A Hybrid Approach to Very Small Scale Electrical Demand Forecasting

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***Abstract*—Microgrid management and scheduling can considerably benefit from day-ahead demand forecasting. Until now, most of the research in the field of electrical demand forecasting has been done on large-scale systems, such as national or municipal level grids. This paper examines a hybrid method that attempts to accurately estimate day-ahead electrical demand of a small community of houses resembling the load of a single transformer, the equivalent sizing of a small virtual power plant or microgrid. We have combined the advantages of several forecasting methods into a novel hybrid approach: artificial neural networks, fuzzy logic, auto-regressive moving average and wavelet smoothing. The combined system has been tested over two different scenarios, comprising communities of 90 houses and 230 houses, sampled from a smart-meter field trial in Ireland. Our hybrid approach achieves results of 3.22% NRMSE and 2.39% NRMSE respectively, leading to general improvements of 11%-28% when compared to the individual methods.**

Keywords*—*demand forecasting, hybrid, microgrid, VPP

I. INTRODUCTION

The smart grid has recently emerged as a new development platform for the electrical grid. The currently deployed electrical grid relies on a system that is mostly unidirectional in nature, based on centralised large power plants that generate the bulk of our daily demand. At the moment, the general noticed trend is towards an increase in demand due to the electrification of appliances and the emergent electrical vehicles, the latter which could account, together with PHEV, for 20%-50% of the total vehicle market share by 2030 [1]. The growing demand needs to be matched by additional power sources, while we also have to take into account the limited resources of fossil fuels remaining. Other issues need to be addressed as well: transmission losses, together with the wasted heat [2]; CO_2 emissions resulting from fossil fuels; and the development of self-healing abilities. Integration of renewable sources is a key component in both the attempt to match demand requirements as well as reducing the CO_2 emissions and decreasing our dependency on fossil fuels.

On the long-term, renewable sources could become a major component in the electrical network. In a grid that employs many generators based on renewable sources, the failure of one element can be quickly covered by the swarm of other sources, drastically reducing the possibility of general grid failure. A challenge of such a distributed system provides difficulties in integrating renewables without affecting the nominal voltage and frequency levels of the grid.

A potential solution to mitigate the aforementioned problems is the organization of the grid in a decentralised fashion, where it relies mainly on distributed electricity resources such as generators and storage facilities belonging to microgrids or virtual power plants (VPPs). A microgrid consists of a set of power generation and storage units such as wind turbines, solar panels, combined heat and power (CHP) systems, fuel cells, batteries and fly wheels. Microgrids are by nature entangled to consumers, leading to lower transmission costs and enabling use of the additionally generated heat from the CHP stations. They can operate as an autonomous grid or connected in parallel with the main grid. In case of blackouts occurring in the electrical grid, microgrids can disconnect from the main power network and function in islanding mode, thus continuing to provide electricity to its own community of users and allowing the main grid to perform the recovering operations without interfering with the customers. After the reconfiguration of the network, microgrids can be reconnected individually at different time steps to maintain the stability of the network. On the other hand, VPPs are an aggregate set of supplies with different owners which act as consumers, grouped together to trade electricity with the grid and supply the consumers in a cost effective manner, while maximizing the use of renewable energy sources.

Consumer behaviour impacts the supply side, thus affecting generator scheduling over the day. Demand forecasting procedures have been employed in order to know in advance the power requirements of the grid, enabling efficient use of the available resources. Electricity market operators rely on short term load forecasting, with auctions and biddings performed between the market operator and the generators prior to the day of supply, based on day-ahead demand forecasts.

The combination of microgrids, VPPs and their associated community of consumers, when compared to large generators, have three options with respect to the use of electricity. They can generate electricity and sell it back to the grid if it surpasses the demand, import electricity for usage, or store electricity, depending on the market conditions and the availability of the renewable sources. Participation in the market depends on these entities' estimated own loads. To ease the decision process of the microgrids or VPPs, small scale demand forecasting procedures can be employed. The issue of small scale forecasting has risen recently due to the power generation capabilites of VPPs and Microgrids. In order to participate in the electricity market as bidders, sellers, or frequency control reserves, these units have to be able to define their supply or demand. We have considered this generation ability as very small scale when compared to previous forecasting attempts, as the typical combination of microsources provides power in the range of 1MW in microgrids. Therefore, accurately estimating the load of such very small scale systems can provide a crucial advantage for entities participating in the energy market.

This paper focuses on demand forecasting on very small scale, and is organized as follows: Section II describes the related work in short term load forecasting in general, as well as at microgrid and VPP level; Section III presents the design of our hybrid approach to forecasting at very small scale; Section IV is dedicated to the results obtained by the hybrid approach and comparisons to individual methods; and Section V presents the conclusions drawn from the performance of our approach and future changes in the grid that need to be accounted for in next generation demand forecasting.

II. Background and Related Work

There are many examples of successfully implemented large-scale electricity prediction, such as at national level, where demand forecasting is an essential component in the generation of the electrical grid [3]–[6]. At the microgrid level (small scale), prediction has been recently considered of interest [7]–[10]. Unfortunately until now prediction accuracy has seen a noticeable decrease when compared to large scale. Our observation is that, at the moment, results are not very encouraging, with errors between 5.15% and 13.8% MAPE at university and village level respectively [7], [10]. We believe that this might be due to the highly unpredictable behaviour of individual consumers. Such behaviour can affect the daily electricity demand shape of the community, but on wider samples the deflections from the average daily shape tend to be assimilated.

While microgrids can be seen exclusively as generators, the penetration of renewable energies has brought electricity generation capabilities to individual users. The most popular situation is the one of solar panels, which can easily be installed on rooftops, but there are also examples of small wind turbines and CHP systems employed by more remote households/farms. Additionally, electric vehicles can behave both as consumers and storage facilities in case of emergency, being able to provide energy back to the household when necessary. The collaboration of households having the purpose of efficiently using the energy produced develops further towards the concept of a VPP. If we consider exclusively the generation facilities of a community of such users, the resulted VPP can be seen as a microgrid as well. We envisage such a system in a cooperative environment, where the subnetwork belonging to a transformer allows users to exchange electricity therefore minimizing power flow from the main grid. Moreover, electricity can be sold back to the grid for the sake of maximizing the use of renewables. These decisions heavily rely on the future electricity usage of the community, which cannot be predefined due to the nature of human behaviour. Day-ahead demand forecasting is therefore employed in such cases.

In order to simulate such a collaborative environment we are relying on data from an ensemble of households, which was collected during a smart-meter trial in Ireland. A set of two scenarios comprising 90 houses and 230 houses are considered in order to replicate the demand of a single transformer and observe the scalability of the forecasting approach.

On such a small scale, previous results have shown the advantages of different forecasting methods, such as artificial neural networks (ANN), neuro-fuzzy (NF), auto-regressive integrated moving average (ARIMA); neither of the approaches clearly outperformed the others [11]. In the particular test case neural networks have proven good at evening peak estimation, fuzzy logic performed well on the morning peak estimation, and auto-regressive techniques have shown good overall results without particular accuracy in critical areas when compared to the previous approaches.

Peak prediction is essential in generator scheduling, real-time market pricing for electricity and also helps in determining possible transformer or network overloads. Overall accuracy is required for total power consumption over the day and in determining the length of autonomous or islanded functioning of the power generating VPP. Therefore the next logical step is to combine all the previously mentioned advantages of individual methods into a hybrid system.

III. Design

This paper relies on empirical analysis of several forecasting methods results on very small scale. According to the work presented in [11], four methods have proven superior at different intervals of the day: ANNs, wavelet neural networks (WNNs), NF and ARIMA. While all methods rely on historical load information, some of them include weather information such as temperature and humidity for the day-ahead electrical load prediction. This uses both past weather records together with the forecasted weather for the next day. The training is performed over weekdays exclusively, due to the significantly different shape of the weekends. Moreover, bank holidays together with Christmas days, which have particular demand curves as well, are also excluded from the training samples.

This section describes each individual method in general together with the particular approach for our case, and then describes and motivates the choice for the hybrid architecture.

A. Artificial Neural Networks

ANNs have been proven as a reliable method for electricity forecasting in the past [7], [12]–[14]. They consist of a number of inputs, outputs, and hidden intermediate layer(s), where an attempt to match the computed outputs with the desired outputs is performed, known as the training of the network. The training procedure is based on an evolving weighted mathematical relationship between the different individual elements (neurons) of the layers. A set of given inputs and desired outputs is initially given for training.

Our neural network is made of three layers: an *input layer* of 55 neurons, with 24 neurons representing the load of the same weekday of the previous week (one for each hour), 12 neurons for past and forecasted temperature, 12 neurons for past and forecasted humidity, and 7 neurons for the code of the weekday; one *hidden layer* of 15 neurons, fully connected to the input and output neurons; and an *output layer* of 24 neurons, one for each hour of the next day's load forecast. There are two sets used for the training of the network, the initial training set of 210 weekdays, and a second validation set of 60 weekdays that is employed in order to avoid the overfitting of the network. For the implementation of the neural network we have used the Fast Neural Network Toolbox [15], an open source ANN where modifications were easily performed in order the adjust the ANN to our requirements.

B. Wavelet Neural Networks

Since the data used in our analysis is based on a relatively low number of users, chaotic, unpredictable variations of the daily load shape can be found, replicated in the form of spikes from the average shape. In order to alleviate the side effects of these deviations from the norm, a signal processing technique is employed on top of the usual ANN approach. The input of the neural network uses a denoised version of the original day demand shape processed with MATLAB's signal processing toolbox, with smoothed, diminished fluctuations, as seen in Fig. 1. The random spikes occurring along the demand are therefore diminished, by rebuilding the total demand from filtered wavelets. The output of the neural network though is still the same desired unfiltered output as in the ANN case.

C. Neuro-Fuzzy

Fuzzy logic has been successfully combined with neural networks in forecasting approaches for small scale systems [16], while former results in larger scale already surpassed the accuracy of traditional ANNs [12], [17]. The resulting method, defined in literature as neuro-fuzzy, involves fuzzy inferences of the historical data, therefore enabling the network to rapidly deal with uncertainty. The mentioned network assumes a set of inputs which are further fuzzified for processing, with the resulting output being defuzzified in turn to obtain the desired result.

Our NF approach considers three inputs for the neuro-fuzzy network: the load of the previous day, the forecasted temperature and the forecasted humidity. Each input set is hour based, resulting in 24 such networks for a whole day's forecast, one for each hour of the day. Accordingly, the output of each network is the forecast of the corresponding hour. Similar to the ANN procedure, a validation set is used to avoid overfitting. This is done with MATLAB's ANFIS toolbox.

D. Auto-regressive Integrated Moving Average

ARIMA is a classical approach to forecasting, being originally described in the 1950s [18]. The method is popularly known as a Box-Jenkins approach to time series modeling and forecasting [19]. There are three parts in dealing with time series modeling and forecasting, according to the ARIMA model: integration of the series, employed in order to remove non-stationary component; auto-regression, that splits the series into separate terms with corresponding parameters, in a polynomial form; and a second additional polynomial that denotes the moving-average component. Recently ARMA and ARIMA have been used with quite promising results in load forecasting [20]–[22].

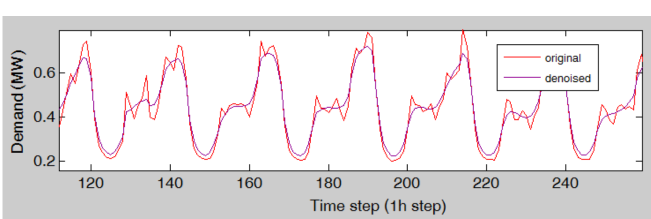


Fig. 1: Original and Denoised Demand

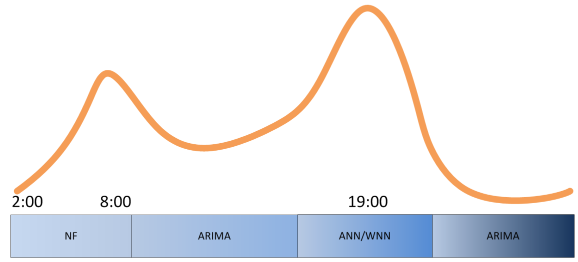


Fig. 2: Methods Combination over 24 hours

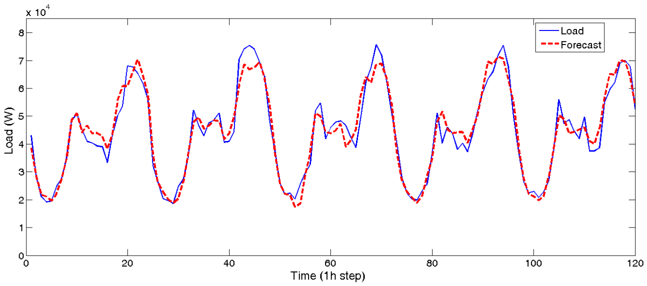
The model used in our forecasting approach relies solely on the past weeks power demand data in order to predict the following day's demand and is implemented using MATLAB armax function.

E. The Hybrid

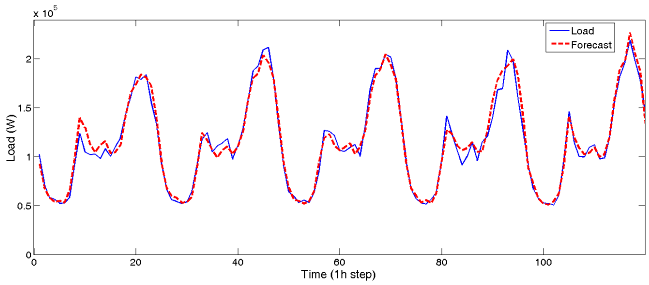
Based on the previous results we have devised a system that combines all of the four methods in one day, at predominantly their best performance intervals, as seen for example in Fig. 2. The algorithm runs tests over sets of four consecutive weeks of real and forecasted data and selects the best method for each of the 24 hours of the day. The four weeks are chosen for the algorithm decision process due to the possible occurrence of outliers, therefore the nearest historical days are aided with the closest former days in order to avoid such issues. In the chosen cluster of 230 houses for experiments the hybrid layout is the following: night time (2 AM) until and including the morning peak (7-8 AM) is generally represented by the neuro-fuzzy network; the time between the morning peak and the evening peak (8 AM-5 PM) is mostly modelled by ARIMA; the evening peak time (5-9 PM), with a longer time-span than the morning peak and a higher demand, tends to be better modelled by ANNs and WNNs (scenario dependent), while the final part of the day (until 2 AM) seems to be again better modelled by ARIMA. Note that the shape represented in Fig. 2 is a rough approximation of the daily demand, with the predominant methods of separate intervals of the hybrid shown as an example. Actual encountered values of the power demand are better shown in Fig. 1.

IV. Results

The hybrid approach to forecasting was evaluated using historical energy consumption data recorded during a field trial held by the Commission of Energy Regulation (CER) in Ireland. The trial recorded smart-meter data from anonymised residential and commercial users on a half-hourly basis during 2009-2010. The resulted recorded information contains both data from users with different tariff plans and pricing systems that adapt their demand to the variation of prices, as well as data from a control set of users for which power demand was not affected by electricity price changes over the day. The control set of users imply no constraint in their daily demand, therefore no action of demand side management. We



(a) 90 houses



(b) 230 houses

Fig. 3: Hybrid Forecasting over One Week

have chosen a subset of households from this control set, since the included households didn't benefit from any demand-side management programmes, and therefore demand restrictions did not apply. Additionally, in order to fulfil the requirements of weather information in the neural and fuzzy networks, hourly recordings from OGIMET were employed, comprising temperature and humidity information [23].

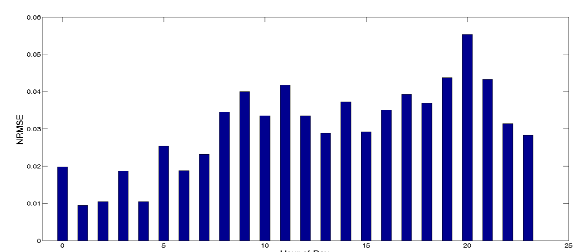
The obtained data was used for both training and testing our hybrid approach, as well as for training and testing the other forecasting approaches on which our approach is based. Two scenarios of different scale were used for this purpose, which can be related to areas with different densities, such as rural or urban cases. In the first scenario, consumption data from 90 houses is used, while in the second consumption data from 230 houses was used. Both of these represent the demand of a single transformer. For larger scale, this was modelled by a 630 kVA transformer that supplies roughly 230 houses [11]. Following a similar computational procedure, a 300 kVA transformer is devised for the set of 90 houses.

The half-hourly smart-meter information was down-sampled by averaging to 24 recordings per day, and then further normalised. The normalizing procedure is a requirement for neural and fuzzy networks inputs, and was also applied in the case of weather information. Training and forecasting is performed on the same set of houses. Since each cluster of houses has its own pattern, performing training on one set and forecasting on another leads to a significant loss of accuracy. We believe this is due to the possible differences in the anonymised household units, where some households belong to families while others to single individuals. Therefore, training has to been done for each set of houses before the forecasting procedure.

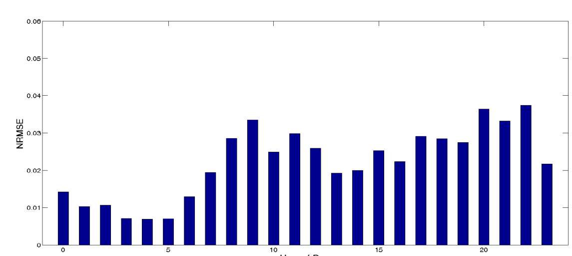
In Fig. 3 we can see the forecasting done for both scenarios over one week, through the hybrid method. A better estimation is achieved in the 230 house scenario, shown in Fig. 3b, where higher number of houses leads to a smoother overall user demand behaviour, thus leading to an easier prediction. The more chaotic behaviour in the smaller scale scenario comprising only 90 houses is shown in Fig. 3a, and can be attributed to the considerable impact of individual users.

The algorithm behind the hybrid approach has devised in both cases a dominant ARIMA component with a complementary ANN/WNN part in the evening peak. WNN has shown very good features in the 90 house scenario, where noise is eliminated and therefore accuracy is higher when compared to the more traditional ANN. The decision process in the morning peak estimation switches between NF, ANN and WNN, with NF proving quite successful in the 230 house scenario but having lower contributions in the 90 case. In the smaller scale scenario, both ANN and WNN contribute more to the morning peak estimation.

Results in Fig. 4 show the accuracy over each hour of the day for both scenarios. A normalized root-mean-square error (NRMSE) was used to evaluate the forecasting accuracy, averaged over the 10 days on a 24 hours basis. The highest NRMSE errors are observed around the two critical points, morning and evening peaks, although the differences are quite small on the larger scale scenario when compared to the 90 house scenario. Noticeably, the best prediction is found around night time. For comparison purposes against each separate method, ten random consecutive days have been chosen, totalling 240 hours. As we can see in Table I, the hybrid approach outperforms all individual methods, with improvements ranging from 11% in the ARIMA case up to 28% in the NF case. The best result achieved over one day provided 1.6% NRMSE accuracy, compared to the average 2.39%. This might mean that a day's changes when compared with historical data are



(a) 90 houses



(b) 230 houses

Fig. 4: NRMSE over Two Weeks

TABLE I: Scenario comparison

Method	NRMSE (%)	
	90 houses	230 houses
ANN	3.93	2.89
WNN	3.89	2.98
Neuro-Fuzzy	4.5	3.33
ARIMA	3.62	2.74
Hybrid	3.23	2.39

more accurately estimated when user behaviour implies less ”chaotic” behaviour. Although the differences from ARIMA might not look significant, they occur in the short intervals of the two critical points, which are of particular interest and have a dedicated area of peak prediction in the literature.

V. Conclusions

In this paper a novel hybrid forecasting method for day-ahead demand has been presented. The accuracy achieved goes as low as 1.6% NRMSE for particular days, on average reaching 3.23% NRMSE in the 90 house scenario and 2.39% NRMSE in the 230 house scenario. Our hybrid method's algorithm has generally selected ARIMA as the backbone of prediction, but ANN, NF and WNN have all played important roles in improving the accuracy; ANN performs very well in estimating morning and evening peaks, or peaks in general, proven also by the related literature; WNN has been instrumental in eliminating the noise of individual behaviour in the cluster, therefore reducing the chaotic influence of single users in very small scale; NF has provided considerably accurate results during night time, where the user behaviour tends to be more routinised, and also close to the morning time peak. The results obtained in the combined version propose our hybrid method as a potential forecasting approach for very small scale systems such as microgrids or VPPs. The implementation of small scale forecasting can provide several benefits, such as efficient use of renewable sources, economical (market) assistance, diminished peak load on the electrical grid, CO_2 emission reduction, and scheduling assistance in the case of blackouts.

Our expectations are that the forecasting procedures will change once renewable sources take a higher role in the electrical grid. Storage facilities and electrical vehicles will make use of the available renewable electricity, which in turn require forecasting at wind and solar level. Demand side management will also affect the daily demand shape, which we believe will lead to a more even curve, with lower peaks during the day, but a higher power usage during night time. The next step therefore is to test the hybrid forecasting approach in an environment where consumers receive forecasting information and adapt to different constraints in terms of price, user comfort and utility.

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