $SHDN_{w,i,t}$, over the period scheduled. Eqs. (16) and (17) indicate the discomfort index of a controllable appliance depends on whether the appliance is being used during the standard/shifted operating period, implying, e.g., the discomfort index will be "0", influenced by the shifted binary variable $B_{w,i,t}$, or assume a positive value.

$$STUP_{w,i,t} - SHDN_{w,i,t} = S_{w,i,t} - S_{w,i,t-1} \quad \forall t > 1 \tag{15}$$

$$DI_{w,i}^{-} \geq \frac{1}{T_i}\left[\sum_{t=1}^{NT} t \times B_{w,i,t} - \sum_{t=1}^{NT} t \times S_{w,i,t}\right] \tag{16}$$

$$DI_{w,i}^{+} \geq \frac{1}{T_i}\left[\sum_{t=1}^{NT} t \times S_{w,i,t} - \sum_{t=1}^{NT} t \times B_{w,i,t}\right] \tag{17}$$

Eq. (18) describes the limitations related to the energy transactions between the SH, the grid, and the restrictions imposed by the BESS in each time scenario. Considering the technical constraints related to the operation of BESS and home EMS with the grid, Eq. (19) describes the dynamics of BESS in each time interval, determining the amount of energy stored in the BESS based on the energy stored in the previous period, the charge and discharge efficiency and the charge and discharge power. This is also guaranteed by other constraints like the minimum and maximum energy stored over time and the status of BESS operation, controlled by a binary variable. More details have been provided in [19].

$$\begin{aligned} &P_{w,t}^{G2H} - P_{w,t}^{H2G} + P_{w,t}^{PV} \\ &= D_{w,t}^{Fix} + D_{w,t}^{Shift} + \sum_{j=1}^{NS} P_{w.i.t}^{Ch} - \sum_{j=1}^{NS} P_{w.i.t}^{Dis} \end{aligned} \tag{18}$$

$$E_{w,i,t} = E_{w,i,t-1} + \eta_i^{Ch} P_{w,i,t}^{Ch}\Delta t - \frac{1}{\eta_i^{Dis}} P_{w,i,t}^{Dis}\Delta t \tag{19}$$

III. STUDY CASES AND RESULTS

For the hybrid forecast model, the data used (wind/solar/load) were collected from different sources, such as REN [20], REE [21], and OMEL [22]. The data used to consider the previous 14 days was discretized into hourly periods, allowing the forecast for the next 24 hours. It should be noted that the forecasting tool does not use exogenous data. The hybrid forecast model was developed in MATLAB R2023b. The energy community's management model was developed in Python, using the Jupyter Notebook v3.12 environment, dotted with the Gurobi v11.0.0 optimizer.

Figs. 3 denotes the shifted and fixed loads profiles, respectively in kW. Here, fixed loads are considering the lighting, TVs, and other users' not-shiftable appliances. Considering the shifting loads, and the maximum user's comfort level i.e., $\tau = 250$, the home EMS will run considering the possibility that even with the signals provided from the grid, the priority is to provide the maximum comfort, otherwise, the penalization will be high. Even so, the home EMS was capable of shifting some loads, and creating new scheduling profiles as will be shown in the next results.

Fig. 4 shows the summary of all historical data, considering the period of 336h, with a time-step of 1h, for each profile (wind, solar, load) in kW. The community is composed of 5 SHs, with a contracted power of 10.35 kVA each, participating in peer-to-peer (P2P) energy transactions, allowing the purchase and sale of energy within the energy community, or with the grid itself, which transactions were limited to a maximum capacity of 40% and 35%, respectively. Solar forecast with winter days was normalized (black line) and presented in Fig. 5. The solar installations in each SH consist of 6 panels of 395 Wp each, i.e., a capacity of 2.38 kW per SH. Table 1 shows the BESS-incorporated SHs.

Fig. 5 shows the tariffs allowed in Portugal divided into simple, two-step, and three-step tariffs, announced and updated every year by the main regulator [23]. Table II shows a summary of the schedule and users' preferences to use their shiftable load. All the forecast simulations ran considering 6 attempts looking for the best average MAPE for the LSTM model. All the smoothing parameters of Holt-Winters were adapted accordingly with the forecast profile (wind, solar, or load). Hence, the hybrid forecasting model considered training data a set of 312 hours, and the test data are the previous 24 hours before the forecast. Figs. 8-10 show the forecasting results for the wind, solar, and load, considering an average MAPE of 13.30, 15.89, and 3.78, respectively.

Fig. 10 shows the scheduled and shifted load profiles between SH 4 and 5, as an example of the effectiveness of results from the solar generation forecast introduced in home EMS with maximum index comfort adjusting the loads of different houses, helping the grid to reduce the peak load.

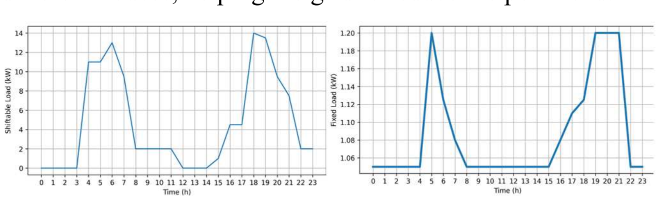

Fig. 3. Shiftable (a) and fixed (b) loads considered in the home EMS model.

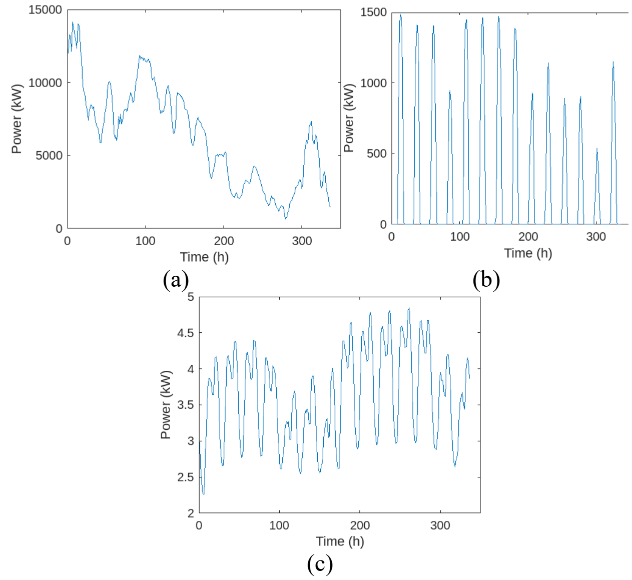

Fig. 4. Historical data, (a) wind power, (b) solar power, and (c) load.

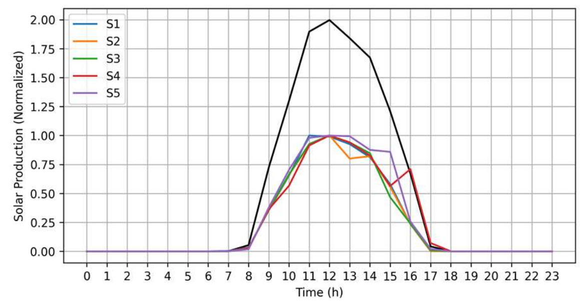

Fig. 5. Normalized solar profile considered in home EMS model.

TABLE I. MAIN PARAMETERS CONSIDERED IN BESS

E_0 (kWh)	E_{24} (kWh)	P_{max}^{Ch} (kW)	P_{max}^{Dis} (kW)	η_{Ch}	η_{Dis}	E_{max} (kWh)	E_{min} (kWh)
2.0	2.0	2.5	2.5	0.9	0.85	4	1

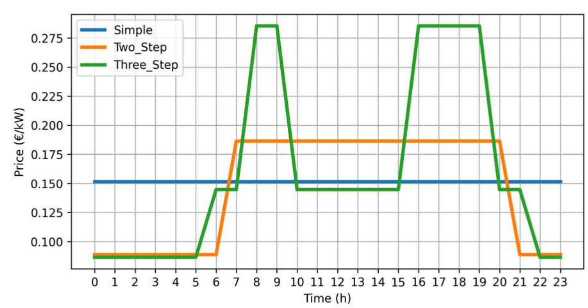

Fig. 6. Tariff considered in the home EMS model.

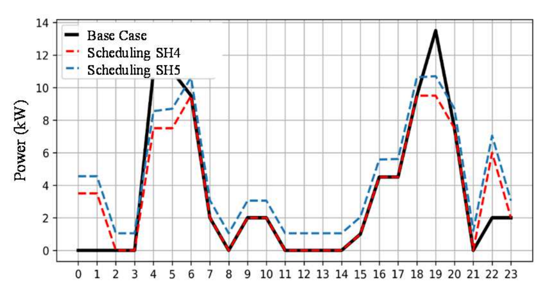

Fig. 7. Home EMS scheduling results, considering the base case (black) and shift loads on SH 4 (red) and SH 5 (blue).

TABLE II. RESUME ABOUT SCHEDULED LOADS AND USERS' PREFERENCES

Load	P_i (kW)	Δt (h)	Base Case Start (h)	Base Case Finish (h)	Pref. 1 (h)	Pref. 2 (h)
Wash. Mach.	2.0	3	15:00	18:00	08:00	18:00
Dry. Mach.	4.0	1	18:30	19:30	18:30	22:30
Dishwasher	2.0	2	09:00	11:00	09:00	18:00
W. Heat. (T_1)	3.5	2	04:00	06:00	00:00	06:00
W. Heat. (T_2)	3.5	2	16:00	18:00	09:00	18:00
Ch. EV (T_1)	7.5	3	18:00	21:00	18:00	00:00
Ch. EV (T_2)	7.5	3	4:00	7:00	00:00	08:00
AirCond. (T_1)	2.0	2	6:00	08:00	00:00	08:00
AirCond. (T_2)	2.0	2	18:00	20:00	15:00	20:00
AirCond. (T_3)	2.0	2	22:00	00:00	20:00	00:00

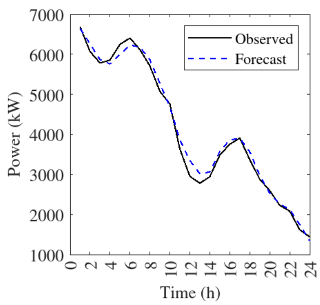

Fig. 8. Forecasted (blue) and real (black) wind power profile.

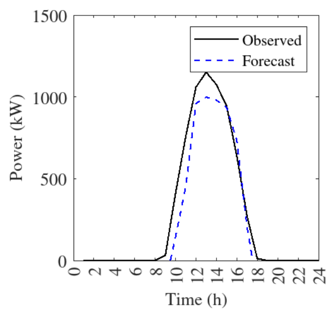

Fig. 9. Forecasted (blue) and real (black) solar power profile.

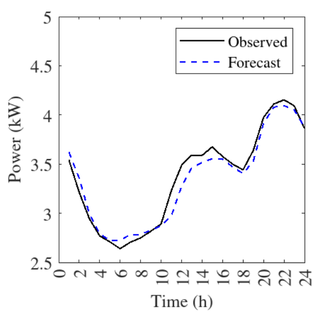

Fig. 10. Forecasted (blue) and real (black) load profile.

IV. CONCLUSION

In this work, a hybrid forecasting model was presented to help the HEMS insert in an energy community composed of five houses, considering the forecast data from solar and load. The successful combination of LSTM and Holt-Winters techniques allowed, with the reduced computational burden (around 1 minute), acceptable MAPE values for wind (13.30), solar (15.89), and load profiles (3.78). The forecasted results helped HEMS to manage the production and need of SHs, by shifting the loads, even considering that users desired the maximum comfort. In future research, it is suggested to extend the studies about the hybrid forecasting model developed facing more randomness from solar generation, detailed comparison, and further analysis result, introducing more differences between the SHs and EVs behavior.

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