Residential Electrical Demand Forecasting in Very Small Scale: An Evaluation of Forecasting Methods

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***Abstract*—Applications such as generator scheduling, household smart device scheduling, transmission line overload management and microgrid islanding autonomy all play key roles in the smart grid ecosystem. Management of these applications could benefit from short-term load prediction, which has been successfully achieved on large-scale systems such as national grids. However, the scale of the data for analysis is much smaller, similar to the load of a single transformer, making prediction difficult. This paper examines several prediction approaches for day and week ahead electrical load of a community of houses that are supplied by a common residential transformer, in particular: artificial neural networks; fuzzy logic; auto-regression; auto-regressive moving average; auto-regressive integrated moving average; and wavelet neural networks. In our evaluation, the methods use pre-recorded electrical load data with added weather information. Data is recorded from a smart-meter trial that took place during 2009-2010 in Ireland, which registered individual household consumption for 17 months. Two different scenarios are investigated, one with 90 houses, and another with 230 houses. Results for the two scenarios are compared and the performances of the evaluated prediction methods are discussed.**

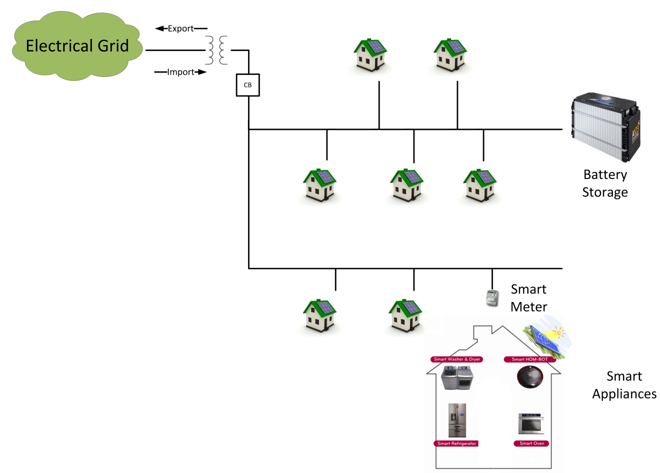


Fig. 1: Distribution Network Endusers

I. Introduction

The electrical grid was designed to deliver electricity from large power plants to the consumers in a three step structure: generation, transmission and distribution. This system has one-way flow of electricity and rudimentary one-way communications. Losses occurring from the generation side up to the user endpoint amount to approximately 8% of the total generated electricity, as a result of transmission losses, while only one third of the fuel is converted to electricity, with the resulting heat lost [1]. Electricity transmission losses are very low when compared to heat losses, with the distance rendering heat transmission towards consumers impractical in case of large power plants situated in plain field.

The emerging smart grid attempts to solve several existing problems in the current grid by reducing generation costs, transmission losses and CO_2 emissions, enabling two-way communications, self-healing and islanding capabilities, and integrating renewable sources. Distributed generation has a valuable role in diminishing the distance needed to deliver electricity, thus reducing the transmission costs. They can also provide heat towards the users, through means like combined heat and power (CHP) systems, due to the relatively low distance to the users when compared to large power plants. Therefore, microgrids and virtual power plants (VPP) are emerging as subsystems of the smart grid capable of providing the electricity needs of their own communities. Self-produced electricity has three possible flow options: to be consumed by the community, stored for further use, or to be exported to the main grid. In order to fully maximize the potential of microgrids and VPPs, demand-side management (DSM) has to be implemented for the consumers in applications like smart household device scheduling. DSM can help in reducing user and generator costs and CO_2 emissions by minimizing daily peaks and employing the renewable sources available at that moment. To do that though, plans of the consumers energy needs for the following day are acquired together with knowledge of renewable electricity availability from the likes of solar panels, micro-hydro turbines, wind turbines or CHP generators.

One of the ways of improving the capabilities of DSM is demand forecasting. Several different forecasting systems have been developed to deal with this problem [2]. Although high precision, as low as 1.97% mean absolute percentage error (MAPE), has been achieved on large scale (for example national and municipal level [3]–[6]), microgrid, VPP and transformer level forecasting has only recently emerged as a research interest [7]–[10]. The results are not very encouraging, with errors ranging from 5.15% MAPE at university campus level [10], where power demand peaks at 8 MW

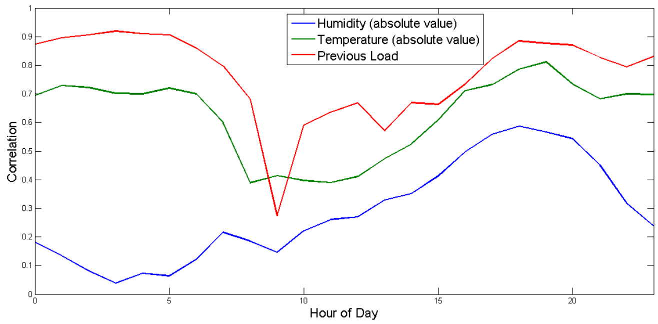


Fig. 2: Variables correlation

during the day, up to 13.8% MAPE at village level, where power demand peaks at 15 kW [7].

For a residential community such as the one pictured in Fig. 1, forecasting needs to be done at transformer level (340 kW demand peak for a 630 KVA transformer). Such a community of houses is suitable for a microgrid or a community based VPP of several dozens of houses that possess renewable energy sources and battery storage capacity like electric vehicles. The transformer can disconnect through a circuit breaker (CB) the community's access to the main grid in case of anomalies or blackouts, thus setting the community on islanding mode. In such cases complete autonomy could be needed, until reconnection to the main grid is safe or possible.

In order to be able to predict the energy demand for a system like this, different forecasting methods need to be investigated on a smaller scale.

II. Design

In this paper we evaluate the performance of a total of six methods that have been previously successfully used for forecasting on larger scale. Particular focus has been given to Artificial Neural Networks (ANN) since they've proven very reliable in non-linear and non-stationary system predictions [11]. Also a set of three closely-related statistics based linear prediction methods, auto-regressive (AR), auto-regressive moving average (ARMA), and auto-regressive integrated moving average (ARIMA) have been selected for comparison purposes. Furthermore, two other well trialled methods of electric load forecasting, Fuzzy Logic (FL) and wavelet neural networks (WNN), have been evaluated in our scenarios.

Each set of methods uses prediction based on previously recorded load. ANN, WNN and Fuzzy-Logic approaches also include weather information, since it is well known that weather has a considerable influence upon the energy consumption [12]. The statistical methods rely on time-series regression in order to make the prediction, thus using only historical demand records. Weather not only affects the energy consumption, but also the energy production in the case of renewable energy sources. A correlation test shows the relation between the current load and the load of the previous day, the temperature of the current day and the humidity of the current day. We can notice from Fig. 2 the high correlation of the

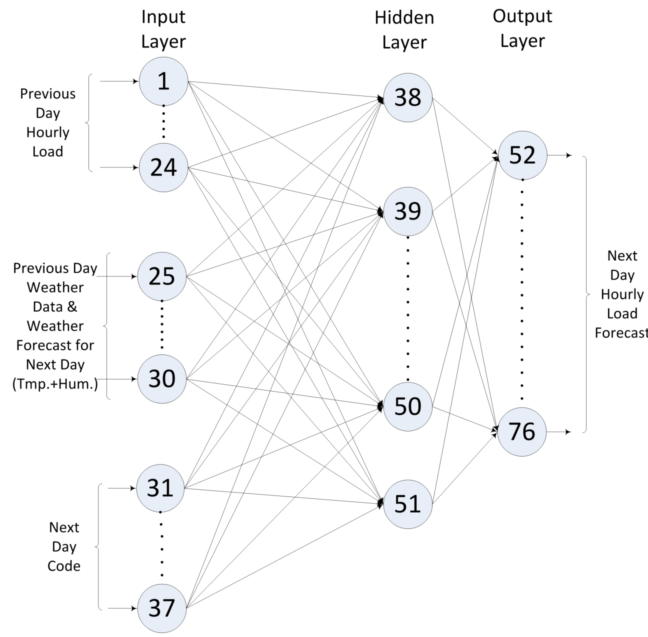


Fig. 3: ANN Structure

current load with the previous load and the forecasted temperature. There is also a significant influence of the forecasted humidity as well, more prominent in the second half of the day.

Two different scenarios were devised to test the methods. The first scenario covers 90 houses, reaching a peak of 140 kW, while the second scenario covers 230 houses, peaking at 340 kW. This is done in order to test the scalability of the predictive methods, since former evaluations were generally based on scales of tens of GW [4].

A. *Artificial Neural Networks*

There are several approaches to day ahead estimation through neural networks [2], [11]. Some of the most common are networks with 24 outputs [13], one for each hour based on a former set of days, and networks with 1 output [14], giving the prediction for the next hour based on the former ones. The two approaches were both considered. After running a set of experiments, results proved better for the 24 output version, so in this paper focus on the multiple output approach has been considered. The input of the neural network is based on the same day of the week as the one we are trying to predict. In addition to that we have employed historical weather information together with the forecasted weather for the predicted day. This involves dry bulb temperature and humidity. Input contains day of the week information to represent the five unique weekdays. A three layer multilayer perceptron was designed.

As we can observe in Fig. 3 we have a total of 55 input neurons, 24 for the previous load (one for each hour), 12 for the previous temperature and humidity (6 each), 12 for the forecasted temperature and humidity (6 each), and 7 neurons for the day of the week code. The hidden layer has given

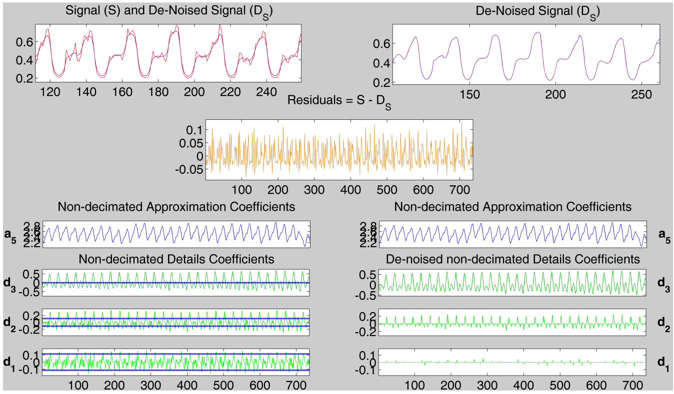


Fig. 4: Electricity Demand Decomposition

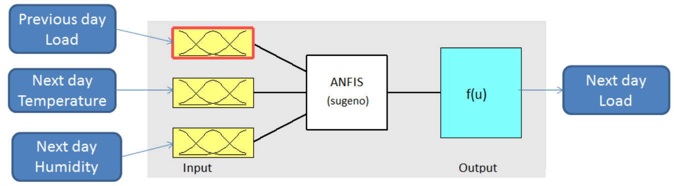


Fig. 5: Neuro-Fuzzy Structure

best results with a set of 15 neurons in our case. The output layer has 24 neurons, one for each hour of the day, set in chronological order. This brings us to an overall amount of 96 neurons for the network.

Several learning algorithms were investigated for the neural network training. Resilient backpropagation (RPROP) performed the best when compared to QUICKPROP [15], SARPROP [16] and cascade training, so it was further exploited for our prediction purposes. Both the input and the hidden layer have an extra bias neuron for weight adjustment. The network is fully connected, totalling 1224 links between neurons.

We have used three sets of data, one for training, one for validation, and one for testing purposes. The training set is used for configuring the weights of the neurons based on the available input in order to reach the desired output. The validation set takes care of overtraining issues, so that the neural network will not overfit the network based only on the selected samples of the desired outputs in the training set. The testing set is used to check the performance of the neural network after the training has been accomplished, comparing the predicted results with the actual values for the forecasted day. The first set spans over 210 weekdays (70% of total days), the second over 60 weekdays (20%), and the third over 30 (10%) weekdays. The input layer and hidden layer weight activation functions were selected based on the best results obtained for the validation set, in order to avoid overfitting.

B. Wavelet Neural Networks

Due to the very small scale of the load demand used for prediction, load denoising is a good way of smoothing the load shape. This eases the training process, as the input for the neural network has less variation over the long timespan of one year, thus exploiting the similar samples. The filtering is part of the wavelet neural network approach (WNN). In our case the time-series is split into 5 different components, based on frequency, and the signal component with the highest frequency is processed in such a way as to retain only the highest peaks for the denoised curve.

Fig. 4 presents the decomposition process over 30 days. On the lower left side four unfiltered signals of the total five are shown, while on the lower right side we have their filtered counterpart. We can observe that only the bottom signal is filtered in order to retain the higher peaks, which are more significant than the other low level variations.

The same procedure as in the ANN case is used further on for the forecasting process, except that for input we have the smoothed version of the load. During the training period the desired output of the neural network is set to be the unfiltered load from the forecasted day instead of another smoothed version.

Our initial tests resulted in lower accuracy when rebuilding the signal from the two predicted parts, the denoised signal and the remaining residuals. This is due to the fact that the residual signal closely resembles white noise. Therefore the residuals are not further considered for prediction.

C. Neuro-Fuzzy

The concept of neuro-fuzzy systems combines the self-learning capabilities of ANNs with the fuzzy inferences developed over historical data. Fuzzy logic inference is able to rapidly deal with fuzzy uncertain problems. FL prediction systems have been previously investigated on a smaller scale, employing in one case a gas turbine of 8.4 MW maximum capacity [10]. Results when combined with neural networks on large scale have proven encouraging, with accuracy surpassing the one of ANNs [17]–[19]. Nevertheless, further research at microgrid level is needed, the initial results providing quite inaccurate values in comparison to large scale [20].

For this evaluation we have designed a neuro-fuzzy system which takes as input the previous day load, next day temperature and next day humidity. Each set of inputs provides the hour forecast for the following day. The Takagi-Sugeno [21] method of inference is used. The structure is shown in Fig. 5. The same three sets for training, validation and testing from the ANN approach are employed. The FL method outputs the forecast for each hour of the day based on three inputs: past load of the same hour of the previous day, temperature forecast and humidity forecast for the predicted hour. The neuro-fuzzy network has a periodicity of 24 hours, with each hour prediction being based on the same hour of the previous day.

D. Auto-regressive Methods

Statistical auto-regressive methods have been widely used for time-series prediction for almost half a century, with ARMA first being presented in [22] and later on popularised together with ARIMA as Box-Jenkins approaches [23]. The models are able to analyse random processes and linearly relate the output of the prediction system based on previous values of the time-series. The series is decomposed through a formula that relates individual coefficients with the former n values. ARMA and ARIMA additionally have a moving average part, where another set of coefficients is considered for the moving average model component. While AR and ARMA deal with weak stationary systems, ARIMA applies differencing on a non-stationary time series, thus removing the non-stationary component and treating the result as a stationary series. Our AR model estimates the following day based on the previous 6 weeks recorded demand ($n = 720$), and uses only one set for training. The ARMA and ARIMA models both estimate the next day based on only the past week's data ($n = 120$).

III. Implementation

We have evaluated the proposed methods on two different scenarios. The two scenarios are on different scales in order to test the scalability of the methods. Further use can be found when applied to simulations such as the ones presented in [24] or distribution level load in case of a residential area transformer.

Our scenarios use information recorded by the Commission for Energy regulation (CER) trial in Ireland over 17 months in 2009-2010. The trial recorded half-hourly smart-meter data from residential and commercial users. In this paper we focus only on the control set of residential users, whose daily demand were not affected by electricity price changes over the day. The samples don't rely on any type of demand response and represent anonymous households and apartments.

The first evaluated scenario covers 90 houses and the second one 230 houses, the last one roughly corresponding to the number of houses provided for by a 630 kVA transformer. The estimate was calculated based on several criteria. First we consider the energy demand of 90 houses which amounts to a maximum of 140 kW for the highest peak. We take into account also the capacity losses occurred, such as the one in Eq. 1.

$$\begin{aligned} S &= P + jQ \\ S^2 &= P^2 + Q^2 \\ |P| &= |S||\cos\phi| \end{aligned} \tag{1}$$

,where S is the apparent power, P the active power, Q the reactive power and $\cos\phi$ the power factor. The power factor is the decisive element in the conversion of apparent power towards active power.

Not only is the true (active) power circulation charging the network, but the reactive power is introducing another randomly varying line congesting element, different from the active power variation. Both components of the apparent power are varying more or less independently. The reactive power's origins are the associated inductive elements (coils) in the home appliances. Until now, as can be seen from the considered data, only the true power circulation is taken into account.

Transformers are designed with an overdimensioning factor of 0.5 from the maximum consumption. Considering a power factor of 0.85(inductive) and having attained a top maximum value of 140 kW from the 90 houses scenario over a period of 1.5 years, the coverage of a 630 KVA should be roughly 340 kW or 230 houses, with respect to the proportions in the first scenario and the considered reactive power circulation.

Added to this information, we have used hourly recorded weather data from OGIMET [25] for the same time span as the smart meter trial. This includes information about temperature and humidity reported in Dublin. The capital city was selected as a reference point for having the largest population in Ireland, assuming most of the surveyed users are from Dublin.

In our evaluation we have focused only on weekdays, due to the fact that their demand is higher and more unpredictable than the demand over the weekends. The load demand was normalized to fit in between 0 and 1 for easier processing in the case of neural networks, according to the formula in Eq. 2. The same procedure was applied to temperature and humidity.

$$\frac{1}{1 + e^{\frac{-(x-\bar{x})}{stdev}}} \tag{2}$$

For the neural networks methods we have used the Fast Artificial Neural Network (FANN) Library developed in [26]. The reason for this choice is that FANN is a highly configurable open-source tool, written in C/C++, which makes it easier to adapt the neural network to our needs and employ it in further experiments.

The AR, ARMA, ARIMA, and Fuzzy Logic approaches were implemented by employing MATLAB's System Identification and Fuzzy Logic toolboxes. Additionally, the load denoising was accomplished with the help of the Wavelet toolbox.

IV. Results

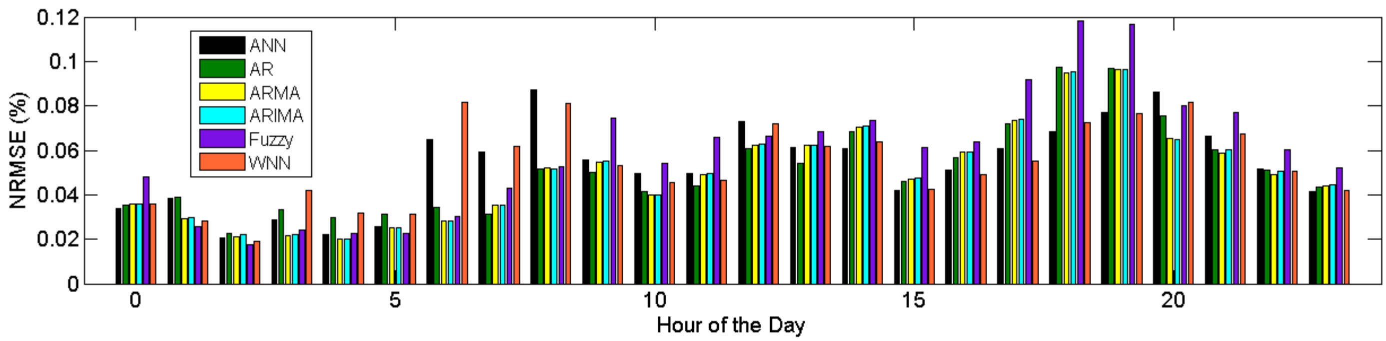
The version of each method that reached the best results according to the normalized root-mean-square error (NRMSE) measurement, described in Eq. 3, has been selected.

$$\begin{aligned} RMSE &= \sqrt{\frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{n}} \\ NRMSE &= \frac{RMSE}{x_{max} - x_{min}} \end{aligned} \tag{3}$$

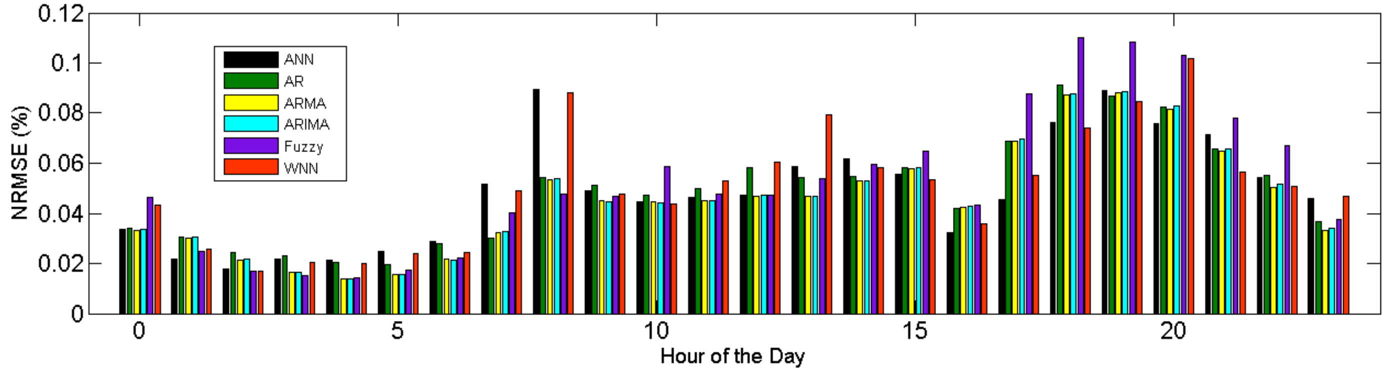
,where x_i the actual value, $\hat{x}_i$ the forecasted value, x_{max}, x_{min} the maximum and minimum values from the tested set.

Tests have been made over a sample of 720 hours, 30 weekdays in between the 20th of August 2010 and the 1st of October 2010.

A prediction for three days during the test interval is shown in Fig. 8. Three consecutive days of the week are forecasted and presented along with the actual load (black colour).



(a) 90 houses



(b) 230 houses

Fig. 6: Methods average

Although in the second scenario we have a smoother, less noisy shape, the chaotic behaviour of the overall demand is still noticeable in both cases, with several spikes during the day, usually a higher one in the early morning and the biggest one at the very end of the evening. The performance for each hour of the day for the six methods is presented in Fig. 6. The three statistical methods, AR, ARMA and ARIMA provide, as expected, very similar results and curve shapes, with ARIMA the best one out of them, narrowly surpassing ARMA in accuracy according to results from Table II. ARIMA is the only auto-regressive method presented due to the curve similarities of the three regressive approaches. They obtain the best average results over a 24 hours period, while not exceedingly accurate in any part of the day when compared to the other methods.

We can observe from Fig. 6 that during the 24 hour period there are two critical points that require estimation, where most of the methods lose accuracy, the morning and the evening peak. These two points are essential for load scheduling and peak shaving algorithms, which contribute in reducing the stress on generators and transmission lines. All the methods provide quite good results during night time, between 10pm and 5am.

While the FL method proves to be overall the least accurate method in both the 90 house and the 230 house scenarios, it has the best results in the first half of the day, which helps in providing accurate results for the morning peak (7-9 AM). The differences are especially noticeable in the 230 house scenario. However, during the evening peak (5-8 PM) the FL accuracy decreases noticeably.

The ANN and WNN approaches perform the best before and during the evening peak, although with significant inaccuracies occurring along the morning peak area (7-8 AM). The WNN method outperforms the ANN one for the second part of the day especially in the 90 house scenario, where there is more noise added in the evening peak. On a 24 hour basis ANN obtains better results, especially in the 230 house case. Still, the two methods follow quite similar curves, more noticeable in the first scenario where their average results are very close.

Therefore, we could say that the FL and ANN methods are complementary, the first one providing good results in the AM interval and the second one having good results in the PM interval.

The load shapes all follow slightly different patterns between different days of the week, with an increasing trend that has been noticed starting from Monday towards Thursday, and then a sudden drop to the lowest power consuming day of the week, Friday. In our experiments, unlike in existing work, where usually there is one morning peak and one evening peak, we are dealing with two morning peaks and 1-2 evening peaks. To account for this, the day of the week best predecessor for forecasting is the same day of the week before instead of just the day before.

There are also unforeseeable daily shapes such as the one in Fig. 7, which have a considerable influence upon the overall performance of the system, increasing the average NRMSE. In our test sample of 30 days we had 3 such days, all different from each other and dissimilar from our previously modelled shapes. We can notice three separate morning peaks and two evening peaks in the presented figure.

Another observation to be made would be that, compared to other daily demand shapes such as the one in [8], our scenarios provide an additional second morning peak, usually lower than the first. This could be another critical point in the evaluation of the prediction systems. One potential explanation could be that in a scenario of thousands of houses the two morning peaks merge into one, but in our case we are dealing with a very small scale scenario.

V. Conclusions and Future Work

In this paper we have evaluated six forecasting methods on two different scenarios. From the obtained results we can conclude that there is no method that cleary outperforms the others. Results are ranging from 2.94 NRMSE (ARIMA) in the 230 houses scenario to 4.24 NRMSE (FL) in the 90 houses scenario. Accuracy proves to be lower than in large scale tests, due to the added noise and significant influence of single users over the overall demand. While the regressive approaches provide the best average results, the FL, ANN and WNN methods are very good in morning and evening peak estimation. Peak estimation is an essential part in day ahead prediction, with systems being developed which focus only on this topic. On a large scale all the methods are expected to perform well. However, there is a clear difference in accuracy between the two scenarios, where every single evaluated method performs better in the 230 houses scenario, as seen in Table I. The difference is more than 0.5% NRMSE for each approach. The increasingly inaccurate results emphasise the difficulties in very small scale prediction, where noise and chaotic behaviour have more impact. Compensation between consumers occurs on a large scale. For scenarios like the 90 house case every single user can influence the overall demand shape for one day by changing their daily behaviour or by employing power demanding appliances, thus generating more noise. A simple on-demand water heater (5 kW) switched on at a different time of the day can shift the overall demand with more that 10% for one hour in the 90 houses scenario.

TABLE I: Scenario comparison

Method	NRMSE (%)	
	90 houses	230 houses
ANN	3.82	3.05
WNN	3.84	3.20
Neuro-Fuzzy	4.28	3.44
AR	3.67	3.05
ARMA	3.61	2.94
ARIMA	3.63	2.93

TABLE II: Methods error
(Case I - 90 houses, Case II - 230 houses)

Hr.	NRMSE (%)											
	ANN		WNN		FL		AR		ARMA		ARIMA	
Scn.	I	II	I	II	I	II	I	II	I	II	I	II
0	2.52	1.94	2.59	2.51	3.73	2.69	2.73	1.96	2.76	1.93	2.76	1.94
1	2.67	1.27	1.92	1.47	1.77	1.44	2.80	1.78	2.23	1.75	2.30	1.77
2	1.58	1.03	1.45	0.97	1.36	0.99	1.60	1.41	1.51	1.24	1.58	1.26
3	2.05	1.25	2.85	1.18	1.72	0.88	2.47	1.32	1.68	0.95	1.72	0.95
4	1.77	1.24	2.19	1.16	1.53	0.83	2.02	1.19	1.46	0.80	1.45	0.80
5	1.95	1.43	2.32	1.38	1.71	1.00	2.04	1.14	1.65	0.89	1.64	0.90
6	4.25	1.67	5.18	1.40	2.51	1.29	2.65	1.61	2.16	1.25	2.15	1.23
7	3.87	2.97	4.15	2.84	3.16	2.32	2.39	1.73	2.66	1.87	2.66	1.88
8	5.98	5.18	5.64	5.11	3.62	2.76	3.73	3.15	3.59	3.10	3.59	3.11
9	4.17	2.83	4.01	2.76	5.21	2.72	3.74	2.97	3.98	2.60	3.98	2.58
10	3.71	2.59	3.43	2.53	4.14	3.40	3.18	2.73	3.27	2.57	3.28	2.55
11	3.84	2.69	3.76	3.07	4.81	2.75	3.48	2.89	3.62	2.60	3.65	2.60
12	5.14	2.74	5.24	3.49	4.35	2.74	3.97	3.37	4.06	2.71	4.08	2.72
13	4.24	3.40	4.39	4.59	5.03	3.13	3.94	3.15	4.41	2.70	4.42	2.70
14	4.54	3.58	4.59	3.36	5.44	3.44	5.04	3.17	5.29	3.06	5.31	3.06
15	3.41	3.23	3.41	3.09	4.65	3.74	3.47	3.38	3.87	3.35	3.93	3.36
16	3.65	1.87	3.45	2.06	4.58	2.50	4.00	2.43	4.08	2.45	4.06	2.47
17	4.66	2.63	3.90	3.19	7.06	5.08	5.14	3.98	5.30	3.98	5.37	4.03
18	4.68	4.42	4.98	4.29	8.76	6.36	6.60	5.27	6.59	5.05	6.64	5.08
19	5.42	5.16	5.64	4.90	8.23	6.26	6.33	5.03	6.33	5.11	6.35	5.12
20	6.04	4.38	5.55	5.89	5.78	5.96	5.48	4.78	4.92	4.73	4.93	4.78
21	4.80	4.13	4.79	3.27	5.51	4.52	4.55	3.79	4.50	3.75	4.56	3.81
22	3.63	3.13	3.62	2.93	4.25	3.88	3.65	3.19	3.50	2.92	3.54	2.98
23	3.05	2.66	3.15	2.71	3.75	2.17	3.11	2.12	3.19	1.92	3.24	1.97
Avg.	**3.82**	**3.05**	**3.84**	**3.20**	**4.28**	**3.44**	**3.67**	**3.05**	**3.61**	**2.94**	**3.63**	**2.93**

There are also a few other observations to be made. The ANN and WNN methods can make day ahead prediction based on the weather forecast, but depending on the accuracy of the weather forecast the prediction could be extended by up to one week ahead with similar results. They rely heavily on proper weather prediction. The other methods depend only on the previous load and have prediction range of up to 24 hours ahead. Performance degrades after that interval. A different version of the regressive and FL methods could be designed that considers only the same days of the week, rendering week ahead prediction plausible, or even increasing the accuracy of day ahead prediction.

Although on a transformer level scale (second scenario) the given results are relatively accurate for some of the methods,

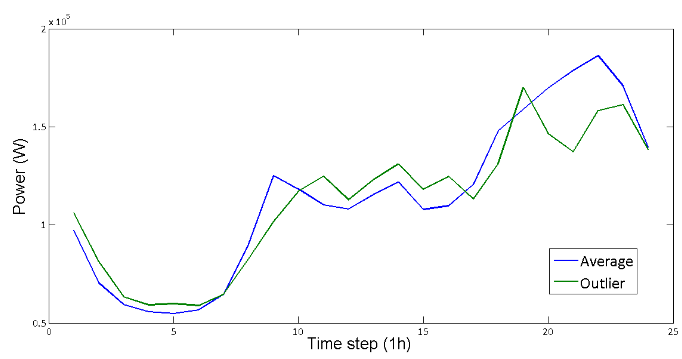
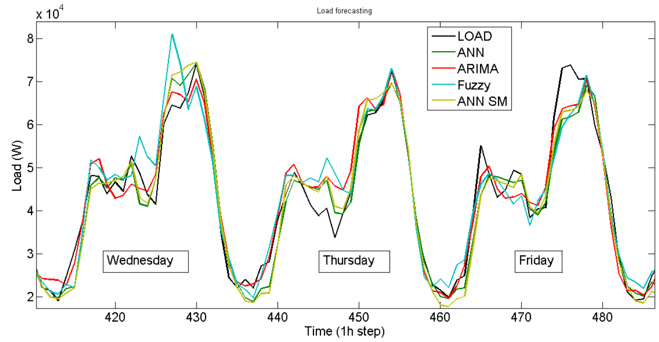
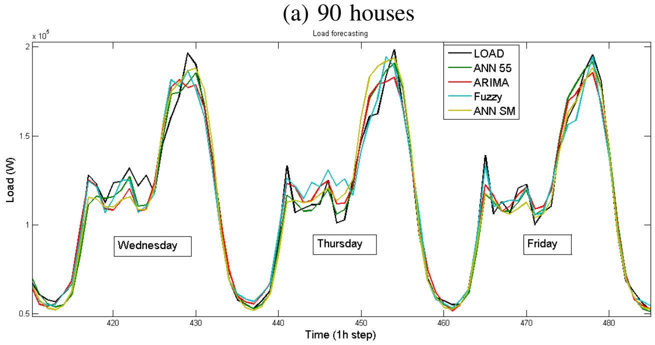


Fig. 7: Outlier shape



(a) 90 houses



(b) 230 houses

Fig. 8: Load forecasting over three consecutive weekdays

it is quite obvious that we cannot select one method at the expense of the others. We either have the choice of good morning peak prediction (FL), good evening peak prediction (ANNs), or good overall prediction (ARIMA). Even though the last case provides us with the best results, it still generates high errors in the evening peak, a critical point since the highest power usage of the day is during that time. There are also investigations to be made upon samples affected by demand response and by the integration of renewable sources, which will most definitely influence the daily load shapes and therefore the accuracy of the methods.

In conclusion, we can only suggest a combination of several methods in order to provide better overall results than the ones obtained. On a 24 hour basis there are methods that deal better with peak times and methods that deal better with low times. Our expectations are that by using their advantages in a combined approach the error levels would be lowered to a practical implementation of very small scale prediction. This is a topic of further research in the field.

Acknowledgment

This work was supported, in part, by Science Foundation Ireland grant 10/CE/I1855 to Lero - the Irish Software Engineering Research Centre (www.lero.ie)

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