Short-term Electricity Consumption Forecast with Artificial Neural Networks - A Case Study of Office Buildings

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***Abstract*—To achieve climate and carbonization goals, electricity grid participants, such as buildings, must reduce their footprint trough renewable generation. Introducing storages can help buffering the fluctuating nature of renewable energy sources but only with future knowledge of consumption and generation, can batteries be scaled sensibly to economically viable options. An efficient energy management system and accurate energy forecasts are necessary to proactively work within battery limits, providing a short-term (day-ahead or hour-ahead) energy production plan which can then be utilized for demand response applications like load peak minimization, self-consumption optimization, intelligent energy storage, and predictive control. Focus of this paper is the accurate energy consumption prediction of office buildings and a case study, based on measurement data. The output of a prediction algorithm is intended to serve as input to predictive control models for a storage system, which enables efficiently managing energy storages and balancing consumption.**

***Index Terms*—artificial neural networks, energy consumption forecast, measurement data, smart office building**

I. Introduction

The penetration of renewable energy generation is increasing rapidly due to the need of reducing the utilization of conventional and environmentally harmful energy sources. Photovoltaic (PV) technology is being spread worldwide, with PV panels being installed in fields, on buildings' roofs and surfaces, on road networks and even as energy source for low power telecommunication equipment. The strong dependency of the photovoltaic power output on environmental parameters, such as solar irradiation and cloud conditions, leads to a fluctuating power generation, which occasionally cannot be consumed locally. However, local consumption of power produced from renewable energy sources and as well as self-consumption maximization reduce the transmission losses and overload of power lines [1]. The combination of a storage system with an appropriate control mechanism contributes significantly to self-consumption optimization and results into an efficient energy consumption. Hence an energy management system which utilizes models to forecast the energy demand as well as the PV power generation of the next hours or days, enables an efficient and optimal charging control of energy storages. Therefore, models to accurately forecast the energy demand of buildings are important for the energy transition.

Energy consumption forecast methods can be classified in various categories: engineering methods or physical models, statistical, and the artificial intelligence methods. Physical models can be very accurate, however, the difficulties lie in the absence of the necessary information about each part of the system, as well as on the poor transferability to other objects. Engineering methods usually introduce a very long process and require a lot of computing power [2].

Statistical approaches rely on periodicity and the fading of outliers in the crowd. For short-term forecasting, statistical methods try to find similar load behavior from past data while combining other influencing parameters such as environmental characteristics. However, the complexity and the non-linearity of the relationship between the load behaviour and the rest of the parameters, makes it hard to achieve an accurate output with statistical methods [3].

Artificial intelligence and specifically Artificial Neural Networks (ANNs), have the ability to solve non-linear and very complex problems and offer a relatively high accuracy. They learn from a set of training data, make high speed predictions and generalizations, they do not require detailed information about the system, and they are fault tolerant [4]. ANNs have been used several times in research studies on energy forecast in buildings. In [5] a feed-forward ANN was used to forecast the energy consumption of electric lighting in office buildings, based on the irradiation, day, and time as input parameters, with forecast interval of 15 minutes. The average root mean square error of the model was 17.25%. ANNs and Fuzzy Logic (FL) for short term load forecasting based on temperature data were investigated in [6], with the ANN method providing better results, in one hours resolution. The average error of the ANN method was 0.5% while that of the FL method was 4.91%. The total energy consumption of a passive solar building was predicted in [7] with the use of multiple-layers Feed-forward ANN (FANN). The input parameters were the temperature and solar radiation data, generated from a simulation program, with a coefficient of

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multiple determination equal to 0.9991, which was considered to be very satisfactory. An ANN with feedback loop was used in [8] for short-term load prediction of buildings. Forecasted, current, and past temperature and load values as well as hour and day information were used as input data to the ANN model. With a window length of just 21 days of past input values in hourly resolution, the Mean Absolute Percentage Error (MAPE) of the model was 1.945. ANNs were used in several more studies, [9] [4] [10] [11], for short- and long-term load forecasting in buildings and power grid.

Support Vector Regression (SVR) was used in [12] for energy consumption forecasting of residential buildings, based on past consumption values, actual temperature and solar flux, as well as time and day input. The output of the model was given in daily, hourly and 10 minute resolution with a standard error of $11.39 \pm 2.73\%$, $11.30 \pm 0.65\%$ and $10.47 \pm 0.29\%$ respectively. SVR was examined also in [13], but for long-term grid load forecasting. Linear Regression is simple and uses linear functions for fitting, however it is not appropriate for complex and non linear load forecasting [9] [13]. SVR minimizes structural risks and errors of the model on new sets of data but it has no scalability and requires high memory and speed [9]. Least Squares Support Vector Machine has proven even less appropriate for load forecasting than SVR, since it has less ability to generalize as it uses all the data points to define a solution.

For the case study presented in this paper, ANN was chosen as the most appropriate method for energy consumption forecast in office buildings. The paper is organized as follows: section II provides an overview of the ANN architecture and parameters regarding energy consumption forecast in office buildings, section III describes the case study parameters, available training data sets and results and IV presents the outlook and conclusions.

II. Concept and Modelling

A neural network consists of one input and one output layer and of one or more hidden layers, inspired by the biological neural system. The ability of a neural network to learn from its environment and to improve, makes it appropriate for application on the field of energy consumption forecasting. The layers consist of one or more processing elements, the neurones, which are connected to each neuron of the other layers, depending on weights and biases, as shown in Figure 1. The weights define how strongly or not the neurones are connected to each other; the adaptation of weights constitutes the learning process of the neural network. Each neurone in the hidden layer receives input data, it is multiplying them with a weight and passes them to the next layer through a transfer, non-linear, mostly sigmoid, function. The product is summed and when it reaches the output layer the error between the ANN output and the target data is computed and sent backwards to the hidden layers (back propagation) in order to adapt the weights again. This procedure is repeated (epochs) until the average sum squared error is minimize [14] [15] [16] [17].

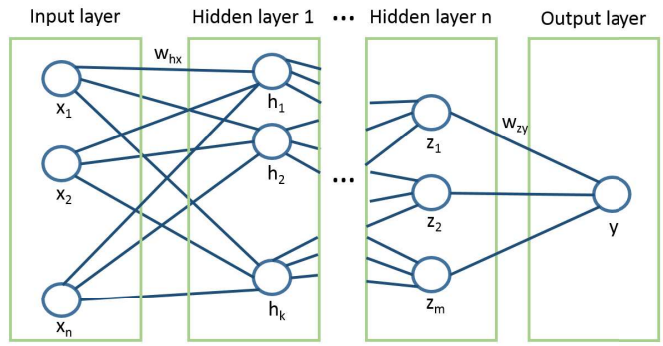

Fig. 1. Artificial Neural Netowork Architecture

In a FANN, the nodes of one layer are connected to nodes only of the next layer, whereas in recurrent ANNs nodes of one layer can be connected to nodes of every other layer. FANNs proved successful in case of load forecasting in previous studies, whereas recurrent ANNs "do not provide clear practical advantages over ... feed forward networks with limited time windows" [18]. Weather related data such as temperature, solar irradiation, are determinant as far as lighting, heating and cooling in a building are concerned. Especially for the case of office buildings, the consumption behavior of the users is also determinant; this information can be extracted from the past consumption values and thus the consumption profile of the building. Working times as well as holidays and weekends must be also imported as additional input information to the ANN model, so that the output can be correspondingly adapted, since such characteristics affect greatly the consumption pattern of an office building, in contrast to the consumption pattern of a household for instance. Figure 2 depicts the proposed concept architecture for the application of an ANN model to consumption forecast based on measurement data.

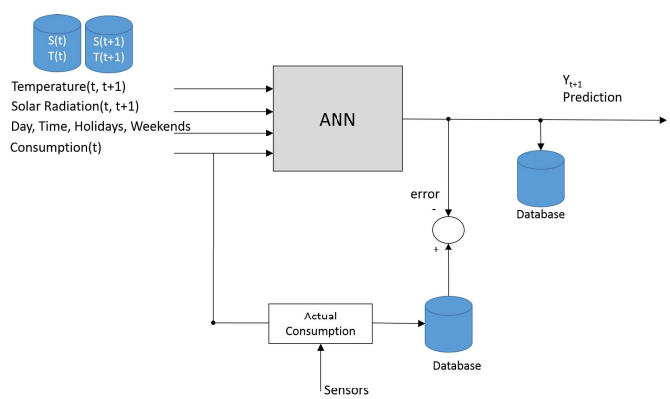

Fig. 2. Inputs and outputs of proposed ANN

III. Case Study and Results

The proposed ANN model is developed and trained for a specific case study of an office building. Available recorded

consumption data are energy consumption of the "bigger" consumers of the building, mainly pumps, as well as weather data for the year 2015. The necessary weather input data for the same year were provided by a weather provider with 10 minutes resolution and were interpolated to match the 15 minutes resolution of the consumption data.

A. First Implementation

The first step was to examine the available data and find possible errors, since corrupted data would affect negatively the quality of prediction. A draft model was composed by input data of solar irradiation of month m, the temperature of month m, the type of day (weekend or working day), the consumption data of month $m-1$ (past consumption) and the cosine of the time. The target data are the consumption data of the month m. Additionally, the consumption data were inserted as averages of 1 hour in the model (moving average window), in order to filter out deviations which do not contribute to the learning process but rather confuse the ANN which tries to adapt the weights and fit the output to every single change of the consumption. Moreover, the consumption data consist mainly of heating pumps' electricity consumption data, hence the profile appears to show abrupt changes. The solar irradiation as well as the consumption data were normalized by the average consumption over the year. More characteristics of the ANN implementation are:

- Past consumption data of month $m-1$ and target consumption data of month m are inserted as average values of 1 hour (moving averages)
- Temperature data of month m, are inserted as average values of 2 hours
- Average values are used to smoothen frequent and abrupt changes, avoiding a noisy ANN
- The ANN is a feed forward network, with 2 hidden layers of size 5(neurons)
- The window size of the input data is chosen to be 30 days
- The resolution of all input data is 15 minutes

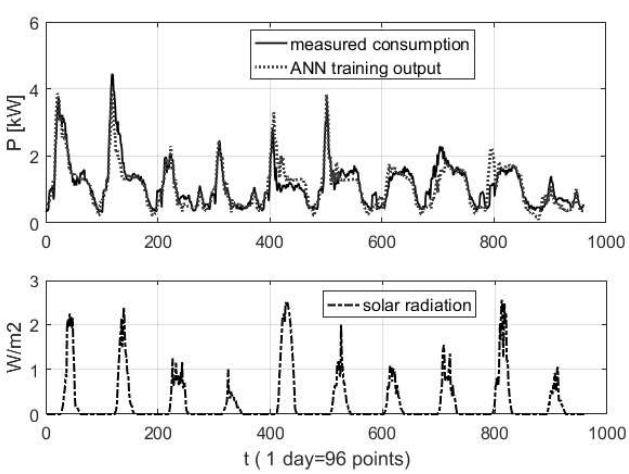

Fig. 3. Training of ANN model, 2nd-12th of April 2015

This structure of the ANN and the particular input data resulted in a Mean Square Error (MSE) of 0.0295, which is 2.95% of the average of normalized yearly energy consumption from the given data. This includes of course also the error of the weather data. The training as well as the application of the ANN model was carried out with measured input weather data, whereas in the final application it will automatically receive input from weather forecast providers. Usually, the mean absolute percentage error (MAPE) is used as measure of prediction accuracy, however, when the target data contain zeros it cannot be applied. Alternative relative accuracy measures can be used; e.g., in [19] various accuracy measures were examined, such as the mean relative error (MRE), the mean error relative to the predicted value (MER), the Sum Mean Average Percentage Error (SMAPE) and the log difference or log change between actual and predicted values. With the latter being applicable mostly to economics and thus to symmetric relative changes, the first being not applicable due to zeros in the observed data, the MER and SMAPE error introduce appropriate accuracy measures for energy consumption forecast. However, their interpretation cannot directly indicate the quality of the estimation. The Mean Square Error (MSE), which represents the average squares of differences between predicted and actual values, suggests an appropriate accuracy measure to evaluate the quality of the estimator, that is the ANN model. The closer to zero the MSE is, the better the estimation. The upper part of Figure 3 depicts a part of

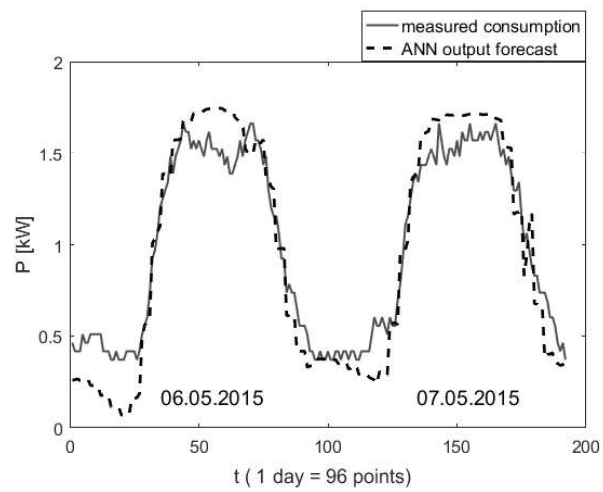

Fig. 4. Forecast of ANN model, MSE=0.0295

the training of the designed ANN (10 days from 2nd until the 12th of April 2015). The sub-plot in the lower part of the figure depicts the solar irradiation, pointing out the inversely proportional relation of the electricity consumption and the intensity of solar irradiation. Figure 4 depicts the application of the trained ANN on new data (6th until the 7th of May 2015), so the forecast of energy consumption for this time period. The fact that the available consumption data concern mostly only pumps, results in a less smooth consumption profile with several steps up and down. This strengthens the decision to

use average values and not raw input consumption data.

In order to prove the capability of the specific ANN model to make correct electricity consumption predictions on holidays as well, an additional input was necessary. A method to calculate the national, fixed and movable holidays was developed, whose output was inserted to the ANN model. The model was tested on forecasting a set of days, the 13th and 14th of May, with the latter being an Austrian holiday, albeit a Thursday. As shown in Figure 5, the ANN model can adapt well to new data and can reliably predict the electricity consumption.

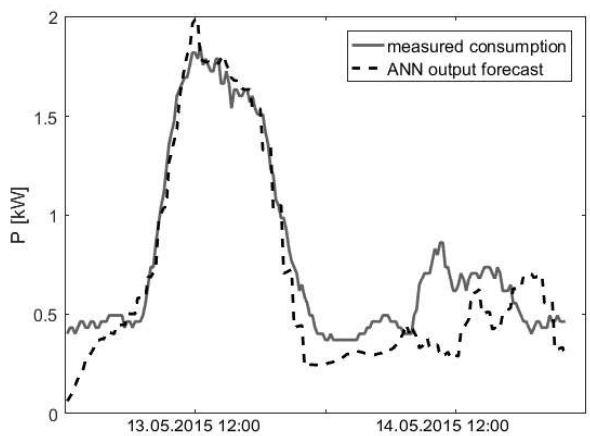

Fig. 5. Forecast of ANN model for two days including a holiday

B. Variation of ANN Input Parameters

In order to optimize the ANN and hence minimize the error of the model, a number of additional simulations and investigations were carried out, varying the length of the input data window and the moving average windows as well as the number and size of hidden layers.

Length of Input Data Window

The length of the input data window is an important parameter, since it determines which seasonal characteristics will be taken into account during the learning procedure of the ANN. It should be mentioned that a batch/off-line instead of an online training of the model was selected. In an online training the input values are inserted continuously into the model, and the weights are updated after each input is presented. Batch training is however computationally more efficient, given that a data base for data storing is available. The training is then triggered every n days. Another advantage of batch training every n days, is that new characteristics of the electricity consumption pattern, due to, e.g., higher or lower number of employees, structural change of the building which affect its thermal behavior, can be included in the learning process. Table I depicts results from training the ANN with alternating window length of input values. A window length of 23 days results in an MSE lower or in the range of 0.05, which is 5% of the average normalized consumption data over the year, for 5 months of the year. However, other lengths of input data windows, result in even lower average MSE over all months. A compromise between a very good MSE for some months of the year and a moderate MSE during the entire year must therefore be made.

TABLE I
COMPARISON OF THE MODEL'S MSE ON APPLICATION, WITH VARIABLE WINDOW SIZE OF INPUT VALUES WHILE TRAINING

Months	**Days**			
	21	*22*	*23*	*24*
February	0.3163	0.5172	0.6684	0.3490
March	0.8556	0.3377	0.2078	0.2300
April	0.3609	0.2783	0.3419	0.3375
May	0.1790	0.1896	**0.0504**	**0.0057**
June	**0.0431**	0.1231	**0.0402**	0.0870
July	0.0949	**0.0422**	**0.0254**	**0.0465**
August	**0.0297**	0.1498	0.1054	0.0923
September	0.0981	0.0934	**0.0358**	0.1134
October	0.0753	0.2357	0.2030	**0.0324**
November	0.0888	**0.0546**	**0.0486**	0.1283
December	**0.0527**	0.1559	1.2549	0.2890

Moving Averages

Subsequently, various averages (moving windows) of the input data, with emphasis on the past consumption data inserted to the ANN, were investigated and compared. Figure 6 shows that the utilization of average values gives better results than using raw consumption data as input to the ANN, as mentioned also in Section III.A. Figure 7 shows the resulting consumption data after application of two hours moving averages. It is clearly seen, that the utilization of moving averages improves the consumption profile, since it results in a smoother one, excluding high frequency variations which do not contribute positively to the forecast. Therefore, measurement errors are also avoided, e.g., zero values which should normally not be present, as the energy consumption of a building is most probably never zero. Specifically, average values of 3 and 4 hours of past consumption data apparently give the best results. It is observed that the error of the ANN model is higher during the winter months and low during the summer months,e.g., May, June and July appear to have a very low MSE, especially in the case of 3 and 4 hours of input average past consumption data. This correlates also with the observation made by varying the length of the input data window, with 23 days resulting in good MSE for the summer months but worse MSE for the winter. Further investigations on additional appropriate input were therefore carried out.

Derivatives

The first and second derivative over time of temperature and solar radiation input values and their effect on the accuracy measurement, as well as the number and size of hidden layers were evaluated through test runs. The first derivative introduces the rate of change of future temperature and solar radiation to the ANN model, which is a direct indicator of increase or reduction of the power consumption in the build-

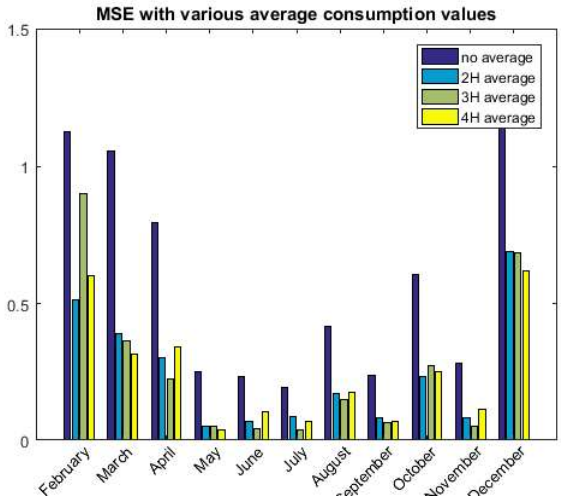

Fig. 6. MSE with various average values

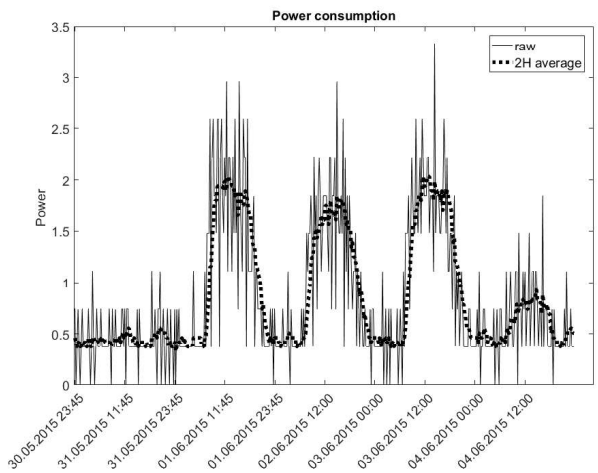

Fig. 7. Raw and average consumption values

ing. The second derivative measures how the rate of change of these quantities is changing, representing the concavity of the first derivative. Figures 8 and 9 depict how the derivatives, first and second, of temperature and solar radiation affect the MSE of the ANN for two different sizes of ANNs; one with 2 hidden layers of size 5 (neurons) and one with 3 hidden layers of size 7. ANNs with more hidden layers and more neurons on each layer are theoretically able to build a more accurate correlation between input and output data, however there is a risk of over-training the ANN, resulting in worse forecasts, as confirmed by the mentioned figures.

C. Final Results and Discussion

According to the above analysis, derivatives proved to be useful input, the utilization of averages instead of raw input data is valuable, and a small number of hidden layers and neurons, for short term forecast of buildings, are sufficient for accurate predictions within an acceptable error range. Figures 10 and 11 depict the forecast of the ANN model

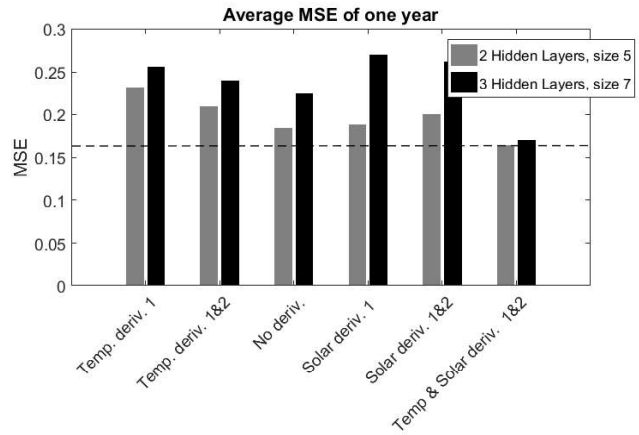

Fig. 8. MSE comparison between ANNs of different size and derivative inputs

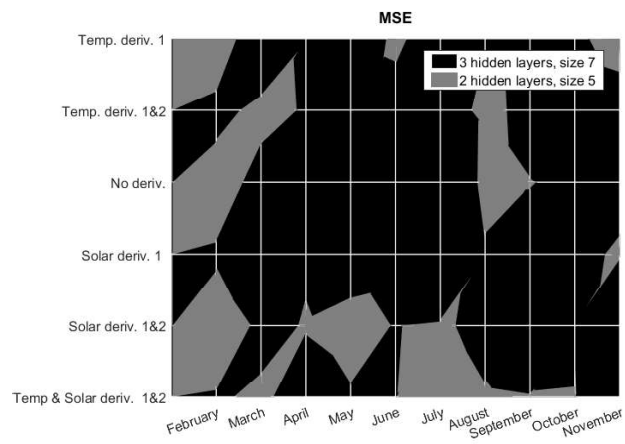

Fig. 9. MSE with additional differential input to the ANN model, bottom view of a three-dimensional graphic, where the z axis represents the MSE. The overlapping of a surface points out higher MSE

for 11 days in a summer and a winter month, respectively. The ANN model can predict successfully the reduced energy consumption on weekends (e.g., 14 - 15 November 2015 , Figure 11) and also holidays (e.g., 4 June 2015, catholic holiday, Figure 10). Further investigation of the parameters of the ANN can still improve its performance. The utilization of this specific ANN for forecast of the energy consumption of another building is challenging. Of course the network has to be trained again, since the thermal behavior of a different building will be definitely not the same as of that the building whose data were used for the training of this developed ANN.

IV. Conclusion and Outlook

This paper describes the choice of ANNs for predicting the consumption of a building in a case study. The developed ANN, based on collected, error corrected, and normalized data, can sufficiently predict the electricity consumption on working days and holidays as well. The development of an events calendar, not only for national holidays, but also for specific

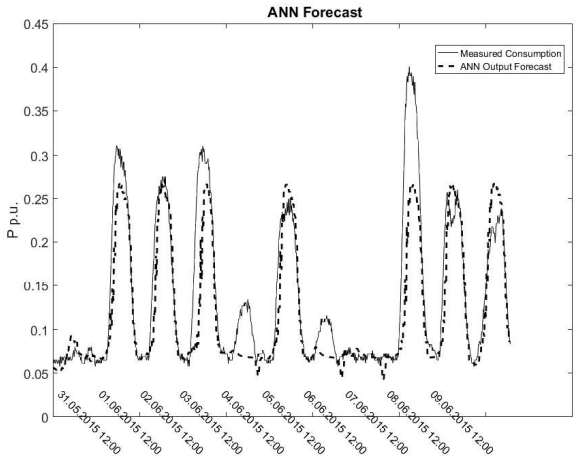

Fig. 10. MSE with additional differential input to the ANN model, bottom view

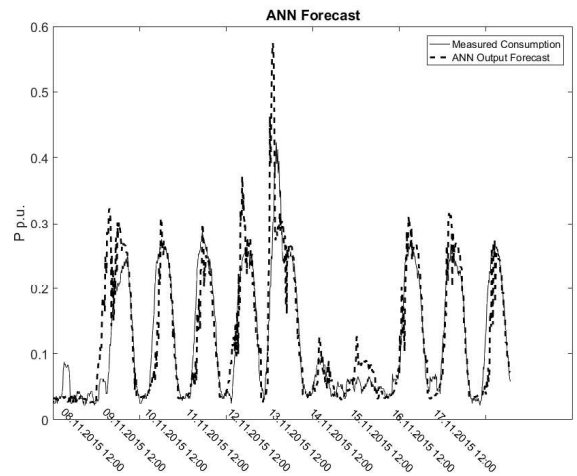

Fig. 11. MSE with additional differential input to the ANN model, bottom view

events related to the type and utilization of the building, is necessary for an accurate consumption prediction. Knowing the energy demand of the building in advance constitutes one of the prerequisites to optimize the self-energy consumption of buildings with PV and batteries at their disposal. Development of self-learning models able to predict the energy demand of different buildings (ability to generalize), is a great challenge. From buildings' self-consumption optimization to renewable energy share maximization, artificial intelligence offers great research and implementation opportunities.

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