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Flexibility Forecast at Local Energy Community Level

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Flexibility Forecast at Local Energy Community Level

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***Abstract*—Large-scale integration of intermittent renewable energy resources into power systems increases the need for flexibility services such as frequency and voltage control. In the future, system operators need to utilize more flexible energy resources from all levels of the system in order to fulfill flexibility needs. Aggregated customers in form of a local energy community (LEC) are potential resources which can provide a part of the required flexibility. In this regard, accurate forecasting of flexible capacities of a LEC is essential. This paper proposes a methodology to estimate the flexibility of a LEC based on the LEC's predicted consumption. In addition, the paper suggests a novel prediction method which is based on a three-branch architecture using recurrent neural networks (RNN) and long short-term memory (LSTM) units to forecast the consumption of the LEC considering its temporal dependencies. Finally, the proposed prediction methods are implemented on a case study and the results are compared with each other.**

Keywords—flexibility forecasting, flexibility estimation, RNN LSTM, electricity demand prediction, local energy community

I. Introduction

The high penetration of intermittent renewables into power systems along with the growing number of distributed generation (DG) has increased the flexibility needs at different voltage levels of the power system. As a result, system operators (SO) need to adopt more flexible energy resources (FER) to increase the network's hosting capacities for accepting more uncertain and renewable power [1]. Small-scale customers with various FERs, located at distribution networks, can potentially benefit the future power system by forming a LEC [2]. The main target of a LEC is typically to reduce the total cost or make profit through flexibility services provision to the distribution system operator (DSO) and/or transmission system operator (TSO). However, to deploy these flexibilities, the LEC needs to correctly forecast the amount of flexibility that it could provide as flexibility services utilizing the energy resources of its members.

The accurate prediction of LEC's available flexibility requires the accurate prediction of LEC's total consumption. In this regard, some proposals tried to develop models for electricity consumption prediction using either statistical methods or machine learning algorithms (e.g. [3]–[8]). Although the electricity consumption is naturally uncertain, one can extract a pattern by modeling the short-term and long-term temporal dependencies. In this way, [9] aimed to model the short-term dependencies using RNN while [10]–[14] suggested to integrate LSTM units to consider long-term dependencies as well as short-term ones. These mentioned studies were dealing with predicting the loads of the non-responsive (i.e. non-active/flexible) customers. They did not consider the responsive active customers which could provide the required flexibility for the DSO and TSO.

In the context of flexibility forecasts, [15] proposed a method to predict the response of the aggregated loads using the RNN algorithm. However, the work did not introduce the network architecture of RNN in detail. In addition, as mathematically proved by [16] the prediction models using "vanilla" RNNs suffer from the vanishing or exploding gradient, which affects the prediction accuracy. In order to solve this issue, this paper introduces a model to improve the flexibility prediction of LEC members' controllable loads/flexibility resources. The main contribution of this paper can be summarized as follows:

1) This paper proposes a method to estimate the flexibility of the LEC based on the predicted controllable loads of its members. In our model, members of the LEC receive flexibility signals indicating the flexibility directions. The members react to these signals accordingly to provide the SO with the required active power (*P*)-related flexibility.
2) The paper develops a novel three-branch RNN-LSTM architecture for predicting the consumption of the community. The proposed model is also compared to the existing one-branch architecture and the results are demonstrated by simulations based on real-life customer data.

The rest of the paper is organized as follows. Section II presents the methods of estimating flexibility of the LEC based on the predicted consumption. Section III introduces the proposed prediction model and the network architecture utilized for forecasting LEC's load. Section IV implements the model on a case study and compares the results. Finally, Section V concludes the paper.

II. Flexibility of LEC

In this study, we assume that the LEC manager is responsible for coordinating the LEC's members, passing the flexibility signals to the members, predicting LEC's flexibilities and sending these predictions to the system operators. Fig. 1 visualizes the considered model. The LEC manager is assumed to transfer flexibility signals from the SO to the LEC's members. These flexibility signals are in the shape of "up", "down", or "none", regarding each time slot. If the signal is "up", the LEC manager requests the LEC's members to provide upward flexibility (i.e. decrease active power load/consumption or increase active power generation). Accordingly, the members try to inject the active power to the grid by, e.g. reducing their consumption/demand. In contrast, if the flexibility signal is "down", the members are required to decrease their generation/production or increase their consumption at a specific time slot. Finally, when the LEC manager sends "none" signal, it states that the members do not need to change their consumption/production.

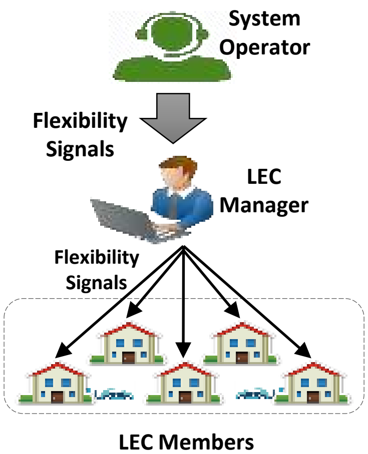

Fig. 1. The architecture of the proposed LEC

The SO should send the LEC manager its flexibility need. Based on these signals, the LEC manager predicts how the LEC's members must react to these signals. If the members of the community are responsive, their home energy management system (HEMS) controls their flexible appliances and devices based on flexibility signals. Thus, the control of these appliances is dependent on the flexibility signals. In addition, most of the controllable devices of the LEC have temporal dependency. In other words, their operation during the current time slot is affected by their operation in previous time slots. As a result, the demand of the community with responsive members is not only dependent on the flexibility signal at the current time slot, but also the signals of the previous time slots affect the current load value.

The LEC manager must take into account the direction of flexibility signals (up/down) to be able to predict the flexibility of its members. It is considered that the LEC manager predicts the flexibility of its members for a specific time period. Therefore, the flexibility signals of that time period should be known by the LEC manager. The flexibility signals of the LEC are in shape of a vector with "up", "down" and "none" signals for each step during that time period. For instance, if the LEC manager aims to forecast the hourly flexibility of the LEC for the one-day horizon, it should know 24 "up", "down", and "none" flexibility signals.

In order to forecast the flexibility of a LEC, manager needs to forecast the community's load with and without the flexibility signals. Hence, the flexibility of the LEC is a result of subtracting the value of the LEC's load without flexibility signal from LEC's load in with the flexibility signal [15]. Eq. (1) mathematically shows the LEC's flexibility.

$$Flex_t^{for} = P_t^{for}\left(\forall u_t^{flex} \neq \text{"none"}\right) - P_t^{for}(\forall u_t^{flex} = \text{"none"}) \tag{1}$$

Where, $Flex_t^{for}$ is the forecasted flexibility of the LEC at t, $\mathrm{P_t^{for}}\left(\forall \mathrm{u_t^{flex}} \neq \text{"none"}\right)$ is the total load with flexibility signal $\mathrm{u_t^{flex}} \neq \text{"none"}$. In comparison, $\mathrm{P_t^{for}}(\forall \mathrm{u_t^{flex}} = \text{"none"})$ is the LEC's load without flexibility signal (or when the flexibility signal is "none").

In addition, a novel model is proposed to obtain more accurate prediction of flexibility. In this model, the LEC manager only predicts the loads of the controllable devices/load of the LEC. A community member such as a household, has some uncontrollable and controllable (i.e. flexible) appliances and devices. The TL of this member is the total consumption of these appliances [17]. However, only flexible (i.e. controllable) appliances can provide flexibility. We assume that there is HEMS (or a sub-metering device) in each household, measuring the consumption of controllable devices and the LEC manager has access to the measured data. In this regard, the LEC manager predicts the flexibility based on the controllable loads of the LEC as follows:

$$Flex_t^{for} = Pc_t^{for}\left(\forall u_t^{flex} \neq \text{"none"}\right) - Pc_t^{for}(\forall u_t^{flex} = \text{"none"}) \tag{2}$$

Where, $\mathrm{Pc_t^{for}}\left(\forall \mathrm{u_t^{flex}}\right)$ is the consumption of the controllable appliances of the community with flexibility signal $\mathrm{u_t^{flex}} \neq \text{"none"}$. In comparison, $\mathrm{Pc_t^{for}}(\forall \mathrm{u_t^{flex}} = \text{"none"})$ is the LEC's controllable load without flexibility signal.

III. Consumption Forecast Using RNN and LSTM

Recurrent Neural Network (RNN) is a type of Neural Network (NN) with the capability to consider the temporal dependencies. In this way, it utilizes feedback connections to model the dependencies of the outputs within specific time period. For instance, it can relate the output at time slot t to those of previous time slots (t-1, t-2… t-m). For this purpose, the RNN adopts back-propagation through the time period to model these dependencies between output nodes [10]. However, the learning process associated with modeling time dependencies between outputs can adversely affect the prediction since there is a possibility that the gradients representing temporal dependencies vanish or explode over time. Ref. [16] explain the problem with more details.

One solution to the mentioned problem is to use LSTM activation function. The LSTM has a transient memory as well as three gates, one for the input, and two for outputs including "forget" and "remember" gates. The input going through the LSTM activation function can either be forgotten or kept as an output. During the training phase, the algorithm can adaptively learn how to activate the transient memory. In this way, the long-term dependencies as well as short-terms ones that have strong effects on the outputs are being preserved while those with minimum impacts are forgotten. Hence, the LSTM can lead to a more accurate forecast of the loads of the LEC by modeling the long-term dependencies of the LEC's demand as well as the short-term dependencies resulted from thermal controllable and/or storage-based devices.

A. Model Inputs

The LEC's load profiles can be affected by different inputs. One key input can be the day of the week. This input is an important factor impacting the consumption behavior of the households. For example, the consumption behavior of the household during weekend is typically different from working days. In addition to the weekday, flexibility signals are other effective factors that should be taken into account. As previously mentioned, the flexibility signals are sent by the SO to the LEC manager. Since the members of the community are assumed to be responsive for monetary outcomes, they will react to these signals through their controllable appliances. The predictions or actual values of the LEC's loads in the previous time slots are other inputs of our prediction model. In this paper, we restrict the time dependencies of the load to 24 hours (i.e. day-ahead). It means that at each hour, the values of the previous 24 hours are considered for predicting the current consumption. Thus, for the LEC's load at each hour, the prediction problem can be formulated as follows:

$$P_t^{for} = f_i(P_{t-24}^{\frac{for}{act}} \dots P_{t-1}^{\frac{for}{act}},\ u_{t-24}^{flex} \dots u_t^{flex},\ W_{t-24} \dots W_t) \qquad (3)$$

Where, W_t is the weekday on which the loads are predicted. Eq. (3) states that the forecast of the LEC's load at each hour requires the forecasted or actual values of the LEC's load at the previous 24 hours, the flexibility signals of the current hour (u_t^{flex}) as well as those of the previous 24 hours, and the weekday on which this consumption happens. The function $f_i(.)$ is obtained by training the proposed RNN model. Note that the related bias vectors as well as the weights of the function are built during the training phase of the model. The training datasets are extracted from the historical data of the LEC.

B. Model Description

In order to obtain a desirable forecast model, we should consider the following characteristics for the proposed prediction model [10]:

1) The prediction model needs to be adaptive and learn the training data automatically, without any manual intervention.

2) It needs to be able to model the short-term and long-term temporal dependencies of consumption as well as non-linear behavior of members' consumption.

According to the proposed model, each input of the problem should go through the following layers:

- Layer 1: This layer represents the input layer. The time granularity of the inputs are considered 1 hour and the time horizon of the prediction is 1 day. The training sample is denoted by X_{train} and $X_{train} \in \mathbb{R}^{D\times 24}$ where D is the number of training days.
- Layer 2: This layer is the LSTM layer playing the role of encoder layer. It accepts the input layer and the output of this layer sends as the input to the next layer.
- Layer 3: Similar to layer 2, this layer is the LSTM layer. However, it is analogous to the decoder layer.
- Layer 4 and Layer 5: These two layers correspond to the conventional NN. The output of the 5th layer is a 24-element vector representing the forecasted consumption of the LEC for each hour of the day, considering that specific input.

Since we define three type of inputs for our model in which each type of input builds an individual model. Thus, our proposed model has three branches and three different outputs are obtained for each type of input. The final step is to chain the outputs and introduce a model that accepts the combined outputs. The final model defines one unified output for the whole model. We define three layers with one hidden layer for the final model.

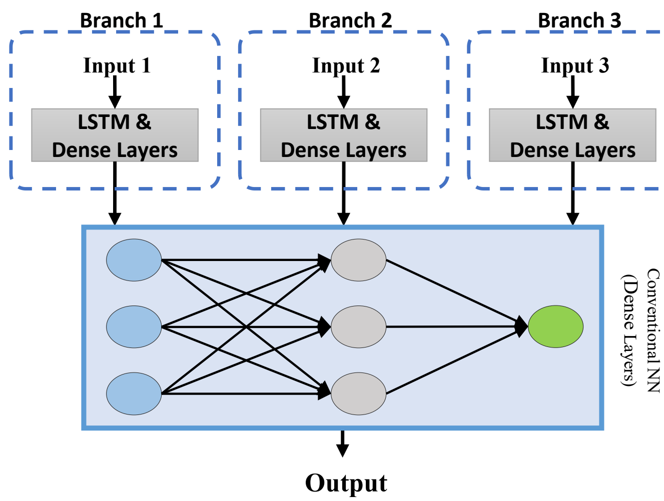

Fig. 2. The network architecture of the proposed predictoin model

Fig. 2 summarizes the proposed model and visualizes the related architecture. In this architecture, ADAM algorithm is employed to optimize the weights regarding each layer because it leads to the faster convergence than the conventional gradient descent algorithms [18]. ADAM algorithm utilizes a first-order gradient descent optimization which can be a suitable for a model with a high number of parameters [18].

IV. Case Study and Simulation Results

The proposed model has been implemented on a case study which is a hypothetical micro LEC which contains a number of residential households. We utilized the real-world consumption data of some residential households located in City of Vaasa, Finland, to build the uncontrollable loads of the LEC members. We then consider that each member controls its controllable loads, i.e. air conditioner (AC) and electric water heater (EWH), based on the flexibility signals sent by the LEC manager. Note that AC and EWH are the only controllable appliances of the LEC members. Regarding the households' thermal comfort, the house temperature should maintain between 21°-26° Celsius degrees and the hot water temperatures can only vary between 40°-60° Celsius. We assumed that these temperature ranges are set by the households in advance.

The flexibility signals were randomly generated for 24 hours of 30 days. According to these signals and the mentioned members' settings, the controllable devices are scheduled for 30 days, regarding 24-hour time resolution. The consumption of the ACs and EWHs are added to the uncontrollable loads of the households and utilized as training, testing and validation data for the developed and proposed model. In addition, to the consumption data, the flexibility signals and the weekday of the consumption are employed as inputs of the model. We used the consumption data of 29 days as training, testing and validation data and also used the last day of the month to predict the load.

Fig. 3 illustrates the steps of implementing our model to obtain the prediction. For scheduling and building the responsive loads of the members, GAMS software was deployed while the data analysis and the prediction model were conducted in Python using Pandas, Numpy, and Keras modules. In order to evaluate our prediction model, the coefficient of determination or R-squared (i.e. R^2) indicator is adopted.

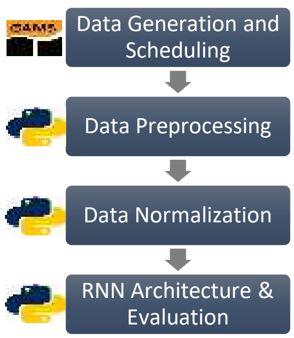

Fig. 3. The lists of steps taken to implement the prediction model

A. Consumption Forecast

The LEC's total demand was predicted for one day, using the historical data. Firstly, the prediction was made by the proposed model and the results are compared with the actual consumption data. Subsequently, we also developed another prediction model as a reference to compare our model with it. In this regard, we use a one-branch prediction proposed by [10]. Regarding one-branch model, the input layers including weekday, flexibility signals and previous consumption are chained. Afterwards, the inputs go through the LSTM and regular NN layers to generate the output. Fig. 4 demonstrates the results of different predictions, considering the proposed and one-branch models. Table I also depicts the R^2 indicator for the consumption predictions. According to these results, the proposed model consisting of three branches performed better compared to the one-branch model.

TABLE I. THE R-SQUARED INDICATORS FOR DIFFERENT PREDICTION MODELS

	Proposed prediction model	One-branch prediction model
R^2 indicator	**0.84**	0.67

The proposed prediction model was also utilized to forecast the controllable loads of a local energy community. In this way, the 29-day historical sub-metered data on LEC's controllable loads which obtained by scheduling are used to forecast the LEC's controllable loads. As previously stated, the LEC is considered to have ACs and EWHs as the members' controllable loads. The historical data include total consumption of these appliances for each hour of the previous 29 days. The results can be found in Fig. 5. As the Fig. 5 shows, the prediction model follows the actual load perfectly with a R^2 indicator equals to 0.99.

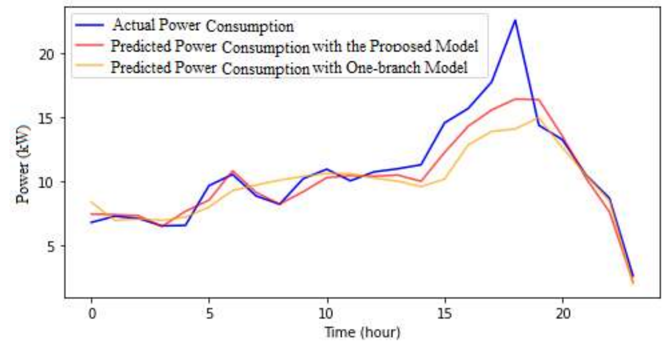

Fig. 4. The prediction of the LEC's total load obtained from the proposed three-branch model and the existing one-branch model

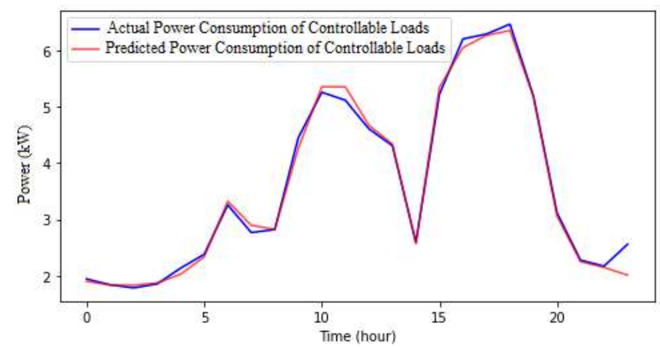

Fig. 5. The prediction of the LEC's controllable load using the proposed prediction model

B. Flexibility Forecasts

Having forecasted the loads of the community and controllable appliances according to the actual values of flexibility signal, the loads were forecasted again without flexibility signals. The values of loads without flexibility signals are subtracted from those with flexibility signals to estimate the flexibility of the community. First, the flexibility is estimated by subtracting the prediction of total load with flexibility signal and the prediction of total load without flexibility signal, as stated in Eq. (1). Then, again flexibility is estimated by subtracting the prediction of controllable load values with flexibility signals from those without flexibility signals, as proposed in Eq. (2). These values are depicted in Fig. 6. The values are compared with the actual flexibility obtained by scheduling of the controllable devices located in the community.

As the figure 6 illustrates, the flexibility values obtained by controllable load (i.e. CL) prediction can estimate the LEC's flexibility with an acceptable accuracy. In contrast, this estimation did not lead to accurate results using the total load (i.e. TL) prediction. Although the total trend has similarities, 6a did not even predict the right direction for the flexibility at some time slots. For instance, it did provide the accurate prediction for the flexibility direction at hour 4. However, the proposed model for estimating flexibility (6b), could predict the direction of flexibility accurately.

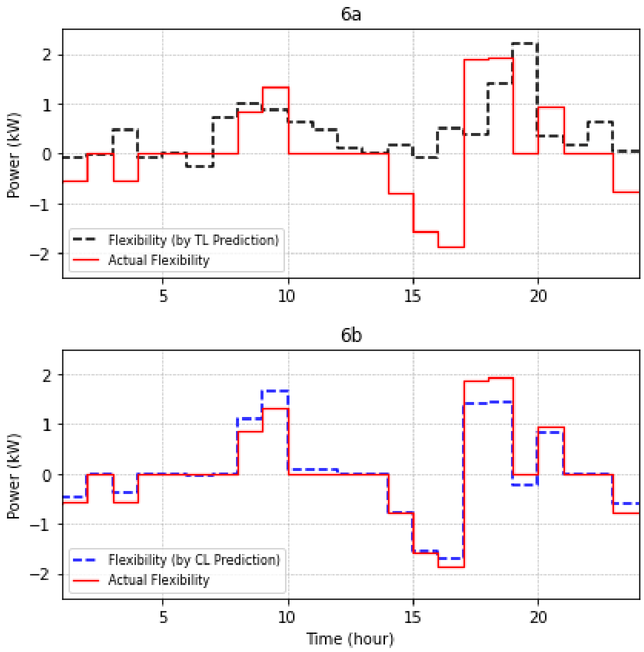

Fig. 6. Flexibility estimated by (6a): predicting the LEC's total load (TL) and (6b): predicting the LEC's controllable load (CL)

V. Conclusions

This paper focused on predicting the flexibility of a LEC. For this purpose, it was proposed to use the consumption of controllable loads with and without flexibility signals to estimate the flexibility of the community. To predict the consumption of the community, the paper introduced a three-branch RNN-LSTM network architecture.

The proposed prediction model was implemented on a case study consisting of a hypothetical LEC. The obtained R^2-indicator-value for the proposed prediction model proves that it can forecast electricity consumption with an acceptable. The indicator also demonstrates that the flexibility forecasts obtained from predicting LEC's controllable load lead to more accurate results compared to those resulted from predicting the LEC's total load.

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