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High-resolution net load forecasting for micro-neighbourhoods with high penetration of renewable energy sources

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ABSTRACT

Though extensive, the literature on electrical load forecasting lacks reports on studies focused on existing residential micro-neighbourhoods comprising small numbers of single-family houses equipped with solar panels. This paper provides a full description of an ANN-based model designed to predict short-term high-resolution (15-min intervals) micro-scale residential net load profiles. Since it seems especially relevant due to the specificity of local autocorrelations in load signal, in this paper we put stress on the systematic approach to feature selection in the context of lagged signal. We performed a case study of a real micro-neighbourhood comprising only 75 single-family houses. The obtained average prediction error was equivalent to 5.4 per cent of the maximal measured net load. The issues, i.e.: (1) the feasibility of micro-scale residential load forecasting taking into account renewable energy penetration, (2) the feasibility to predict net load with dense temporal resolution of 15 min, (3) the feature selection problem, (4) the proposed prosumption- and comparison-oriented prediction model key performance measure, could be of interest to engineers designing energy balancing systems for local smart grids.

1. Introduction

Efficient electrical load forecasting is one of prerequisites for successful management of power system operation [1]. Decentralization of electricity generation causes changes in power grids, forcing operators to seek technical and economic solutions requiring efficient energy balancing at local level [2–9]. Hence the need for research on micro-scale load forecasting. In this paper, we present a case study of successful short-term net load profile forecasting for a micro-neighbourhood comprising of 75 single-family houses located in the Netherlands. Most of the houses under study were equipped with photovoltaic panels and were contracted to feed the surplus energy back into the local smart grid. After having put substantial effort towards proper selection of endogenous inputs for a prediction model, we employed an Artificial Neural Network (ANN)–a Multilayer Perceptron (MLP)–as a tool for load profile forecasting. The work has been done in the course of the European Unions Seventh Framework Programme under the e-balance project [10]. The prediction problem defined in the project involved estimation of a 24-h ahead net load profile at high, 15-min resolution. These two parameters of the predictor were defined by the project requirements, together with the size of the neighbourhood and the suggestion to apply a neural network for the task. Additionally, due to limited computational resources of the target deployment system the complexity of the neural network used by the solution should be as small as possible. The predicted profile was further used by an energy management algorithm to plan the control of the smart (or just controllable) appliances available in the deployment. This set-up is a common approach for the Smart Grid applications and allows optimizing the future energy systems with distributed energy production sites and controllable loads.

2. Motivation and state of the art

Throughout the years the problem of large-scale load forecasting at national, regional, or city level has been extensively examined. It is already widely used for years, e.g. in power plant control or in other large-scale approaches in the area of power system operation. For these purposes satisfactory forecasting solutions have been proposed and implemented. There are many approaches based on different mechanisms that work for scenarios with a defined temporal resolution on a defined scale. These two parameters are the most critical dimensions in the energy related forecasting problem statement. And it is important to

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mention, that for both these dimensions aggregation reduces the overall dynamics that needs to be captured by the forecasting mechanism. The temporal resolution defines the duration of a single amount of time, for which the forecasting is being made, i.e. energy related values representing their respective periods form a time-series that shall be extended with values located in the future. And it makes a significant difference, if it is done for 15-min, hour, or day values, since shorter time intervals express higher variance in the individual values, for longer ones the values are averaged, reducing the variance. Similar, with respect to the scale, covering only a single household by the forecasting causes the task to be less trivial. As we have pointed out elsewhere [11], uncertainties introduced into energy load profiles by randomly timed human behavior can limit or–in the worst-case scenario–preclude efficient high-resolution energy load profile forecasting at single-family house scale, even in the short term. Such a conclusion leads to an important question on the minimum aggregation scale allowing for efficient short-term energy load profile forecasting. This relation has been already investigated [12] and it was confirmed that for larger scale the prediction results are significantly better. Though we may not be able to provide here either exact or universal answer to this question, in this work we describe a successful solution for load forecasting at micro-neighborhood scale comprising only 75 single-family houses.

Several papers provide an analysis of the approaches proposed in the area of energy related forecasting. An earlier survey [13] provides an overview describing the state of the art as it was in 2002. The approaches using different techniques, like multiple regression, exponential smoothing, iterative reweighted least-squares, adaptive load forecasting, stochastic time series, ARMAX models based on genetic algorithms, fuzzy logic, neural networks and expert systems are presented there, together with the explanation of the respective technique. More recent surveys present the advances in the field of energy related forecasting [14–23]. The techniques mentioned in there are already more oriented towards the state-of-the-art problems in the energy grids.

These techniques can be divided in several classes, like: statistical approaches, artificial intelligence approaches, knowledge-based expert systems, and hybrid approaches combining the others. Each of the class depends on its own way for building the model of the system to estimate its future behaviour based on a set of defined input parameters. The statistical methods include mathematical models, like the multiple regression or exponential smoothing, just to mention a few. These approaches require prior analysis of the historical data and applying different procedures to predict the future behaviour of the system. Expert system solutions also require prior analysis of the system behaviour in order to identify a set of rules that can then be further used to foresee how the system will behave in the future based on a set of events or triggers defined by the input parameters. The solutions from the artificial intelligence area try to model the system using techniques like neural networks, where an identified set of parameters is used to train the model. Simple solutions from that area require prior analysis of the problem and identifying the relevant system parameters, but more complex ones can even find these parameters. Indeed the ability to train the model about the system behaviour as the system runs and to do that with limited computational effort was the reason why we decided to use a simple artificial neural network (ANN) for the purpose of energy exchange predictor. Further, in the training sessions the ANN identifies the most important and less important input parameters by defining the weights related to these and by that it is possible to evaluate the initial choice of input parameters. The last class of solutions are the hybrid ones, for instance, the current expert system solutions migrate into the direction of artificial intelligence, where the rule set definitions are less digital (if-then like), but more fuzzy and for instance based on neural networks.

Todays power system operators face challenges concerning the decentralization of electricity generation. Power grids are undergoing a substantial change towards the prosumer model, where either individual clients or local community stakeholders introduce power coming from renewable energy sources into their energy demand profiles [2,3,5]. Though the literature on electrical load forecasting is extensive, it lacks reports on studies dedicated to examination of existing residential micro-neighbourhoods comprising small numbers of single-family houses equipped with solar panels. Actually, there are some works on micro-grids [24,2,5–8,16,17,25–28], some investigate even individual households [12,29–31], but they do not take into account single-family-house estates that feed solar panel (or other) energy back to the grid. This aspect connects the consumption and production of the household in one action being indeed the energy exchange. Depending on the metering way applied in the deployment the consumption and production can be investigated separately, or not. Our settings required us to investigate the worst case scenario–the net metering–where these two values are merged in one. The energy exchange prediction is not mentioned so far as it causes the predicted values to be both positive and negative, as well as zero, for ideally balanced households. Besides, literature on micro-scale forecasting usually reports research on micro-grids able to disconnect from macro-grids and to operate autonomously under some conditions.

The prosumer model also creates a growing technical and economical need for load forecasting at a high spatial resolution. Micro-scale forecasting deals with energy load profiles which lack smoothness of large-scale aggregations and involve autocorrelations specific to individual customs and/or local conditions [32]. The existing literature on micro-grid load predictions does not concern endeavours to examine prediction models with the temporal resolution as low as 15 min. Before testing our case it was unclear to us if such temporal density, combined with the small number of single-family prosumers involved, would not preclude successful predictions. A denser temporal scale yields better boundary conditions for efficient optimization of micro-grid power system operation.

We also find that available reports on load forecasting methodology propose arbitrary solutions regarding the number of, and the lag between, measurements of electrical load serving as inputs to prediction models [6,7,15,16,18,28,33], any additional parameter that is considered in the model, like solar radiation or air temperature, plays a role and can influence the accuracy of the forecasting. Since it seems especially relevant to the specificity of micro-scale load profiles shaped partially by local customs and conditions, in this paper we put stress on the systematic approach to feature selection in the context of lagged signal. We hope that by emphasising our approach and by reporting explicit heuristics we are able to fill the gap in literature and to give example of how to reduce chaos in feature selection decisions.

Another important issue is selection of metric that allows to evaluate the results of a forecasting approach, i.e. its accuracy, represented by the error rate related to the achieved prediction. The accuracy of the forecasting strongly depends on the temporal resolution and the scale–as it was already mentioned. Aggregation in these two domains simplifies the forecasting task. With respect to the applied technique, of course those based on artificial neural networks (ANN) are the most interesting to us, but any other approach achieving great accuracy is interesting. There are ANN-based approaches that operate on monthly energy data and provide forecasts reaching two years in the future, while achieving mean absolute percentage error (MAPE) at the level between 3 and 5 per cent [34,35]. But these approaches also operate on a very large scale, e.g. country level energy consumption.

Slightly better results were achieved by the approach [36]. It uses data with temporal resolution of an hour, operates on the building scale and achieves MAPE of 2.88 per cent for short-term energy load prediction. Another ANN-based approach [37] proposed for the same temporal resolution and operating on multiple building level (college) achieves with its ANN MAPE of 5.31 per cent. Yet other research [29] reports an MAPE error of down to 6.69 per cent for 15-min data resolution and 190 households.

For individual households the accuracy is much worse. The best

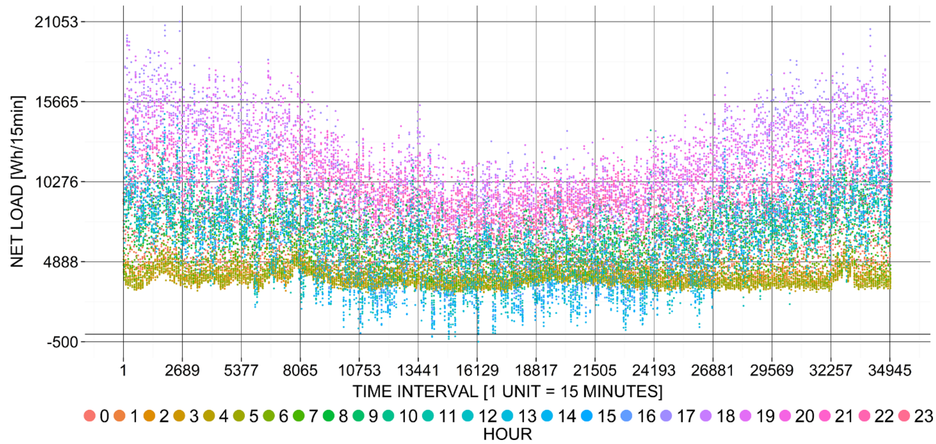

Fig. 1. Neighbourhood net load data (E_N) as a function of time interval (1 unit = 15 min) and hour.

result in [31] achieved for one of the settings is MAPE of 22 per cent for 30-min data resolution. Further, this approach used a huge recurrent neural network with hundreds of neurons, resulting in enormous training time. Our setting assumed live training as new data is available from the energy meter, so the size and complexity of the network is of utmost importance.

Since traditional prediction accuracy measures found in the literature do not allow to reliably compare models created for various scales, performing predictions for various future times, and involving net load values of different magnitude, especially values oscillating around the zero in micro-grid prosumption cases, we propose our own key performance indicator based on normalization of net load values. We strongly advise to use the measure reported in this paper in future reports concerning net energy load predictions. Similar error indicator approach for the case on predicting heating consumption was proposed in [23], the authors called it the MARNE indicator and the values are normalized by the maximum capacity of the supply. The aim of the accuracy measure is to allow comparing one approach with others, but also to evaluate applicability of individual approaches in a specific deployment context. The former aim is a complex task, because most of the research groups working on the prediction problem use their own data sets expressing different level of predictability. And different settings for temporal and spatial scale of the data processing, combined with the use of different error indicators cause inability to reliably compare approaches with one other. For the latter aim, it is important to estimate the needed flexibility margin on the energy management side in order to compensate for forecasting errors. The management level may be the grid network operator, who then operates on the aggregated level with multiple households, but it may also be the management at the level of individual households that is very possible in future smart energy networks. There are several ways to cope with the prediction errors. Again, it is all deployment specific and different approaches are possible, depending on the available equipment, its features, as well as the required responsiveness of the undertaken actions and running algorithms. Taking the e-balance target scenario as an example, the smart grid approach operates on two different levels. First, it estimates (predicts) the required energy amount for 24 h ahead in 15-min chunks and reports these as a kind of order for the energy management on the higher level in the grid. Then, in case there are differences between the prediction and the real energy exchange, real-time actions are taken by the energy management algorithm on the smart appliances to fit to the prediction. This step is of course only applied if necessary (critical) and only to the possible level, depending on the available flexibility.

All four issues, i.e. the feasibility of micro-scale residential load forecasting taking into account solar energy penetration, the feasibility to predict net load with denser temporal resolution, the feature selection problem as well as the proposed prosumption- and comparison-oriented key performance measure could be of interest to engineers designing energy balancing systems for smart grids.

3. Problem definition

Let $E_C \geqslant 0$ denote the sum of energy consumed by a neighbourhood, let $E_G \geqslant 0$ denote the sum of energy generated by a neighbourhood, let $E_L \geqslant 0$ denote the sum of energy lost by a neighbourhood, let $E_W \geqslant 0$ denote the sum of energy withdrawn from the macro-grid to a neighbourhood, and finally let $E_F \geqslant 0$ denote the sum of energy fed to the macro-grid from a neighbourhood. A variable E_N representing the net energy load of a neighbourhood can be defined as follows:

$$E_N = E_C - E_G + E_L = E_W - E_F \tag{1}$$

The variable E_N was subject to prediction modelling and its components define the aspects that have to be taken into account while designing the parameters that influence E_N. The requirements of the e-balance project determined high, 15-min resolution of the E_N variable [38]. Data compatible with this requirement had been provided by one of the e-balance project partners, Liander [39]. Aggregation of the data collected throughout the whole year 2013 from smart meters mounted in 75 single-family houses adding up to the micro-neighbourhood resulted in a time series comprising $365 * 96 = 35040$ net energy load values measured in Wh per 15 min. Fig. 1 illustrates the net load time series data as a function of time interval and hour. As can be seen in the visualization, during the mid-year season at mid-day hours solar generation happened to cover nearly all the neighbourhoods demand for energy, and at a few points in time the neighbourhood was able to feed some surplus energy back to the macro-grid. Irradiation data from a weather station covering the neighbourhood area was also available. The data was collected in 1-h intervals throughout the whole year 2013 and measured in J/cm2 per hour. The forecasting problem boiled down to the estimation of a future E_N value, located 24 h ahead (or more specifically: ninety-six 15-min time intervals ahead), based primarily on other available E_N values: one measured at the present interval t_0 and several values measured at past intervals.

4. Model Description

An Artificial Neural Network (ANN)—a Multilayer Perceptron (MLP)—served us as a tool for load profile forecasting [6,16,17,20,40]. Reports on using several other methods can be found in literature, yet the ANN family seems to hold a prominent position among them due to its inherent ability to deal with non-linearity [1,15,19,40]. Systematic effort had been put into establishing both a proper number and a proper structure of endogenous (lagged) ANN inputs. The heuristic employed

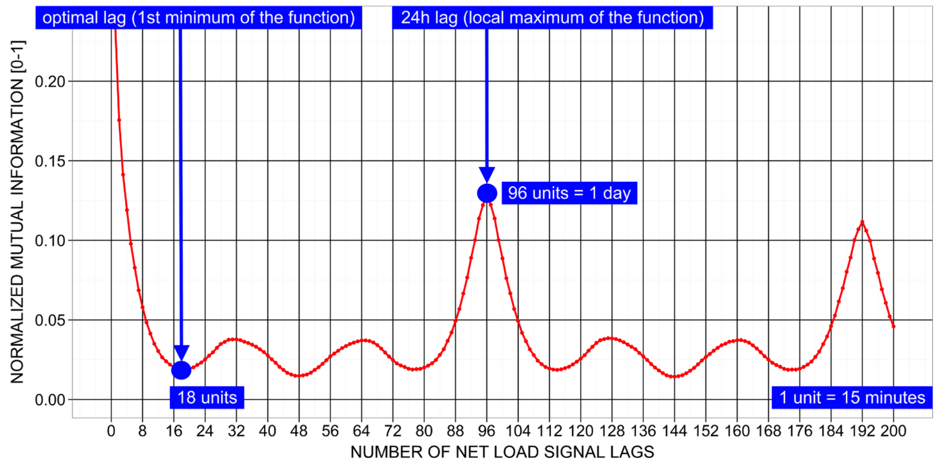

Fig. 2. Normalized mutual information of binned net load signal and lagged binned net load signal as a function of the number of signal lags.

to find the number of E_N measurements to include as predictors of the future value comprised three steps: (1) treating the time series as a realization of a dynamical system; (2) identifying the fractal dimension D of the dynamical system; (3) setting the number of predictor inputs $n \geqslant 2 * D + 1$. With the use of the correlation integral method we determined the fractal dimension $D = 3$ and established the number of endogenous inputs $n = 2 * D + 2 = 8$ [41,42].

As to the structure of the endogenous ANN inputs, an optimal lag between consecutive E_N measurements had to be found. Generally speaking, lags are optimal when they minimize the inter-input redundancy in information fed to the ANN. The heuristic employed to solve this second question comprised two steps: (1) calculating n autocorrelation measures representing correlations between the original load signal and n lagged signals, where the consecutive lags rise from 1 to n 15-min intervals; (2) establishing the lag at which autocorrelation measure treated as a function of the number of lags reaches its first minimum [42,43]. We opted for a normalized mutual information index as an autocorrelation measure [44]. We calculated the index as the quotient of the mutual information index and the joint entropy index [45], after having windowed the E_N values into 40 bins. As a result, the number of eighteen 15-min intervals was determined as the optimal lag (Fig. 2).

Following this approach combining and adapting the methodology of several other approaches we obtained the optimal (minimal) structure of the ANN and also identified optimal energy related values to be applied on its inputs. These features are crucial for the computational complexity reasons, as we wanted to be able to train the networks also in the individual households on devices with limited resources.

We put careful stress on the choice of the normalization method for the E_N ANN inputs. We found it important to set a normalization formula which leaves the 0 value unchanged:

$$E_N^{norm}(t) = E_N(t)/\max(|E_N(1)|, |E_N(2)|, \ldots, |E_N(n)|) \quad (2)$$

The established number and structure of the endogenous inputs (E_N) are visible in Fig. 3.

Exogenous variables were also taken into consideration to account for weather conditions, natural cycles and calendar days. As already mentioned, besides the historical energy exchange values it is necessary to identify other parameters that may influence the E_N. The influence of the calendar effects is obvious [30], thus calendar and time related parameters form the largest group of inputs in our ANN structure. Further, we decided to consider irradiation as it mainly influences the energy production by PV that was the main energy production source in our set-up. For other energy sources, like wind mills or combined heat and power devices there may be a need to introduce additional parameters to better capture their influence on the energy exchange in the system, e.g., wind speed or air temperature.

A total of 15 additional ANN inputs were defined in our design (Fig. 3): one input for irradiation data (normalized according to formula analogic to (2), two inputs for the yearly cycle (employing sine and cosine functions), two inputs for daily cycle (employing again sine and cosine functions), seven Boolean inputs for specific days of the week, and three Boolean inputs for public holidays (one for holidays in general, one for the first days of two-day holidays, and one for the second days of two-day holidays). These last two inputs were experimentally added, because we observed an influence of longer public holidays on some of the energy profiles, due to the fact that people tend to travel at that time, resulting in changed energy consumption. We plan to investigate the additional parameters applicable for other deployment settings than the e-balance one. For that we need to obtain energy exchange values to work on.

Several decisions had to be made regarding in-depth ANN parameters [40]: (1) the hyperbolic tangent function serving as the activation function for hidden layer neurons introduces non-linearity to enhance the approximation abilities of the ANN; (2) the linear function serving as the activation function for the output neuron adds up the output values of the hidden neurons to calculate the final prediction; (3) the error backpropagation algorithm served as the learning algorithm for hyperparameters (weights) selection during the ANN training process; (4) the second order Levenberg–Marquardt algorithm was the choice for the gradient descent direction calculation for RMSE loss function minimization; (5) one hidden layer of 16 neurons was settled experimentally for the finite MLP architecture. Only one hidden layer was used as it is generally known to be sufficient for the approximation of functions with practically any shape [46,47], while additional hidden layers would be expected for less complex architecture (less hidden neurons) that improve generalization properties of the ANN approximator by learning increasingly more abstract patterns by the subsequent hidden layers [48]. During the training process, the optimal number of 16 hidden neurons was selected, assuring the smallest prediction error while preserving good generalization capabilities. It was achieved by observing the training and validation errors as functions of number of hidden neurons, and selecting the number for which the training and validation errors became practically equal. For the evaluation purposes we implemented the designed ANN model using the Stuttgart Neural Network Simulator [49]. The core part of SNNS is an open source C kernel designed for building, training, and testing ANNs. The R programming language [50] and R package RSNNS [51] were used as an application programming interface to the SNNS library.

The designed ANN was finally implemented in the Java programming language, using the Neuroph framework [52]. The implementation was deployed on a unit based on the Beaglebone Black [53], so a computationally limited Linux device. This unit was also running the application gathering data from the smart meter, as well as the one

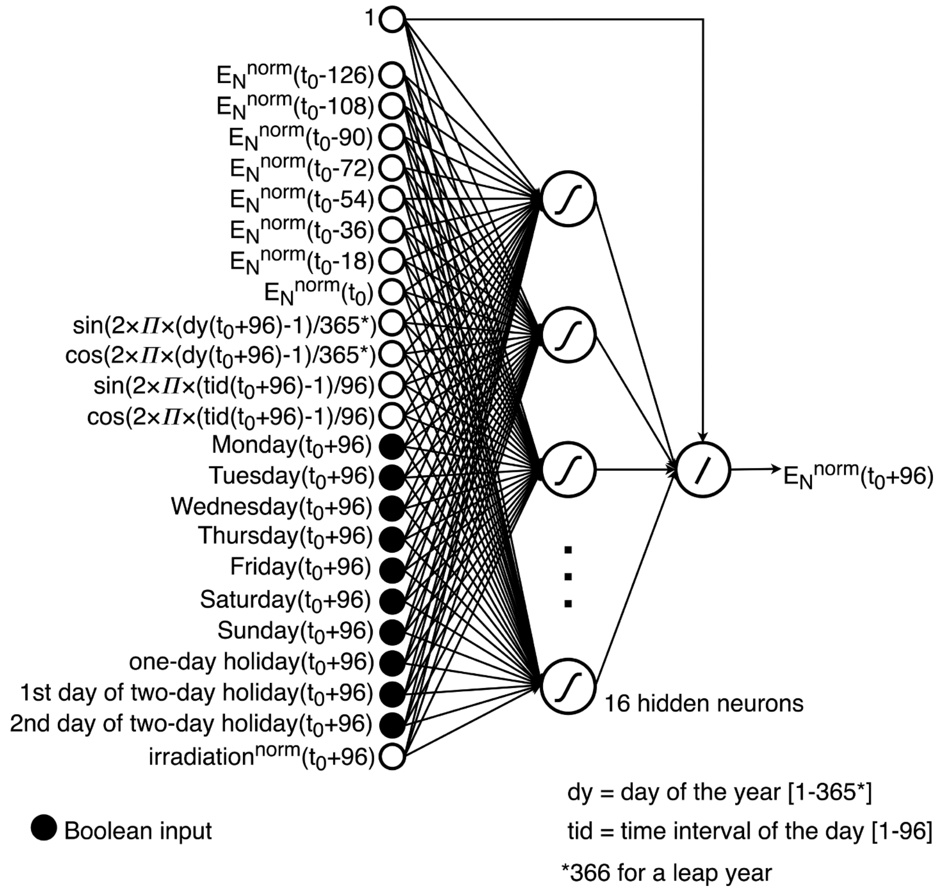

Fig. 3. The established ANN architecture.

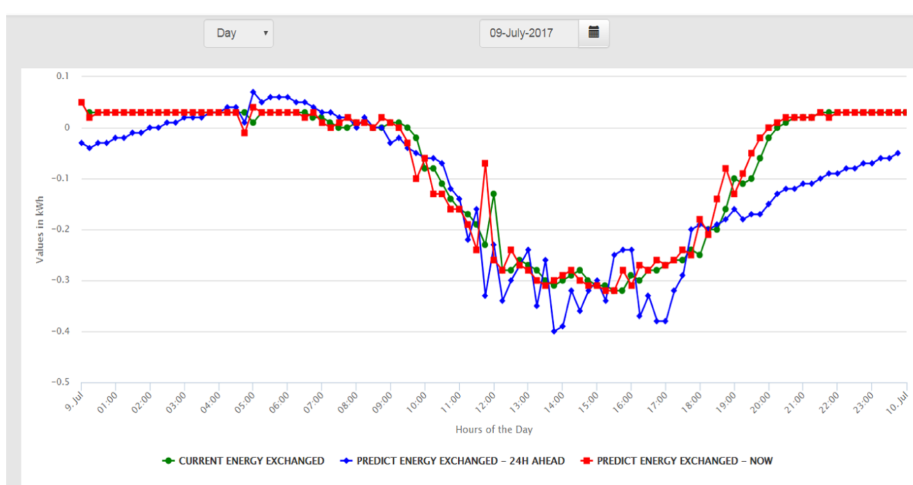

Fig. 4. Example GUI screen comparing the real and predicted energy exchange for a single household.

performing energy balancing operations. That was the reason for avoiding the complexity of the prediction model, what we have achieved with the 16 hidden neurons and one output neuron. Depending on the computational context it took up to 15 s to perform the training of the network for each new incoming 15-min value from the smart meter. The prediction was computed immediately in below one second. Fig. 4 shows a diagram for a single household for 24 h with real values (in green), values predicted 24 h ahead (in blue) and the immediate network response for the current value (in red). This example shows that it sometimes works well with the prediction for single households, but it is rather an exception than a rule.

It is thus absolutely necessary to identify features that may sort the energy exchange patterns in classes and allow to provide better predictions. These features include for instance the irradiation, a parameter that on one hand controls the energy production by PV systems, but on the other defines also the consumption related to the use of light and also sometimes heating. Further, the kind of the day defines the pattern within the day. That is why we distinguish between different weekdays but also between weekend days and holidays. We also capture the day of year to capture seasons. Figs. 5 and 6 show how important this categorization of different days is. These figures show a weekend and a weekday pattern, respectively. Without distinguishing

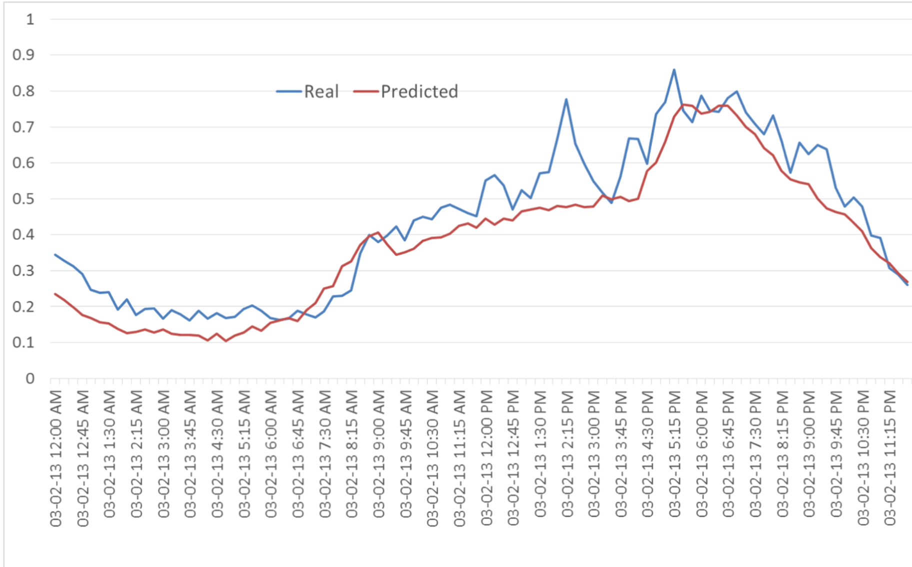

Fig. 5. Example energy exchange pattern and its prediction for a weekend day (03.02.2013).

the day of the week the prediction error would be significantly higher, so using this additional and available parameter helps a lot.

5. Model fit analysis

In the search for a proper key performance indicator for our forecasting method, we excluded Mean Absolute Performance Percentage Error (MAPE), widespread in literature on large-scale load forecasting [16,18,19]. In the case of micro-scale load forecasting, MAPE would take misleadingly overinflated values for small E_N^{norm} values and infinite values for $E_N^{norm} = 0$ [28]. We decided in favour of the Mean Absolute Error (MAE). Eq. (2) employed for normalization of E_N values brings a natural and informative interpretation of MAE for our forecasting model: it represents the average absolute difference between real and fitted (in the case of goodness of fit analysis) or predicted (in the case of goodness of prediction analysis) values, denoted as a fraction of the maximal absolute net load. We strongly advise to use the normalized measure reported in this paper in future reports concerning net energy load predictions. It would allow to reliably compare models involving net load values of different magnitude, especially values oscillating around the zero in micro-grid prosumption cases. Goodness of fit analysis allows us to learn how well the proposed ANN model captures regularity in the real data. Fig. 7 visualizes the detailed distribution of fit MAE for the model trained with the whole-year data. The bottom-most row of the heatmap illustrates the margin distribution of fit MAE over the hour variable. The leftmost column of the heatmap illustrates the margin distribution of fit MAE over the day of the week variable. The bottom-left tile shows that the overall fit MAE was 0.044, denoting 4.4% of the maximal measured net load. Again, this approach is similar to the MARNE indicator approach, proposed in [23], where the individual values are normalized using the supply capacity.

6. Model prediction test

In order to perform a prediction test for our ANN forecasting model, we trained the ANN model with randomly chosen four-week data and tested the model with data representing the next (fifth) week. Fig. 8 visualizes the detailed distribution of prediction MAE for this test. The

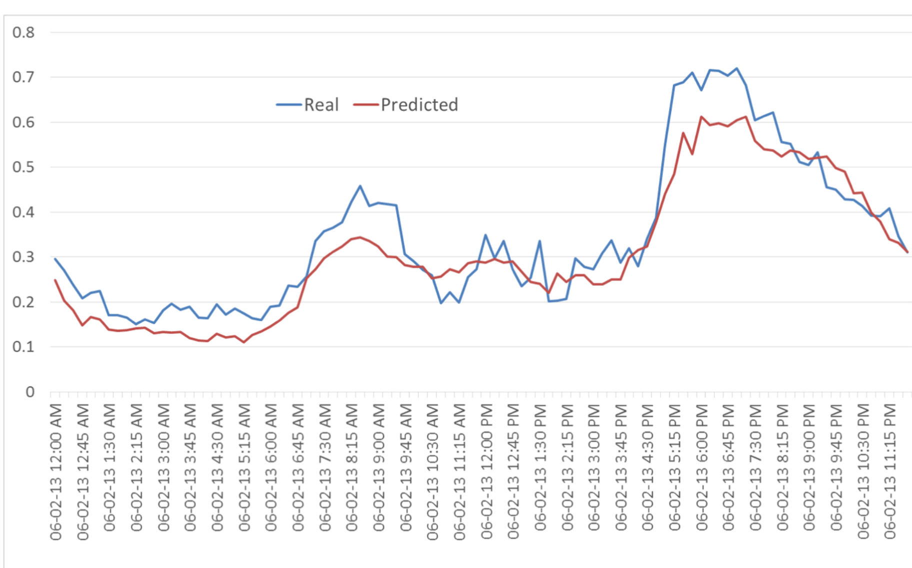

Fig. 6. Example energy exchange pattern and its prediction for a week day (06.02.2013).

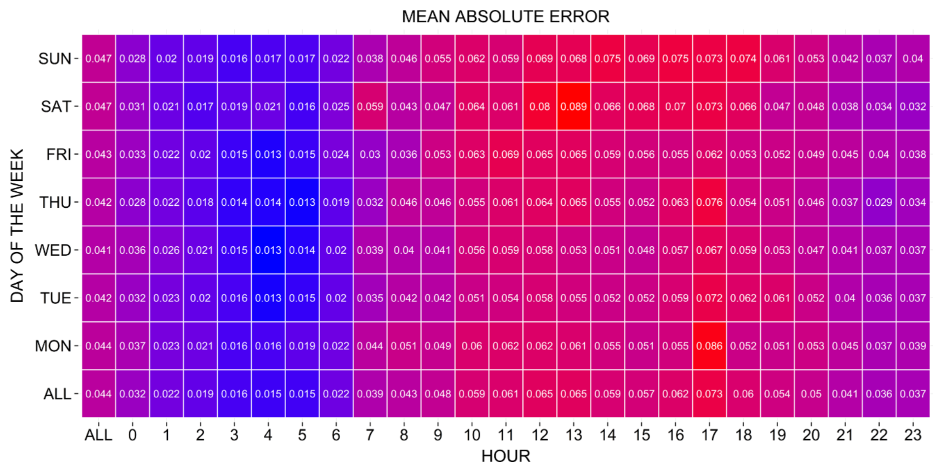

Fig. 7. ANN model fit analysis: distribution of Mean Absolute Error over the hour and day of the week variables for the model trained with whole-year data.

bottommost row of the heatmap illustrates the margin distribution of prediction MAE over the hour variable. The leftmost column of the heatmap illustrates the margin distribution of prediction MAE over the day of the week variable. The bottom-left tile shows that the overall prediction MAE was 0.054, denoting 5.4% of the maximal measured net load.

The prediction problem involved estimation of the 24 h net load profile at high, 15-min resolution. Engineers designing micro-scale energy balancing systems may want to grasp some notion of the limits to accuracy of high-resolution net load forecasting (both in time and the spatial domain). Thus, we found it important to present a detailed look at the prediction error distribution. Fig. 9 visualizes the additive inverse of absolute prediction error of the ANN model as a function of the true normalized net load (E_N^{norm}) and the hour variable. Points above the 0 value on the vertical axis represent ANNs overestimates of the true energy load, whereas points beneath the 0 value on the vertical axis represent ANNs underestimates of the true load at a given time. As can be seen in the visualization, overestimates did not exceed 15.5% of the maximal net load, underestimates did not exceed 30% of the maximal net load, and the vast majority of prediction errors were much lower.

In order to do a fair comparison of the achieved results with results achievable using statistical approaches we implemented an ARIMAX model and used it to perform a prediction based on the same input data. So, the ARIMAX model was created based on the same four weeks of input data and it was used to predict the values for following week. Fig. 10 presents the achieved distribution of the mean absolute error over the hours and days of the predicted week. Compared to the results achieved with the ANN approach (presented in Fig. 8) it can be observed that the ANN results are significantly better with respect to the prediction errors.

7. Conclusions

Our paper addresses several interwoven issues: feasibility of efficient short-term high-resolution (both in time and the spatial domain) residential net load forecasting taking into account renewable energy penetration; systematic approach to lagged feature selection for forecasting models, and prediction error measurement method allowing to compare models involving net load values of different magnitude, especially values oscillating around the zero in micro-grid prosumption cases. We provide a full description of both an ANN-based forecasting model and a feature selection method based on fractal dimension of the net electrical load time series interpreted as a dynamical system. We employ the described methodology and perform a case study of a real micro-neighbourhood comprising only 75 single-family houses.

Nowadays, decentralization of electricity generation causes changes in power grids, forcing operators to seek technical and economic solutions requiring efficient micro-scale load balancing. However, micro-scale load forecasting (being a prerequisite for micro-scale balancing) deals with energy load profiles which lack smoothness of large-scale aggregations and involve autocorrelations specific to individual customs and/or local conditions. Literature on electrical load lacks reports on studies dedicated to existing residential micro-neighbourhoods comprising small numbers of single-family houses equipped with solar

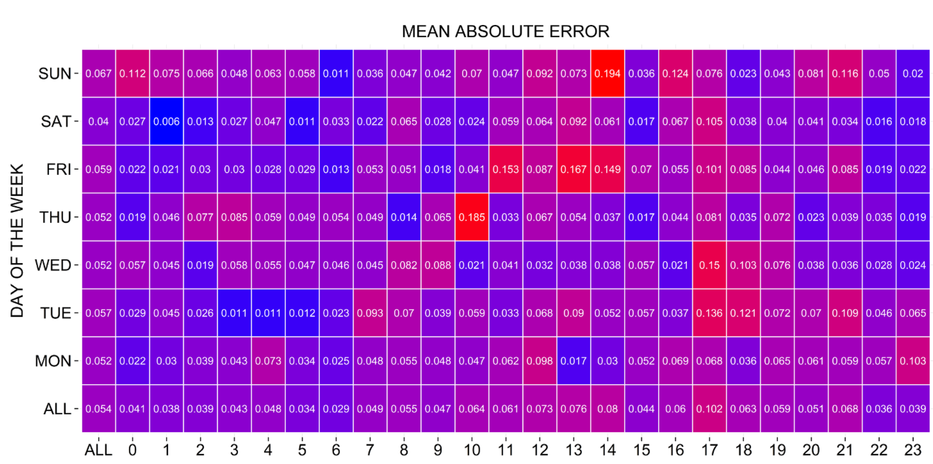

Fig. 8. ANN model prediction test: distribution of Mean Absolute Error over the hour and day of the week variables for the model trained with randomly chosen four-week data and tested with data representing next (fifth) week.

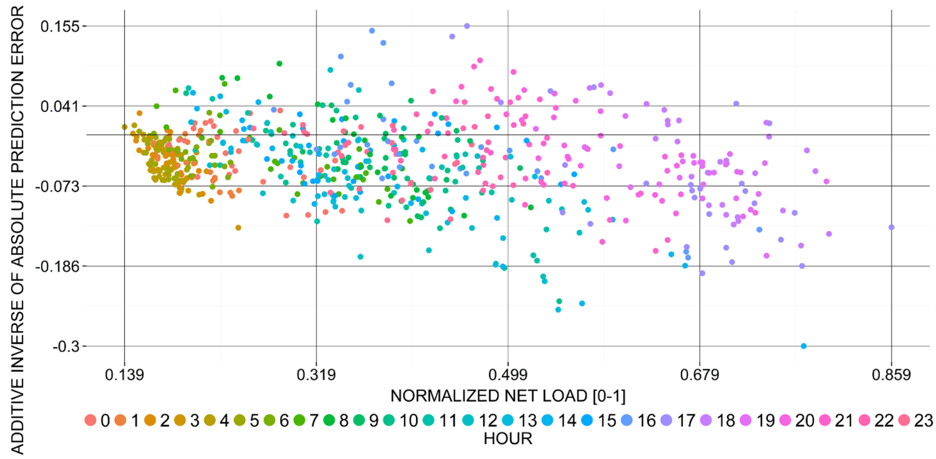

Fig. 9. ANN model prediction test: Additive inverse of absolute prediction error as a function of normalized net load (E_N^{norm}) for the model trained with randomly chosen four-week data and tested with data representing the next (fifth) week.

panels. Hence, our motivation was to fill this gap. The approach presented in the paper allowed us to obtain short-term predictions of high-resolution (15-min intervals) net load profiles with reasonable average MAE error equivalent to 5.4% of the maximal measured net load. We managed to obtain this result after training the proposed ANN model with data representing only four weeks of net load measurements.

Relative shortness of the time series scope needed for efficient model training provides an optimistic perspective on future real-life implementations of the described methodology, though one must remember that our study used the whole-year net load data to solve the lagged feature selection problem. In some situations, engineers may be forced to design energy balancing algorithms without prior access to extensive amounts of local data. Future studies could focus on examining the described feature selection heuristic with the use of shorter range of load measurements. Another limitation of the described research lies in the fact that for the prediction test we were able to use only historical irradiation measurements, whereas a full real-life scenario would require an inclusion of historical irradiation predictions as well. Without a doubt, future studies on short-term high-resolution load forecasting for micro-neighbourhoods with solar energy penetration require some more stress on the issue of exogenous weather-related inputs to the forecasting model.

It is also to be investigated to what extent randomly chosen subgroups of the set of houses create groups that can be subject of the prediction algorithm as well and what the border conditions are for the possible application of the proposed solutions.

The energy exchange or load prediction is part of a larger smart grid application that uses the prediction in order to plan control actions in advance. These actions include setting the power of the power plant or ordering energy from producers. But the energy management can also control household or prosumer level energy control and use the prediction to negotiate with the energy provider. In both cases, depending on the consequences for the deviations between the predictions and real energy values, there may be a need for measures that additionally act in real-time to compensate for imbalance due to prediction errors. These measures include controlling the smart appliances in order to adjust their energy usage or energy production according to the negotiated values. We plan further investigation of such measures as well as two level energy balancing algorithms.

We were able to confirm that the simple ANN solution was able to deliver good predictions for the defined neighbourhood. The predictions we have achieved using the simple ANN model are significantly better than the ones achieved using the ARIMAX model for the same input data. The presented solution was applied in the e-balance project, but we plan to further fine tune the structure of the ANN to improve the accuracy of the prediction, especially for individual households. As it can be seen in Fig. 4 there are relatively large differences between the individual measurements and their predicted values for a single household. We plan to investigate which additional parameters, from the ones that are easy to obtain, like air temperature, to those needing additional sensors, like status of individual appliances or motion detection, influence the accuracy of the predictions and reduce the errors

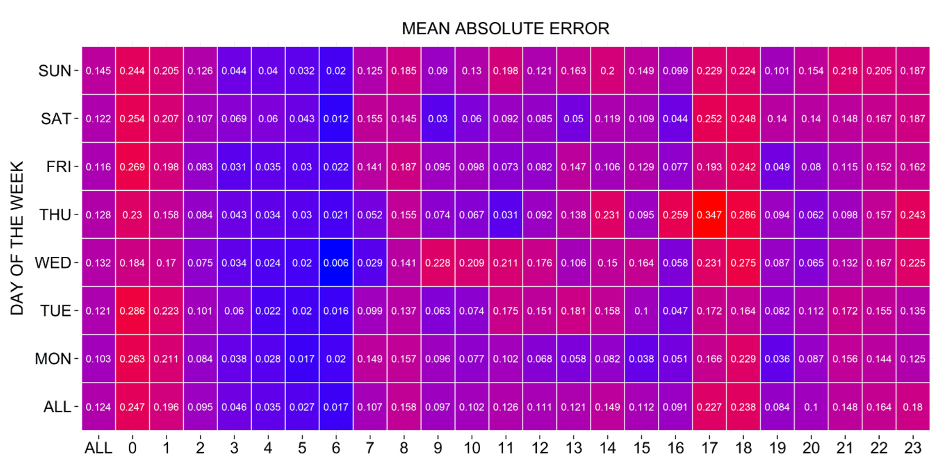

Fig. 10. ARIMAX model prediction test: distribution of Mean Absolute Error over the hour and day of the week variables for the model trained with randomly chosen four-week data and tested with data representing next (fifth) week.

for individual households. Here it is important to reduce the real-time actions to handle the imbalance to the minimum.

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