Short-Term Load Forecasting of building electricity consumption using NARX Neural Networks model

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***Abstract*— Electric grid, as we nowadays know it, is undergoing a significant transformation. What we are now witnessing is an undoubted change of trend towards a decentralized and decarbonized electric grid, where the electric generation based on local resources will take on special relevance. In this context, the encouragement of collective self-consumption becomes one of the key issues when it comes to taking steps forward to this end. One of the aspects that will contribute to this aim is the development of a consumption-forecasting tool. Hence, a load-forecasting model based on NARX Neural Network is proposed in the following paper. The prediction of the next day (24h) load profile of an individual building is carried out aiming an optimal management of the flexible loads so to achieve the maximum self-consumption. To ensure a consistent behavior of the NARX Neural Network model, identification and removing of outliers, together with data normalization and fixing common time interval has been carried out. The first results of the research are promising, being obtained a 17,6% MAPE in NARX and 25,19% with LSTM model, both evaluated during a regular week on winter in adverse conditions .**

Keywords—Collective self-consumption, Artificial Neural Networks, Nonlinear Autoregressive Exogenous, Short-Term Load Forecasting, distributed generation, building electric consumption forecasting

I. INTRODUCTION

In a context where the global energy consumption, and in particular electricity consumption, is steadily rising, the management of energy generation and supply as well as the development of new business models have assumed particular importance. Furthermore, inside the energy sector the electricity has taken a notorious relevance against the coal, gas or fuel due to the electrification trend of important sectors like transport or e-mobility.

Likewise, the electricity consumption is increasing faster than world population, which means an increasingly growth of electricity consumption per capita. In other words, people is consuming more and more electricity every year [1].

Such a significant growth of electricity consumption means a need to improve the general management of the electric system, aiming a correct planning, which will need to achieve an accurate fitting of electricity generation and consumption. Being able, for example, to foresee in short-, medium- and long-term the energy consumption of a country, will give the capability to plan the needed energy production in short-, medium- and long-term, designing in accordance appropriate business models that will help to a better fitting of production and consumption.

Large suppliers have been several years developing techniques and tools that might carry out accurate energy predictions. The target of electricity retailing companies is to forecast as precisely as possible the consumption of all their customers for short-, mid- and long-term, in order to buy the exact energy that is going to be consumed. However, electric energy consumption forecasting is far from being an easy task.

Buildings are responsible of 40% of energy consumption in the European Union (EU) [2] and so the energy supply of buildings is one of the most important challenge that the suppliers must handle. Even though Europe has taken steps forward stablishing legislative frameworks aimed at improving energy efficiency of buildings [3], the consumption linked to buildings is still high. However, considering the opportunity that buildings offer to install photovoltaic (PV) arrays, especially in their roof, this significant consumed energy could be generated locally, at least partially. In this framework, the self-consumption of PV energy is creating great interest in Europe.

In the following work, the above mentioned challenge is going to be handled. The development of the forecasting tool is going to be carried out in the framework of "Programa INTERREG V-A España-Francia-Andorra" (POCTEFA) project called EKATE. EKATE is thought and promoted so to encourage the collective self-consumption of solar energy. The pilot project inside EKATE that is going to be covered in this paper involves the load forecasting of "École Supérieure des Technologies Industrielles Avancées" (ESTIA) 2 building, located in Izarbel technological park in Bidart, France. Toward this end, Artificial Neural Networks (ANN) are going to be applied. The capability of foreseeing next day consumption will allow day-ahead optimal management of the flexible loads of the building in order to maximize the collective self-consumption. For that reason, this paper proposes the use of a model based on NN able to perform the prediction of a single building consumption.

Up to now, different type of ANNs have been used for prediction purposes. Much work has been done in different fields making comparison of well known traditional techniques (ARMA, ARIMAX, SARIMA…) and new ANN structures [4] so as to compare the performance and accuracy of the models. ANNs have been largely used when dealing with time series. This is the case of electricity consumption forecasting, where Long Short-Memory Term (LSTM) or Convolutional Neural Networks (CNNs) [5] have been widely applied due to their performance in accurately modelling both short and long-term dependencies in data [6]. ANNs have been also used to forecast single building consumption, in which the variability of the load profile is significant because of the smoothing effect caused by the presence of other building load profiles [7]. Must be noted that working with real consumption data usually lead data quality and quantity issues. However, some NN structures allow small data sets to carry out predictions [8].

II. DATA DESCRIPTION

With such objective and issue in mind, the available data of the building is going to be studied. Firstly, it must be taken into consideration that this work aims to forecast the electricity consumption of a building, a highly time dependant variable that can be represented by a time series. Therefore, a forecasting model able to manage time series data is proposed.

Together with the load time series, an exogenous input (a time series too) is used. A dependency between the load and the ambient temperature (Ta) can clearly be observed (see Fig. 3 and Fig. 4). Therefore, the temperature itself is taken as an exogenous time series, since it is considered the most influent variable on the load profile. Historical temperatures of the entire year 2020 (12 months) have been obtained from *Meteo France*, with a frequency of 1 measure/hour.

The load time series of 2020 is shown in Fig. 1. The data is recorded every 10 minutes (144 readings/day) over a time period of 12 months. As explained below, this time series has been modified in the data pre-processing step.

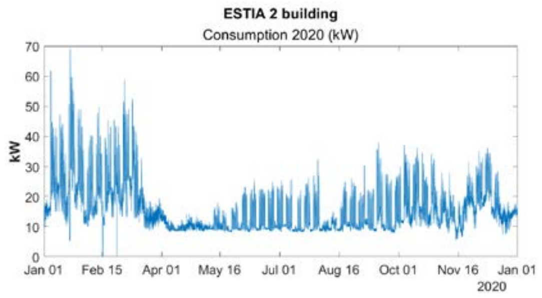

Fig. 1 ESTIA 2 building load profile of 2020

The analysis of the profile presented in Fig. 1 reveals that the load time series has several components that must be taken into consideration. These components include monthly, weekly and daily seasonality. Anyway, the main factor affecting these data is the lockdown linked to COVID-19. Indeed, from mid-March to the end of May and from end of October to the end of the year, most researchers, office workers and students that usually work in ESTIA 2 have had to work remotely. In any case, regarding winter and summer, a significant difference can be seen.

The identification of outliers in load time series has been an easy task in this case. The first deficiency in load registration occurs during the afternoon and night of 20th of February, when the load drops dramatically under 6kW. In addition, other two cases must also be highlighted in 15th and 26th of February in which the consumption drops suddenly to 0kW. Interpolation is used to address the issue about outliers.

In Fig. 2 the above mentioned last two cases have been represented.

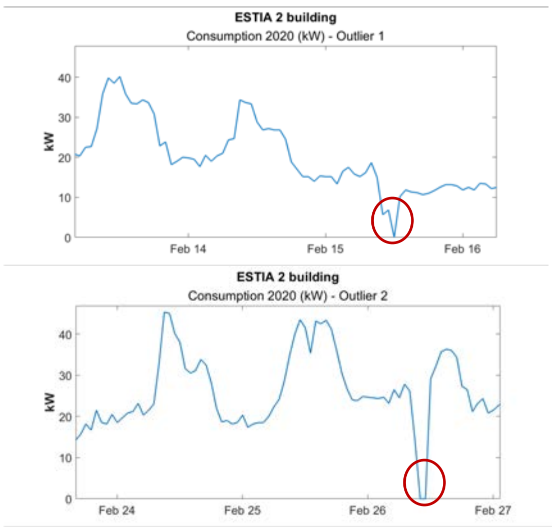

Fig. 2 Two cases of outliers in the consumption profile before pre-precessing

The data has been decomposed and stationarized in order to meet the forecasting modelling method requirements. As first step of data pre-processing, due to the non-conventional measures obtained because of the different periods of lockdown and the transients period between them, January and February data has been selected for the analysis. Consequently, the monthly seasonality effect of the load and temperature time series cannot be considered.

The next step of the pre-processing consists on the preparation of both time series. Load and temperature time series must be prepared in order to have the same time interval. However, as it is mentioned above, load is registered with a 10 minutes time step. This has been solved by calculating the hourly mean value of the load. In this way, both load and temperature time series have a 1h time interval. As a final step, the normalization of data between [0,1] range has been carried out. This is crucial for future steps.
Having a look to Fig. 3 different conclusions can be taken.

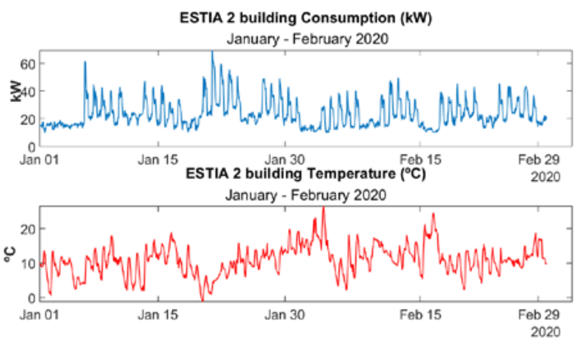

Fig. 3 ESTIA 2 building load and temperature profiles of January and February (winter months)

Firstly, the mean consumption value significantly increases during winter. Then, a significant fact should be highlighted in the analysis of Fig. 3: how the temperature, the exogenous time series, affects the consumption of the building. The comparison of the 3rd week of January and the 1st week of February can be a striking example. While low temperatures predominate during the 3rd week of January, the consumption increases significantly, whereas for higher temperatures, as in the 1st week of February, a decrease in consumption can be seen. Attention should also be drawn to the 1st week of January, where the lack of load peaks show that nobody was working due to Christmas Holidays.

Fig. 4 clearly shows how the load profile varies during the week, pointing the difference between workdays and weekends: whereas higher peaks can be seen during the working days, a smooth of the weekends load is distinguished.

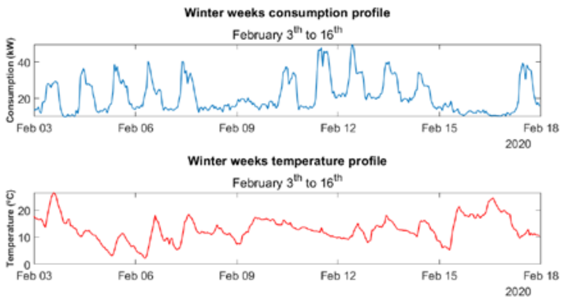

Fig. 4 Two regular winter weeks load profile: February 3th to 17th

Furthermore, it is also a very representative figure in order to see the daily load profile. As day/night changes of the load, two peaks are easily distinguished during the day. These peaks are identified because there is a slight load drop between 12.30an and 14.00am related to lunch break. Not clear trend has been identified regarding how these daily load peaks increase and decrease during the week: in some weeks, the highest load peaks are registered on Monday, and in some others the biggest peaks are seen on Wednesdays or Thursdays.

III. FORECASTING MODEL DESIGN, TRAINING AND EVALUATION

A. Neural Network Structure Design

ANNs are largely used since some years ago. ANNs are designed to simulate the biological neural system. Recurrent Neural Networks (RNNs) are nowadays one of the most frequently used Neural Networks (NN) and are characterized by their capability to process any non-linear dynamic system thanks to their internal connections. RNNs might be an effective approach when data with a high temporal dependency must be used in the forecasting model.

In this research study, a specific class of RNN has been used: Nonlinear Autoregressive with Exogenous Inputs (NARX). Fig. 5 resumes the particular architecture of a NARX used for the prediction of the next day 24h load profile.

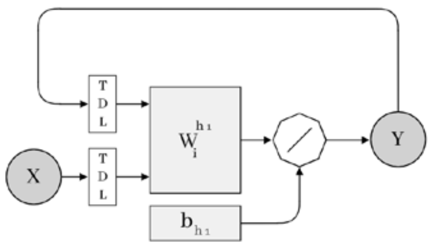

Fig. 5 The general structure of a NARX type Neural Network [6]

In order to build the NARX model, a Multi-Layer Perceptron (MLP) has been proposed. The MLP architecture consist on input, hidden and output layers. This architecture allows an accurate approximation of the non-linear mapping function that is performed during the training process of the forecasting.

NARX Neural Networks have been applied with satisfactory results for time series forecasting, showing significant advantages related to their fast training procedures and their easy implementation. The general equations that describe the performance of a NARX Neural Network implemented by a MLP are presented in [6].

When ANNs are used for forecasting time series, two types of inputs are considered: the target of the forecasting model (the desired output) and other inputs. In this research study, a time window of 14 days has been used. From those 14 days, the entire data set is used for training the model. In this way, the weekly trend is taken into account. The validation and testing isn't performed due to the importance that the last hours have in the day ahead prediction..

As it can be seen in Fig. 6 the target of the model is the measured electricity consumption of the building, which is introduced with a time step of 1h.

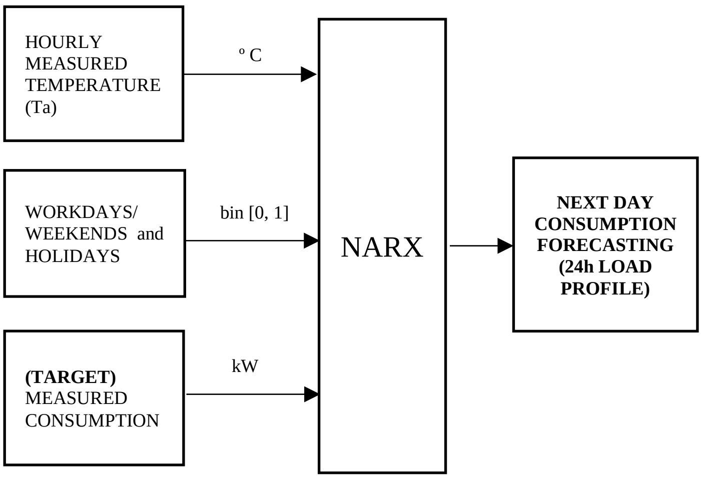

Fig. 6 Definition of inputs and outputs of the proposed NARX model

Regarding the inputs, measured historical ambient temperatures (Ta) of Bidart is used as the first input. Due to the high fluctuation of the load profile during the week, (workdays/weekends difference) high errors were registered. Specially, when the prediction of Saturdays and Mondays was carried out. Furthermore, the model needs to notice also about some special holidays that might fall on workdays (1st of May, 25th of December…). To avoid this, a third input has been introduced (bin [0,1]), improving notably the performance during those days.

After defining the inputs and outputs of the system, the general parameters of the NARX have been reflected in Table I.

TABLE I INITIAL PARAMETERS FOR NARX

NARX type Neural Network design	
Initial parameters	***Values***
Normalization interval	[0,1]
Input delay vector	[1,2]
Feedback delay vector	[1,2]
Nº of hidden layers	1
Nº of neurons in hidden layer	5
Activation functions	Hidden: Sigmoid transfer fcn Output: Linear transfer fcn
Training parameters	Error: MSE Leaning algorithm: Levenberg-Marquardt

During the experiment, an overfitting of the model has been observed. Consequently, the number of hidden neuron units has been reduced from 10 to 5 neurons and the overfitting has been outperformed.

B. Training NARX Model

Taking as the starting point the designed NARX structure parameters defined in Table I, the training of the model is carried out. The target (the measured electricity consumption with a time interval of 1h) and the three inputs (with a time interval of 1h) are introduced in the open loop architecture. In open loop or series-parallel architecture, the measured output (real consumption values) is used as input instead of feeding back the estimated output of the model (see Fig. 7). This architecture makes the training of the system much more consistent and precise. Furthermore, the training is performed following the Levenberg-Marquardt algorithm. This is a commonly used algorithm in Feed Forward Networks and it is further implemented when a fast training is needed [9].

Next, the loop is closed (NARX parallel architecture). Picture b) from Fig. 7, shows how the architecture of the model changes: the target input (measured consumption) is replaced by the output that the network calculates (the estimated output).

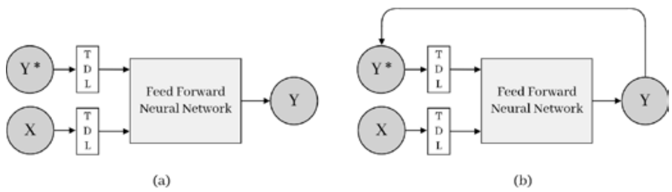

Fig. 7 NARX series-parallel arquitecture (open loop) and parellel arquitecture (close loop) [6]

C. NARX Forecasting Results

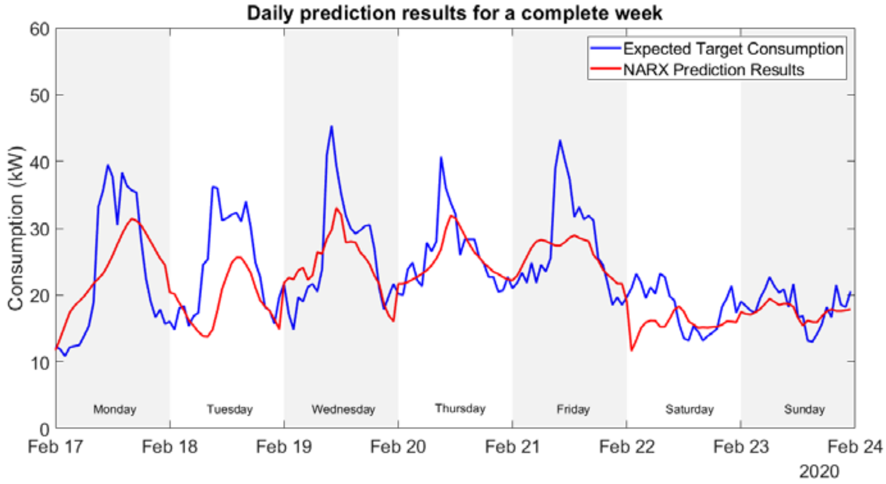

Fig. 8 Daily prediction results of a regular weeek: from February 17th to February 23th.

The trained NARX model is used to forecast over the horizon of 24h. The model is trained once per day, in order to predict the next day consumption. A daily training is performed in order to train the NARX with the closest data possible to the day that is going to be predicted.

Furthermore, the model is assessed by the calculation of MAPE (Mean Absolute Percentage Error) (see Eq. 1) [10].

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_j - t_j|}{y_j} \times 100\ [\%] \qquad (1)$$

The prediction plot is shown in Fig. 8, in which the expected target of the load is contrasted with the results obtained from the NARX model. The plots represent the prediction results obtained during a week, from Monday to Sunday. Furthermore, in Table II, the predictions performed by both models are evaluated by the calculation of the related MAPEs (mean MAPE values of each day of the week in February).

TABLE II NARX AND LSTM MOEDL EVALUATION

DAILY MEAN ERROR VALUE OF A WINTER MONTH (February)		
Day	***MAPE (%)***	
	NARX	LSTM
Mondays	29,63	46,68
Tuesdays	33,05	45,83
Wensdays	27,98	31,68
Thuersdays	25,10	26,27
Fridays	19,09	29,55
Saturdays	19,43	25,82
Sundays	9,63	21,83

IV. RESULTS AND DISCUSSION

The forecasting results given by the NARX are represented in the graph above, as well as, in Table II. It is shown that the model has a consistent behavior, although the calculated uncertainty in some days is slightly high.

Regarding the forecasting plot represented in Fig. 8, although the performance is worse on a couple of days, it has been proved that the model is able to learn the daily trend of load profile during workdays distinguishing night/day load difference. Anyway, the results obtained from weekends are also satisfactory. Regarding Tuesday and Wednesday, where a high MAPE value is registered, an abrupt temperature change has been observed. Whereas the maximum temperature registered on Monday was about 26ºC, the maximum temperature decreases significantly in the next two days until 12ºC. The model isn't able to foresee the consumption increase led to the fall of temperatures, and as it can be seen in the graphs, the predicted curve remains below, reaching only to the consumption values of the previous day (around 30kW).

Table II also shows the mean MAPE values obtained in the month of February by the LSTM model. Although same structure, inputs, time window, training period, etc. has been used, the obtained results are worse. The reasons why the forecasting accuracy is worse with the LSTM must be analyzed, in order to see how the structure and parameters of the model should change to improve them.

The fact of forecasting the consumption of an only building results in a high variability of the load caused by different reasons. On the one hand, more exogenous factors will affect the load profile (irradiance, people´s behavior, wind speed, building orientation…) and of course, the effect of these factors will be bigger. On the other hand, due to the different type of users (researchers, students and workers), the occupancy of the building will vary depending on the day and the week (holidays will change too). Hence, comparing with residential building consumption, load profile variation are bigger.

V. CONCLUSIONS

This paper illustrates the application of a NARX Neural Network model for a Short-Term Load Forecasting problem. NARX model is going to be designed and trained so to get a load profile of the next 24h.

The dynamic nature of the load profile of buildings makes the prediction of this profile a difficult task, especially because of the high dependency that the consumption has with the building occupancy and people's behavior.

An important aspect that must be highlighted when carrying out the load forecasting is the quality and quantity of the available data. The data that has been used in the study case analyzed in this paper was conditioned by the global pandemic caused by COVID-19, which forced people to home lockdown. That is why, the meaningful and thus, useful data that we manage is limited. Nevertheless, it has been proved that the designed NARX model is able to make predictions with satisfactory results even with a small data set. In this sense, an appropriate pre-processing of a small data set becomes a crucial step. Cleansing and restructuring, as well as, normalizing the historical data will allow a better learning of the model, achieving improvements in its performance.

The forecasting of a single building might lead to have a profile with high variability, as well as, higher dependency with more external factors, which makes the accuracy of the forecasting model worse.

All these matters might be overcome making the forecast of more than one consumption points; the curve might become more stable and smooth due to the load compensations in certain hours.

Anyway, another factor makes the prediction of consumption a little worse; it must be pointed out that nowadays the control of the thermostat in ESTIA 2 building is still manual, that is to say, the users of each office can vary the setting point of the thermostat. This fact leads to a rather chaotic behavior of the Heating, Ventilation and Air Conditioning (HVDC) consumption. Within the framework of EKATE, the automation of the system is going to be implemented, avoiding like this the random human factor that might affect the correlation between temperature and consumption.

Aiming to see how other types of NN models perform the forecasting of this particular case, a Long-Short-Term Memory (LSTM) has also been designed. The results have been compared with the ones obtained with the NARX, concluding that, in this case, NARX are able to forecast with a higher accuracy. Some parameters, like the time window (TW) should be change in order to see if the memory cell included in the LSTM model, could accept a higher TW and thus, improve the results.

Regarding the scope of future work, different challenges will be handled to improve the forecasting model. Further improvements related to inputs (predictors) identification is expected to carry out. Specifically, it is foreseen the introduction of irradiance data as an input, due to its apparent influence with the building consumption. The forecasting of the consumption on summer will also be an interesting future work so to see how the cooling system changes the load profile in comparison to the heating system. In addition, two different special case studies will be analyzed: the forecasting of a holiday week (e.g. Summer Holidays) and the forecasting of a week in which holidays falls on workday. In addition, further work is foreseeing to carry out related to comparisons with LSTM and other type of statistical forecasting techniques, such as the use of KNN. Finally, in a long-term scope, the analysis and calculation of the model uncertainty might be an important aspect in which focused on.

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