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From Load to Net Energy Forecasting: Short-Term Residential Forecasting for the Blend of Load and PV Behind the Meter

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ABSTRACT As distribution networks worldwide are experiencing the adoption of residential solar photovoltaic (PV) more than ever, the need for transiting from the concept of load forecasting to net energy forecasting, i.e. predicting the blend of PV and load as a whole, is pressing. While most of the existing literature has focused on load forecasting, this paper, for the first time, contributes to this transition at both single household and low aggregate levels through a comprehensive study. The paper also proposes a multi-input single-output (MISO) model based on an efficient long short-term memory (LSTM) neural network, by which different household energy profiles help provide more accurate forecasts for other households or aggregate energy profile. This technique, indeed, considers the spatial dependencies of households' profile indirectly. Through this study, the underlying problem of short-term net energy forecasting is compared to load forecasting, and it is shown how the inclusion of PV generation behind the meter could deteriorate forecasting accuracy. Moreover, the impact of the level of granularity associated with smart meter data on the aggregated net energy forecasting is discussed, and it is revealed that the higher resolution data can potentially alleviate the accuracy lost. Furthermore, online LSTM, as opposed to proposed batch learning MISO LSTM, is used as a forecasting tool. The results show online LSTM is more resilient to sudden changes at the single household level, while MISO LSTM is efficient for aggregate level. The proposed framework is conducted on two real Ausgrid and Solar Analytics case studies in Australia.

INDEX TERMS Deep learning, long short-term memory (LSTM), recurrent neural networks, residential load forecasting, short-term net energy forecasting, smart meter, spatial-temporal dependency.

I. INTRODUCTION

Residential rooftop photovoltaic (PV) system has been rapidly becoming a component of the modern power system. Also, acknowledging modern platforms, such as peer-to-peer energy trading [1] and micro virtual power plant (μVPP) [2] based on households' solar generation, seems to accelerate the growing trend of rooftop PV adoption at the residential level. Such circumstances necessitate a shift from load forecasting to net energy forecasting as the fusion of load demand and PV generation forecasting problems. This is precisely one of the branches introduced for a decade ahead of energy forecasting in the Global Energy Forecasting Competition 2014 (GEFCom2014) [3]. Although minimal studies recently discuss *net energy forecasting* at low-aggregate and residential levels, the existing research on this topic is too sparse, especially at the household scale, and a more in-depth investigation is needed.

Short-term load forecasting is an essential task to provide reliable operation of modern power systems [4], [5]. Due to power system modernization and decentralization, applications of load forecasting have become even more highlighted in today's distribution networks. Real-time and near real-time monitoring of distribution networks, community

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battery adoption, peak shaving methods and some advantages of demand response technologies are just a few instances that heavily rely on accurate one step ahead load forecasts. For such applications, *net energy forecasting* has a critical important role to play as load forecasting, if not more so. Short-term load forecasting problem has been well established over the years. Different methodologies exist in solving the problem. The common *similar day* method is one of the classical ones, in which a similar pattern is to be found from historical data based on the hour of the day, day of the week and season of the year [6], [7]. Some other studies develop forecasting engines based on explanatory variables carrying valuable information [8], [9]. In other words, feature selection, such as determining the number of lagged and moving average variables, is the central task in such an approach [10]. Moreover, the idea of taking advantage of other regions' load profile to make the forecast for a specific location is studied in [11], where the time-forward kriging method is used for the spatial load forecasting concept. The method tries to find the cross-correlation and auto-correlation among various load profiles at the system level. However, spatial load forecasting traditionally refers to predict the location and load growth for the planning purposes [12].

Although the vast majority of research, including the above literature, focuses on the substation level, load forecasting at the low-aggregate level and, particularity, at the single household level have been of interest to researchers in recent years [13]–[17], mainly due to power system modernization. In this regard, Stephen *et al.*, in [13], apply a clustering technique to provides a forecast for aggregated residential load based on the practice theory of human behavior. Similar clustering techniques are often a successful approach for the *similar day* method [7]. Wen *et al.*, in [14], focuses on the load forecasting of a residential building with a one-hour resolution, while Kong *et al.* consider both individual and aggregte levels in a case with half-hourly data [15]. Thanks to monitoring of the household appliances by separate meters, single customer forecasting improves through more meaningful temporal relationships [16]. Moreover, Hong *et al.* show that the spatial correlations between different appliances used in a household can potentially increase the accuracy of single household load forecasting [17]. However, all the above studies focus on load forecasting, the inclusion of household PV generations behind the meter has been ignored.

Very recently, a handful of works have been carried out, in which the *net energy forecasting* is discussed, mainly at aggregate level [18]–[21]. Sun *et al.* propose a forecasting model at feeder level, which first, estimates the PV penetration, and then, PV forecast is integrated into load forecasting [18]. Application of a similar method is used in [19] for considering different PV penetration scenarios at the aggregate level to achieve an effective demand-side management approach. Kobylinski *et al.* in [20], investigate the short-term net energy forecasting for a micro-neighbourhood, comprising 75 single houses, with 15 minutes' temporal resolution data. Besides, the importance of aggregated net energy forecasting has been shown for a secured energy trading platform [21]. These studies reveal that the PV generation behind the meter increases the uncertainty, which in turn, the complexity of the net energy forecasting problem even at low-aggregate level; however, there is a lack of literature on this topic from a few perspectives, which this paper aims to bridge the gap. Firstly, the research to date has tended to focus on the net energy forecasting at the aggregate level, but not the single household level. For some applications, forecasting of end-user profile seems to be vital. In fact, forecasting at this level is much more challenging compared to the aggregate level. Secondly, the impact of granularity of the data recorded has not been a matter of study on existing works related to net energy forecasting, and therefore, the potential of improving net energy forecasting by different data resolution has remained unsearched.

In recent years, studies show that *deep learning* techniques outperform classical statistical models, such as autoregressive moving average (ARMA) [22]. One of the most efficient deep learning models for residential load forecasting has been presented in [15] based on the long short-term memory (LSTM) neural network. Moreover, a variant of LSTM, called gated recurrent unit (GRU) has been tested in [14]. Application of iterative residual blocks (ResBlocks) in deep neural networks has also been illustrated in extracting spatial and temporal correlations [17]. A predictive model based on the artificial neural networks (ANN) has been developed for the net energy forecasting to apply feature selection technique in the context of lag signals [20]. Tang *et al.* in [23] has used joint bi-directional ANN and deep belief network as a hybrid framework for short-term load forecasting, where candidate features are chosen based on the Pearson correlation coefficient. From the perspective of the machine learning, the above deep learning-based models, fall into the batch (offline) learning category, which means the predictive model is trained based on the historical data at once. In contrast, the model is incrementally trained by feeding instances through the online learning framework [24]. Thus, the batch learning could be less effective compared to online learning in terms of adaptability to sudden changes and high variations. There are online predictive models developed in the area of deep learning [25], [26], though research to date has not seemed to be focused on applying such models to energy forecasting at the single household level.

The primary contribution of this paper relates to the subject matter, although the methodology used comes to support it.

A. CONTRIBUTION TO THE SUBJECT MATTER

Specifically, this paper aims to contribute to the growing area of research, i.e. short-term forecasting of *net energy* behind the meter, by exploring how the inclusion of residential rooftop PV generations could affect load forecasting at both single household and low-aggregate levels. As far as we know, while some limited existing works have used net energy forecasting concept at the low-aggregate level, this is the first time that not only net energy forecasting at the single household level is discussed deeply, but also a comprehensive comparison between load and net energy forecasting is made at both household and aggregate levels. This study also examines the potential advantages that fined-grained data (with the five-minute resolution) could bring to the one-step-ahead net energy forecasting problem.

B. CONTRIBUTION TO THE METHODOLOGY

This paper proposes multi-input single-output (MISO) LSTM for short-term net energy forecasting, by which spatial relationships between various households are indirectly taken into account. More precisely, the energy profiles of all household profiles are simultaneously fed into the LSTM model, while either only one household or the aggregate profile is the target of forecasting. To the best of authors' knowledge, the MISO approach has not been proposed in existing load/energy forecasting model.

Besides the above-mentioned contributions, an existing LSTM-based *online learning* approach is applied for the net energy forecasting to investigate to what extend online learning is capable of capturing abrupt variations compared to batch learning as this is the case in single household level. Moreover, this paper uses the mean arctangent absolute percentage (MAAPE) index recently introduced to overcome the drawback of the popular mean absolute percentage error (MAPE), which occurs in cases that actual value is zero- this case happens in net energy forecasting (*not* load forecasting). The suitability and effectiveness of the MAAPE for net energy forecasting is also shown by comparing it with two other scale-free metrics, including MAPE and normalized mean absolute error (nMAE).

The remaining part of this paper has been organized in the following way. Section II provides methodologies used based on batch LSTM, MISO LSTM and online LSTM. In Section III simulation results are illustrated and discussed with two Australian case studies. Finally, findings are highlighted and concluded in section IV.

II. METHODOLOGY

A. BATCH LSTM MODEL

Since the first introduction of the LSTM, several popular variants have been developed [27]. To predict the next step of the residential load, Kong *et al.* [15] have developed one of the most comprehensive and efficient batch LSTM models, so far. In this paper, a similar architecture is used as a base reference of our study.

The LSTM mainly consists of three gates at each time step, known as input, output and forget, which are respectively indicated by i_t, o_t and f_t. Also, φ and σ functions apply to vector pointwise, which the former is commonly set as tanh, and the latter is the sigmoid activation function. If the LSTM input and generated hidden output are respectively defined as x_t and $h_t, \forall t \in \{1, 2, \ldots, T\}$, there would be an LSTM block for each time step, having a memory cell, s_t, which is responsible for interacting between subsequent inputs to carry valuable

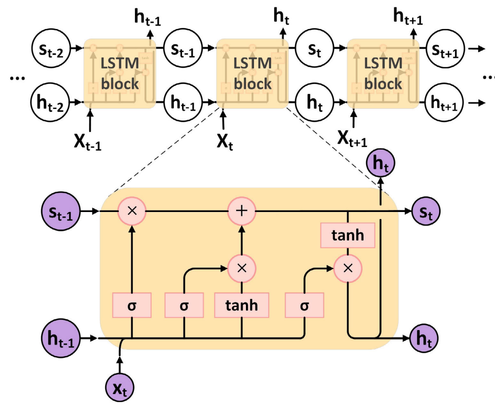


FIGURE 1. LSTM sequential structure.

information over the time series. These relations are depicted in FIGURE 1, while the related mathematical formulation is described as (1) - (6). In the following equations, the symbol is the multiplication operator, and W represents the weight vector. Also, b indicates bias terms.

$$\text{Input gate}: \ f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f) \tag{1}$$
$$\text{Output gate}: \ i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \tag{2}$$
$$\text{Forget gate}: \ o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \tag{3}$$
$$\text{Input node}: \ g_t = \varphi(W_{gx}x_t + W_{gh}h_{t-1} + b_g) \tag{4}$$
$$\text{Memory cell}: \ s_t = g_t \circledast i_t + s_{t-1} \circledast f_t \tag{5}$$
$$\text{Hidden output}: \ h_t = \varphi(s_t) \circledast o_t \tag{6}$$

B. ONLINE LSTM

Unlike batch learning, in the online LSTM, the model evolves continuously as new data arrives. It is worth to mention that this is different from retraining the batch LSTM, frequently, or once a new data is received. With the same LSTM block structure as presented before, the update derivation would be different. To update the online LSTM weight vector W, a common stochastic gradient descent (SGD) algorithm can be used as follows:

$$W_{t+1} = W_t - \eta_t \nabla_{W_t} L \tag{7}$$
$$L = (d_t - \hat{d}_t)^2 \tag{8}$$

where η is the learning rate, and ∇_{W_t} indicates the gradient of loss function L with respect to W_t. Indeed, the loss function L is the squared error over one training sample [28]. However, through the batch learning technique, the loss function is calculated based on the cumulative squared errors.

Amongst several extensions introduced for updating the neural network instead of classical SGD, adaptive moment estimation, known as Adam, is one of the most efficient alternatives which considers the exponential moving average of gradients [29]. Following the same approach as discussed in SGD, this paper utilizes Adam for updating the weights.

C. MULTI-INPUT SINGLE-OUTPUT (MISO) LSTM

A common approach to deal with the short-term residential load forecasting problem is to consider the time series of the specific household load consumption and try to predict the next step value of the household. Here, we call such an approach a single-input single-output (SISO) model, which means the only load consumption input to the forecasting model is the time series that belongs to the household; however, other features, such as calendar or temperature information, might be taken into account. This is same for the aggregated load time series. Apparently, through the SISO forecasting model, only temporal dependencies are considered.

To consider the spatial dependencies in the forecasting, a MISO model based on the batch LSTM network has been used. In better words, the time series of a group of households are set as the LSTM input to predict a target household's time series. Similarly, all the households' time series associated with the aggregate level are simultaneously deployed to forecast the next aggregated value. As depicted in FIGURE 2, data of multiple households are feed to the model, and therefore, spatial relationships among them are taken into account during the training. Indeed, the resulted LSTM model is a multivariate kind with the number of features equal to the number of households available that taken spatial-temporal dependencies into account. It is noteworthy that an approach has been presented for aggregated load forecasting in [15], in which, firstly, all the individual households are separately forecasted, then the resulted values are added up as the aggregate prediction. This approach, indeed, lies in the SISO model as the effect of individual time series on each other are not considered. Moreover, the proposed MISO model can also be applied for load or energy forecasting at the system level, where substation zones are treated like single households in the proposed method.

FIGURE 2 illustrates the complete framework, in which calendar information has been added as well. The normalization with the range of (0,1) and (−1,1) are respectively applied to the households' smart meter data for load and net energy forecasting. Timestamps and calendar information are extracted to be used as separate categorical features. In this regard, the step of the day, the day of the week, and holidays/working days are marked and passed through the LSTM model by a one-hot encoder. The generic form of the LSTM framework has n hidden layers, after which a dropout is used to improve the performance of training by reducing overfitting problem. It is worth noting that the details discussed in this paragraph, such as calendar input, normalization, the encoder, etc., have applied to the batch LSTM described on the previous section as well.

D. MEASURING METRIC

A few common accuracy measures are used in load/energy forecasting area, such as MAE, root mean square error (RMSE) and MAPE. Among them, the MAPE, defined in (9), is the most popular and common index used in load

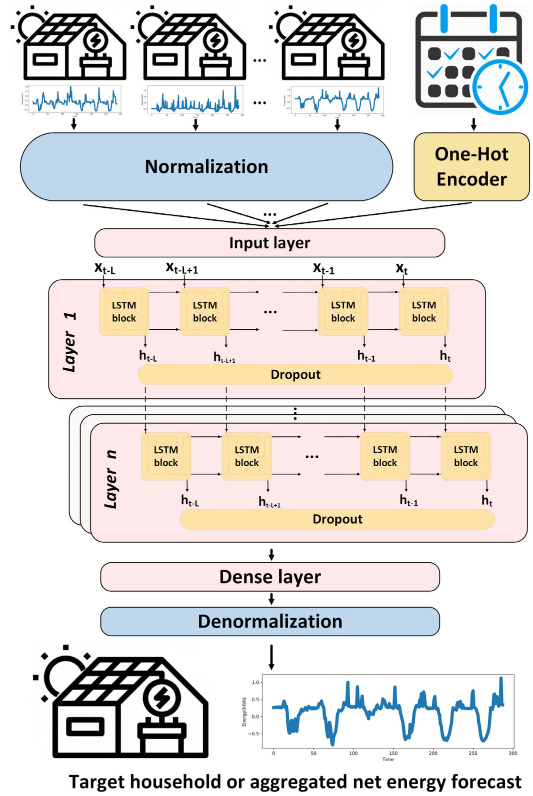


FIGURE 2. Multi-input single-output LSTM to consider spatial dependencies for short-term net energy forecasting.

forecasting, mainly due to its scale-free attribute.

$$MAPE = \frac{1}{N}\sum\nolimits_{t=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| \tag{9}$$

where A_t and F_t are actual and forecasted values, respectively. Also, N is the number of forecasted samples.

Despite the advantages of MAPE, it suffers from a significant drawback when actual values are equal to zero, which almost never the case in load forecasting. It is worth to note that even for a single user, the total load consumption of all appliances is often more than zero. However, for the net energy forecasting, values sometimes oscillate around zero, and therefore, MAPE approaches to infinite and would not have a desirable performance. To address the issue, this paper uses the mean arctangent absolute percentage (MAAPE) index recently introduced in [30], not only retaining the advantage of MAPE but also presents very similar values in some cases and stays more robust against outliers. The MAAPE index is expressed as follows:

$$MAAPE = \frac{1}{N}\sum\nolimits_{t=1}^{N}\arctan\left(\left|\frac{A_t - F_t}{A_t}\right|\right) \tag{10}$$

Obviously, MAAPE is the arctangent transformation of MAPE that inherently retains the MAPE distinguished features. Besides, MAAPE and MAPE represent very similar behavior for a small amount of $\left|(A_t - F_t)/A_t\right|$. Indeed, for the forecasting errors around 0 to 0.5 (0% to 50%), MAPE and

MAAPE produce very close measures due to the similarity of functions y = x and y = arctan(x) in the given range. It is also noteworthy that large forecasting error spikes, which are far from the mentioned similarity range, are penalized more heavily by MAPE. However, because the average forecasting error of both single household and aggregate levels is in the similarity range, this metric reasonably penalizes the forecasting error of load/net energy [30].

III. NUMERICAL RESULTS

The simulations are presented in three main parts (Section III.B to III.D). In the first part, the results illustrate the forecasting challenges comparing load with net energy predictions, while the second and the third parts are based only on net energy forecasting. Specifically, the second part relates to applying On-line LSTM at individual and aggregate levels, and the third part focuses on considering the spatial dependencies. The proposed LSTM-based model has been programmed in Python using Keras package with Tensorflow backend.

A. CASE STUDY AND SETTINGS

Through Australia's National Energy Analytics Research (NEAR) program initiated by Commonwealth Scientific and Industrial Research Organisation (CSIRO), the half-hourly solar generations and load consumptions of thousands of households in New South Wales (NSW) have been collected by Ausgrid, of which 300 households' data is publicly released from July 2010 to June 2013 [31]. Among them, 65 households over a whole winter season in Australia (from June 1, 2012, to August 31, 2012) have been considered in this study. The data is divided into the training, validating and testing subsets with a 70:20:10 split. In addition to the Ausgrid data that has been used for the major parts of our analyses, another dataset from Solar Analytics (case study in Section III.C) has been used to show the impact of higher granularity on the forecasting model. The Solar Analytics data contains rooftop PV generation of 1000 residential sites across Australia, with 5 minutes sampling rate during the year 2019.

Through various trial and error scenarios, the hyper-parameters have been set to achieve optimal solutions. Although the optimal neural network structure might be slightly different from customer to customer, a fixed one has been selected for all customers based on the best average performance. Accordingly, the proposed LSTM comprises 2 hidden layers with 100 neurons on each. The dropout percentage rate is set to 20%, and the look-back step is equal to 2. Also, batch size and epochs are considered to be 64 and 100, respectively. To update the network weights through the iterative based procedure, Adam optimization algorithm is used.

B. LOAD VS NET ENERGY FORECASTING- BASE LSTM

As the Ausgrid dataset contains smart meter records of consumption load and rooftop PV generation of the households by separate measurements, we are able to investigate load forecasting and net energy (summation of demand and generation) forecasting and scrutinize them. In doing so, the base (offline) LSTM, which is proposed in [15] as one of the most efficient and superior models for residential level so far, has been tested on the case study.

FIGURE 3 and FIGURE 4 demonstrate the results for a typical household with average range of volatility (ID: #230) and aggregated load/net energy. It is worth noting that the test period is during 23-31 Aug. 2012; however, time illustration in these figures is limited in a way to have the best presentation of load fluctuations as well as mapping forecast to actual values. Moreover, TABLE 1 illustrates the forecasting summary for load versus net energy at both single household and aggregate levels. Not only does this table show comparison between the accuracy of load and net energy forecasting, but also indicates the functionality of MAAPE comparing to two scale-free metrics, nMAE and MAPE. (the nMAE is calculated as $\frac{1}{n}\sum_{t=1}^{N}|A_t - F_t| \Big/ \frac{1}{n}\sum_{t=1}^{N}|A_t|$, that is the MAE over the average of actual values).

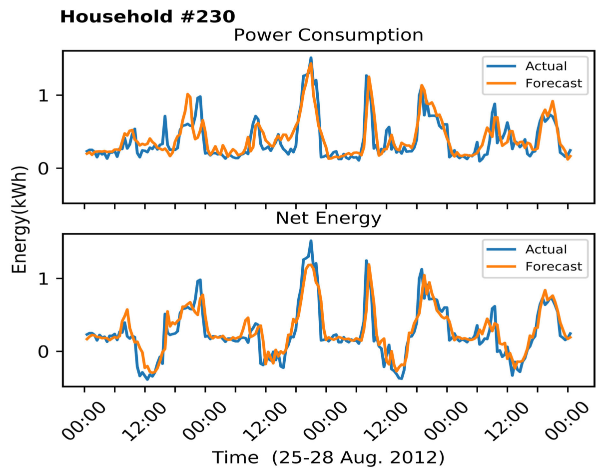


FIGURE 3. Load vs net energy forecasting for a typical household (ID: #230).

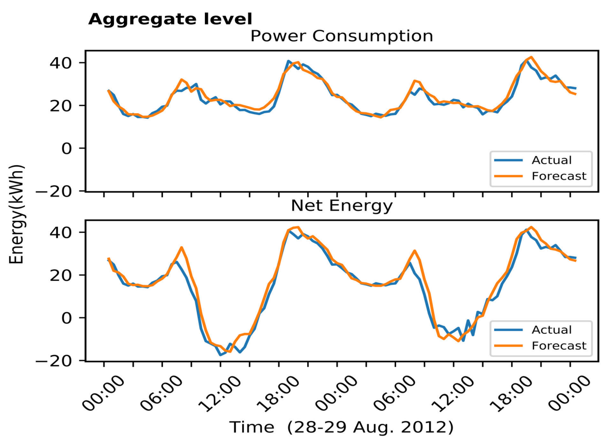


FIGURE 4. Load vs net energy forecasting for aggregate level.

For load forecasting, MAPEs related to the household and aggregate levels are respectively 0.4488 and 0.0813, which

TABLE 1. Free-scale metrics comparison (Base LSTM result).

Level	Load Consumption			Net Energy		
	MAPE	nMAE	MAAPE	MAPE	nMAE	MAAPE
HH[1]	0.4488	0.3478	0.3225	∞	0.4317	0.4168
AGG[2]	0.0813	0.0762	0.0807	0.5844	0.1246	0.2016

The reported numbers for household (HH) level is the average of all individual households' metric.
[1] HH: Household, [2]AGG: aggregate

are close to those reported in [15] with a different case study (0.4 and 0.09, respectively). However, for net energy, the MAPE shows some shortfalls. As can be seen, for single household net energy prediction, this metric approaches to infinite as some zero values are recorded by some households' smart meter. Also, for the aggregate level, the MAPE is unreasonably large (0.5844). Please notice that no zero value obtained by aggregation, but some values are close to zero, and by putting them into the fraction of equation (9), the result would be slightly large. This table explicitly demonstrates the weakness of MAPE when it comes to net energy forecasting. On the other hand, metrics nMAE and MAAPE are close and have similar behavior for load. This similarity is also consistent for net energy at the single household level. However, the result for aggregate net energy level is different. Indeed, MAAPE has put more penalty than nMAE does. As it is expected, to capture the error by nMAE, some of the detail has lost because of the aggregation of errors done before the averaging, and therefore, the error shown by this metric is considerably lower than MAAPE. It is worth to note that MAAPE, like MAPE, computes the error over every data point across the testing set, and then averaged. Thus, higher errors can be captured by MAAPE.

The obtained LSTM forecasting results have also been benchmarked against ARMA and persistence algorithm in TABLE 2, showing its efficiency. In the persistence algorithm, the next value is assumed to be the same as previous value. As it can be seen, the persistence model leads to close, but a little worse, results to those obtained by base LSTM; however, the performance of base LSTM will be further enhanced in the following sub-sections by the online and MISO LSTM models. Furthermore, the MAAPEs for single household and aggregated net energy levels are 0.4168 and 0.2016 based on LSTM model that clearly shows adding another source of uncertainty, i.e. rooftop PV generation, to the load results in lower forecasting accuracy, as it is expected. But the most significant point that can be seen from TABLE 2 is that the amount of error caused by adding rooftop PV generations to the demand loads is very considerable for aggregate level comparing to the residential level. The above sentence means by installing rooftop PV at the residential level our energy forecasts would become approximately 30% worse (from MAAPE 0.3225 to 0.4168) in residential level, while this amount for the aggregate level is far more intense, near 250% (from MAAPE 0.0807 to 0.2016). Although there are a handful of works in which net energy forecasting at the aggregate level (not residential level) has been done with the similar amount of error [20], [21], this is the first time,

TABLE 2. Load vs net energy forecasting comparison between base LSTM and two baselines.

Level	MAAPE					
	Load Consumption			Net Energy		
	Base LSTM	Persistence Algorithm	ARMA	Base LSTM	Persistence Algorithm	ARMA
HH[1]	0.3225	0.3600	0.4787	0.4168	0.4276	0.5902
AGG[2]	0.0807	0.0814	0.1145	0.2016	0.2319	0.2949

The MAAPE index reported for household (HH) level is the average of all individual households' MAAPEs.
[1] HH: Household, [2]AGG: aggregate

to the best of our knowledge, that this importance is raised. Indeed, this issue has been unseen mainly because no comparison has been made or even possible to be made between load and net energy forecasting. The latter case occurs, especially, when many smart meters in the grid do not separately measure households' generations and consumptions. This problem caused would be a significant challenge that needs to be known and responded as the concept of forecasting is shifting form load to net energy in today's smart grids.

To deeply investigate the above mentioned problem, distribution of error for each step of the day (half-hourly data results in 48 steps) has been plotted in FIGURE 5. Each point of the graph indicates the average of MAAPE at a certain time step for all testing subsets. In better words, FIGURE 5 shows the performance of the used LSTM at every step of the day over the testing set.

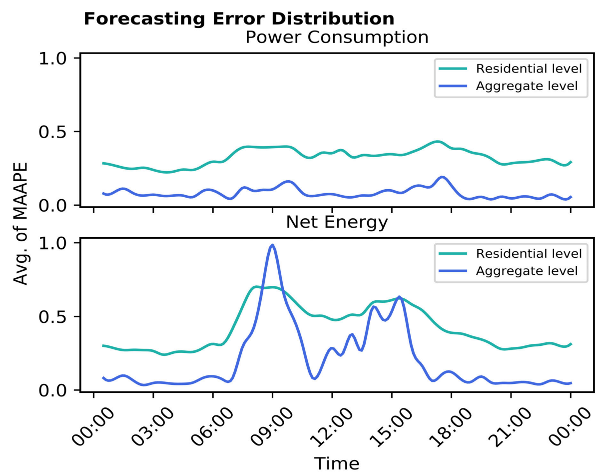


FIGURE 5. Distribution of forecasting error for each step of the day over the training set.

As illustrated, the *load forecasting* error distributions (the top plot of FIGURE 5) for households and aggregated level follows a similar pattern, where the error related to residential level is higher than that of aggregated one, at all steps. Also, it can be observed that errors for morning and evening peaks (between 07:00-10:00 and 16:00-19:00, respectively) are relatively higher than the rest of the day. By including rooftop PV generations, the trend of *net energy forecasting* error distributions (the bottom plot of FIGURE 5) remarkably changes during daylight hours. As it is expected, the errors increase over this period (between 07:00-17:00) for both households and aggregate level due to new uncertain source inclusion. However, surprisingly, the error of aggregate level tends to be closer to the residential one and even can be higher sometimes (such as in 09:00). Two following reasons are most likely to justify such a behavior:

- Firstly, it is worth to note that a decisive factor affecting rooftop PV generation of one household at each time step can be a mass of cloud passing above the rooftop panel. However, for the aggregate level, many masses of clouds are involved at each time step, which in turn intensify the uncertainty. This scenario is worse when working with a case study, including the case in this paper, where the households are not in one neighborhood, such as a complex or a feeder (the drawback of many datasets).
- Secondly, if closer attention is paid to the error distribution of the net energy for the aggregate level, it can be seen that there are two surges. These times happen when sudden changes in load demand and PV generations coincide, i.e. a combination of morning load peak and steep rise of PV generation, or evening load peak and steep drop of PV generation in the evening. In such circumstances, which are similar to the duck curve effect in utility-scale, the two uncertainty sources negatively intensify each other. As a result of that, the aggregate net energy profile experiences a relatively significant difference in value within 1 hour in morning and evening.

C. THE NEED FOR FINER GRANULARITY FOR NET ENERGY FORECASTING

Having the previously mentioned *second* reason next to the fact that the granularity of the case study is 30 minutes, raises the possibility that the data resolution might not be fine enough to track and predict such changes, and consequently, contributes the relatively high error as depicted in FIGURE 5. This has encouraged us to examine the performance of the forecasting model with higher resolution dataset. Although Ausgrid provides valuable dataset for net energy at the household level, its half-hourly resolution places some limits to go beyond. Moreover, as pointed out in [3], lack of dataset for net energy forecasting is inhibiting new findings. Thanks to Solar Analytics dataset with a 5-minute granularity of residential PV generation, we are able to overcome the problem, particularly in our case. Because the forecasting challenge discussed above (FIGURE 5) is the direct effect of rooftop PV generations added to the load, using the Solar Analytics dataset would fairly reflect the trend in net energy forecasting. However, the ideal dataset would be the case study having residential *net energy* with *high-resolution* data.

To obtain sensible results and conclusion, we have selected households' data from Solar Analytics similar to Ausgrid in terms of quantity, location, seasonality and subsets splitting. In doing so, 65 houses in NSW have been selected with a 70:20:10 split over the winter season. As the data is recorded every 5 minutes, they are firstly filtered for every 5, 10, 20, 30 and 60 minutes' intervals to create different scenarios. Through each scenario, the LSTM model is trained separately. The obtained forecasting results over the testing subset are reported in TABLE 3 for different resolution-based scenarios.

TABLE 3. Summary of aggregated PV generation forecasting (LSTM).

Forecasting error	Resolution				
	5 min	10 min	20 min	30 min	60 min
MAAPE	0.1379	0.1477	0.1842	0.2310	0.3547

Firstly, as can be seen from TABLE 3, finer granularity significantly improves the forecasting performance. For instance, the accuracy increases by 67% as the resolution varies from 30 minutes to 5 minutes (form MAAPE 0.2310 to 0.1379). Secondly, if we compare TABLE 2 and TABLE 3, it is revealed that the error of aggregated PV generation forecasting with the resolution of 30 minutes (MAAPE = 0.2310) is close to the error corresponding to aggregated net energy forecasting, i.e. MAAPE = 0.2016 (recalling that the Ausgrid data has a 30-minute resolution). The two mentioned points, indeed, imply that how closer observation (higher resolution) has a considerable potential to enhance aggregated *net energy forecasting.*

Furthermore, to investigate whether or not the higher resolution data could mitigate the problem shown in FIGURE 5, forecasting error distributions pertaining to resolution-based scenarios have been extracted. Top plot of III-D shows the testing subset for which the forecasts have been made. As it is clear, the aggregated PV generation is a non-stationary time series and it is highly affected by cloud movement. Once forecasts have been produced over the testing subset, the distribution of forecasting error can be plotted based on each time step (the bottom plot of III-D). It is worth mentioning that the PV generation of a selected day (8^{th} day of the training subset) has been mapped to the forecasting error distribution plot to illustrate how they vary concerning each other over the daylight hours. As can be seen, the hourly data has a remarkably poor performance comparing to other scenarios; thus, we put it aside in our further discussions. Moreover, error obtained by different resolutions between 11:00 until 16:00 are very similar and relatively pleasant. More importantly, what stands out in this figure is the trend for the resolution of 30 minutes (the exact resolution used in Ausgrid data). By comparing the green graph (related to the 30 minutes' resolution) to the other resolutions, it can be observed that the error due to 30 minutes' data tends to stay high between 08:00-11:00 as well as around 16:00-1700, while other resolutions showing lower errors. These hours specifically include times that aggregate PV generation experiences a relatively steep rise or drop (the same trend discussed in FIGURE 5). By recalling the similar challenge for net energy forecasting, it seems the resolution of half-an-hour is not fine enough to capture sudden changes posed by aggregate PV generation. On the other hand, it is clear from this figure that the 5 and 10 minutes' resolutions are rather resilient to such changes. In conclusion, to achieve accuracy

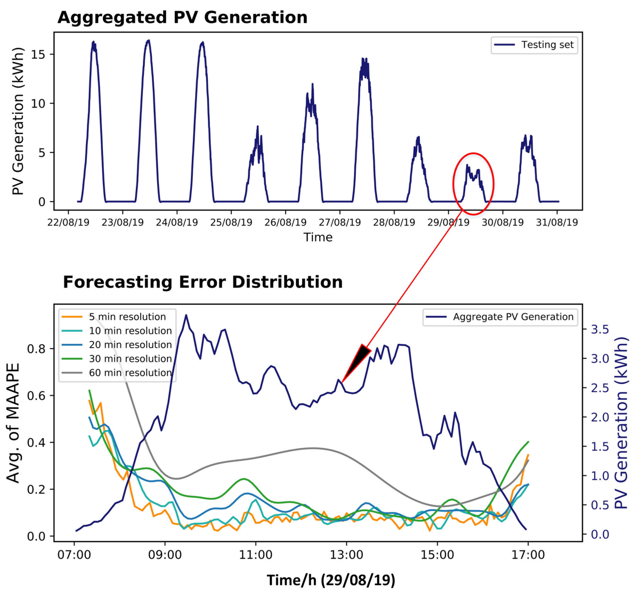


FIGURE 6. Aggregated rooftop PV generation forecasting for various resolution. Top plot: Aggregated PV generation over the testing set. The bottom plot: Distribution of forecasting error over testing subset.

for aggregated *net energy* forecasting to be in the range of *load* forecasting one, a finer granularity is essential.

D. ONLINE LSTM

The online LSTM described in Section II has been applied to the end-user and aggregated net energy time series. The LSTM structure is the same as one used for base LSTM; however, the batch size is considered to equal as 1 through the stateful training. As a matter of clarification, it is worth to note that by *online*, it means the weights are updated once a new observation is received. This is different from re-training the whole model for each new observation.

TABLE 4 reports the corresponding results while compared with the base LSTM. The obtained results show that the online training can improve forecasting at the household level, while forecasting performance at the aggregate level might get worse. For our case, net energy forecasting at the household level has increased by 7.3% (from MAAPE 0.4168 to 0.3867). The main reason for such results is that the fluctuations and uncertainty at the aggregate level are far lower than the household level, which makes the aggregate level forecasting more predictable to household level. Therefore, better performance is achieved through *batch learning*, which is the method used in the base LSTM. On the other hand, online LSTM is more capable of being adapted to new trends of which it has not been trained before. This is why the obtained results by online LSTM for household level outperform those of base LSTM. This type of behavior is more likely to happen at household levels. Households off-holiday travel, rooftop solar panel maintenances or fault detecting periods are typical instances causing unexpected changes in the pattern of household net energy time. However, they could be imperceptible for the aggregate level.

TABLE 4. Online LSTM vs base LSTM- Net energy forecasting results.

Level	MAAPE*	
	Online LSTM	Base LSTM
Household	**0.3867**	0.4168
Aggregate	0.2256	**0.2016**

* The MAAPE index reported for Household level is the average of all individual households' MAAPEs.

TABLE 5. Spatial-temporal LSTM vs base LSTM-Net energy forecasting results.

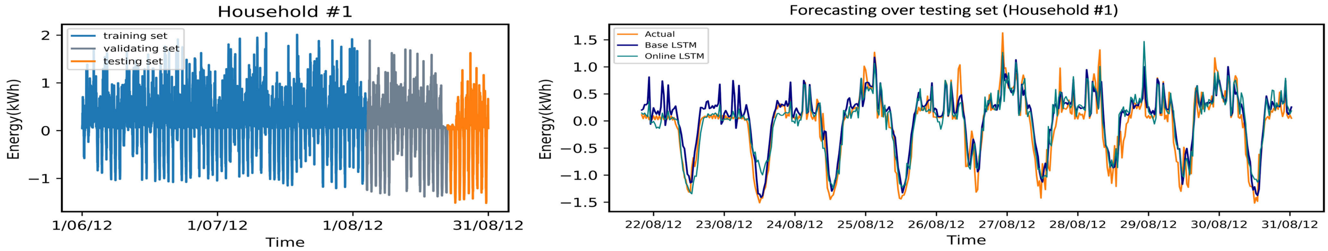
Level	MAAPE*		
	MISO LSTM	Online LSTM	Base LSTM
Household	0.4354	**0.3867**	0.4168
Aggregate	**0.1748**	0.2256	0.2016

* The MAAPE index reported for Household level is the average of all individual households' MAAPEs.

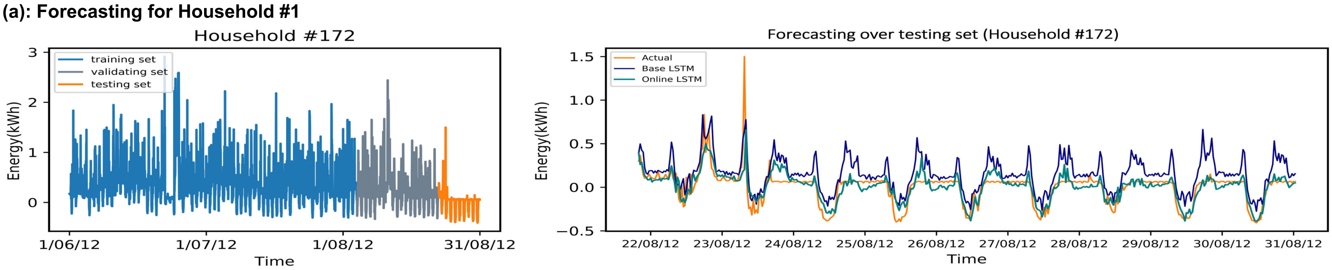
Households numbers 1 and 172 with sudden zero load demand are just two out of many examples within Ausgrid data. As depicted in FIGURE 7, there are new trends in the net energy time series of households. The left hand profiles in FIGURE 7 show the data split over train, validation and test steps. Obviously, if the model is trained and validated according to base LSTM, it is most likely to have poor performance over testing set as the new trends occur within the training set. The forecasted results support the expectation. In FIGURE 7-(a), household number 1, has no demand load for the two first days of the training set. Apparently, base LSTM is not able to forecast this new trend; however, online LSTM is closely following the ground truth over these days. Also, the load demand for household number 172 (FIGURE 7-(b)) drops to near zero from the second day of the training set on. Similarly, online LSTM has the best performance with adapting the changes. As it can be seen, online LSTM has desirably matched the actual values, especially from 29/08/12 to 31/08/12.

E. SPATIAL DEPENDENCY CONSIDERATION- MISO LSTM

To include the impact of all households' net energy data in forecasting a specific household or the aggregated net energy, the proposed MISO version of LSTM has been applied on the case study. Applying a similar network structure and hyper parameter to the based LSTM, the obtained results are tabulated in II, while compared to base and online LSTM. As it can be seen, considering all residential time series as multivariate LSTM has reduced the forecasting error by 13.2% compared to the base LSTM (from MAAPE 0.2016 to 0.1748). On the other hand, this approach could not have a positive effect on household level forecasting. FIGURE 8 shows the box-and-whisker plot of households' net energy forecasting results for the base, online, and spatial-temporal (MISO) LSTM approaches with interquartile range. From this figure, it is clear that the residential errors resulted by online LSTM are more concentrated with



(a): Forecasting for Household #1



(b): Forecasting for Household #172

FIGURE 7. Online vs base LSTM net energy forecasting results for two households (#1 and #172) experiencing unprecedented changes over their training sets.

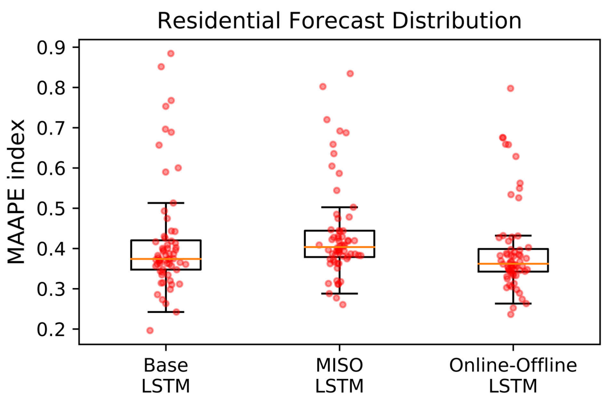


FIGURE 8. Box-and-whisker plot of the 65 households' net energy forecasting for different LSTM approaches.

the lowest average. Moreover, the plots corresponding to the base and spatial-temporal LSTMs shows that the error distribution produced by spatial-temporal LSTM is more condense; however, it has a higher average. As a result, the online and MISO LSTM approaches respectively have the best performance for household and aggregate levels.

IV. CONCLUSION

This study steps towards addressing today's inevitable problem caused due to the fusion in energy forecasting at household and aggregate levels where the customers have installed rooftop solar PV panels. In doing so, this paper, firstly, builds up a forecasting model based on one of the most efficient existing LSTM model (base LSTM) to explore the challenges of short-term net energy prediction. Also, the problem of conventional MAPE index, which becomes an infinite number when the ground truth is zero, is resolved by using the MAAPE index with similar functionality. The obtained results show that the forecasts deteriorate at both single household and aggregate levels while moving from load to net energy forecasting, owing to the added source of uncertainty behind the meter, i.e. PV generation. However, the downturn associated with the aggregate level is more intense, especially during 2 hours in the morning and evening. The evidence indicates over these hours PV generation usually experiences its steepest rise and drop, and the load demand is in the morning peak and the start of the evening peak hours. Besides, the effect of data granularity level is examined by applying the model on a real dataset with 5 minutes' resolution. The figures reveal that to have accuracy for the aggregated net energy forecasting in a similar range of load forecasting one, the need for higher resolution data seems to be essential.

Furthermore, this paper proposes two deep learning approaches based on the LSTM framework to enhance the results obtained by the existing base LSTM. In doing so, online LSTM and MISO LSTM models are developed and tested on an Australian case study. Unlike conventional batch (base) LSTM, online LSTM updates the network weights as new observation received through a single batch. Also, in MISO LSTM, the historical data of all individual households are simultaneously used as inputs to forecast the target time series. The obtained results suggest online LSTM and MISO LSTM respectively improve net energy forecasting at end-user and aggregated levels by 7.3% and 13.2% compared with the based LSTM.

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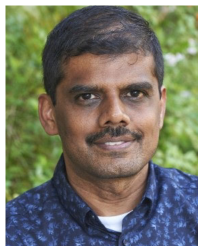

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