An ANN-based Energy Forecasting Framework for the District Level Smart Grids

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Abstract. This study presents an Artificial Neural Network (ANN) based district level smart grid forecasting framework for predicting both aggregated and disaggregated electricity demand from consumers, developed for use in a low-voltage smart electricity grid. To generate the proposed framework, several experimental study have been conducted to determine the best performing ANN. The framework was tested on a micro grid, comprising six buildings with different occupancy patterns. Results suggested an average percentage accuracy of about 96%, illustrating the suitability of the framework for implementation.

Keywords: ANN, District Energy Management, Grid Electricity, Smart City.

1 Introduction

There is an urgent need for transforming the electricity grid management to keep up with the rapid advances in generation technologies, electric power systems and increased integration of distribution energy resources in the low- and medium-voltage (LV/MV) grids [1-2]. At the heart of this transformation is the integration of ICT and energy infrastructures for providing a user-oriented service in an increasingly decentralized grid where (a) electricity from renewable sources is shared in the LV grid and (b) flexibility is managed, to maximize the utility of the service [2]. Conventional static grid, where energy flows from generation units to consumer [3] is being replaced by bi-directional flows of energy and information, resulting in end-users being metamorphosed into '*prosumers*'; i.e. both a consumer and producer of electricity using photovoltaic (PV), wind, combined heat and power (CHP) technologies [2,4], thereby increasing the complexity in managing the grid. To deal with this complexity, the smart grid management concept has been stand out as an adaptive solution to deal with all these complexities. Further, the grid management has also been enhanced to district level which increases the complexity of problem higher levels. Patti et al., [5] proposed a district information modelling and energy management system to control the district energy usage according to the user

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behavior such level of the energy management is highly complex, and has an unpredictable energy consumption pattern. Therefore, it requires intelligent solution to overcome with this types of difficulties. As intelligent system has been successfully utilized in the built environment to control and predict energy consumption such as artificial neural network [6], [7] genetic algorithm [8], rule based systems [9], and ontology based systems [10].
In this paper, an ANN based forecasting model is presented to predict the energy consumption of a smart grid. The forecasting model is aimed to determine next 15 minutes energy consumption according to current energy load in the grid. The paper consists of the following sections; the background, ANN based forecasting model, experiments and conclusion sections in section 2, 3, 4 and 5 respectively.

2 Background

District level grid energy management became one of the most popular topic in the area of the smart grid energy management and built environment. In district level energy management, the idea is to satisfy energy requirement for each building connected to the related district [11]. However, it is not easy task to carry out this process without having a robust forecasting model. As the forecasting models are able to provide a vision to future energy consumption of each individual buildings in the related district, which allow to control and manage the entire district well and also reduce the energy consumption according to the needs while maintaining the thermal comfort levels. The generalized hierarchical smart grid energy management can be illustrated as in Figure 1.

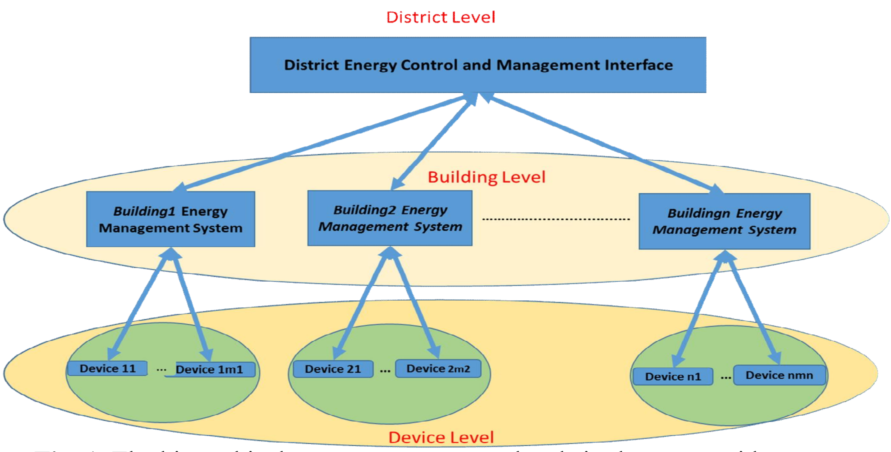

Fig. 1. The hierarchical energy management levels in the smart grid.

As highlighted in Figure 1, the district level energy control and management process consists of three levels, the first and bottom level is the device based control and

management process which provides the communication and energy management of individual devices.
In the second level, the building level energy management and control process appears, and the Building Information and Management (BIM) systems play the key role. As this system provides a holistic management approach to control, manage and visualize the building energy management. The traditional BIM systems have less flexibility in this sense, which contain simple rules to control entire building devices. However, the simplicity may not provide and efficient level of control in the entire buildings. Therefore, several intelligent based solutions have been proposed in the literature to generate much efficient and flexible solutions. Kalogirou, [12] proposed an Artificial Neural Network (ANN) - based solution to predict the energy consumption and generation in the renewable sources in building level to control energy consumption in the building well. Moreover, Ferreira et al. [13] proposed another ANN-Genetic Algorithm (GA) - based solution to control the heating ventilation and air conditioning (HVAC) systems while maintaining the thermal comfort level. Furthermore, Gonzalez and Zamarreno [14] also proposed another a short term load prediction method using ANN in the building environment.
As several studies have been utilized using the intelligent system technologies to control energy consumptions in the building level. However, the new technological developments provide to extend this level to the third level which is the district level. The district level of energy control and management is highly dependent on the controlling of energy requirement of each individual. In this stage, the energy control and management process expands to higher level complicated problems. Therefore, the usage of intelligent systems in this scale is becoming a needs to overcome several issues such as robustness, flexibility, adaptiveness and autonomous decision making process. These abilities provide to control entire grid well and optimize the energy consumption very well [15]. Valerio et al. [15] proposed a district level energy optimizer to control the electricity usage in the grid, and to optimize the prosumer's electricity usage according to the forecasting results. Thus, the forecasting module becomes very critical in the district energy management level due to the simplicity compare to the physical model. A well-defined forecasting model can be deployed into optimizer module to control and optimize the entire electricity grid system well. Therefore, it is highly important to get highly accurate forecasting model to predict each individual prosumers' surplus and demanded electricity on site. Therefore, it will provide a prior knowledge organize entire grid based on that.
In this paper, it is presented an ANN based forecasting system for the MAS^{2}TERING project to determine the individual buildings energy needs which provides the aggregated forecasting results to determine the energy needs of the entire smart grid. This information is then will be utilized in an optimizer agent to optimize the district level energy solution.

3 ANN-based Forecasting Module

Artificial Neural Network (ANN) is one of the most popular forecasting methods in the area of robotics, machine vision, energy management and control, medicine and manufacturing and social science [9]. This is highly related to the capability of the ANN on the complex and intrinsic problems. As a well-trained ANN is able to predict the outputs of complex problems without using any analytical relationships among the inputs and outputs [7], [9].

In this paper, a forecasting service has been developed using ANN for an EC funded project called MAS^{2}TERING. The forecasting service is utilized Irish Smart Grid data [16] to demonstrate the capability of the proposed model on the smart grid in district level. In the proposed model, six different types' buildings according to the occupancy types are considered to illustrate the strength of the forecasting algorithm on different energy consumers. As the occupancy types is one of the key variables to analyze the energy consumption in the buildings [17]. Thus, it has been selected six different buildings and three of them have different occupancy types such as, three buildings have no child live in the building (numbered as building 1, 4 and 6), one building has a family (two adults) with one child (child age below the age of 15) - (building numbered as 5), the second types of building consists of a family with 2 children who are age of below 15 - (building numbered as 3) and the last type of the building has a family with 3 children (ages are below 15) - (building numbered as 2) To predict the each building energy consumption, individual ANN models are generated for each buildings. Each ANN model consists of current energy consumption with time information and external weather conditions. The outputs of each ANN is the next 15 minutes energy consumption, the proposed ANN topology is given Figure 2.

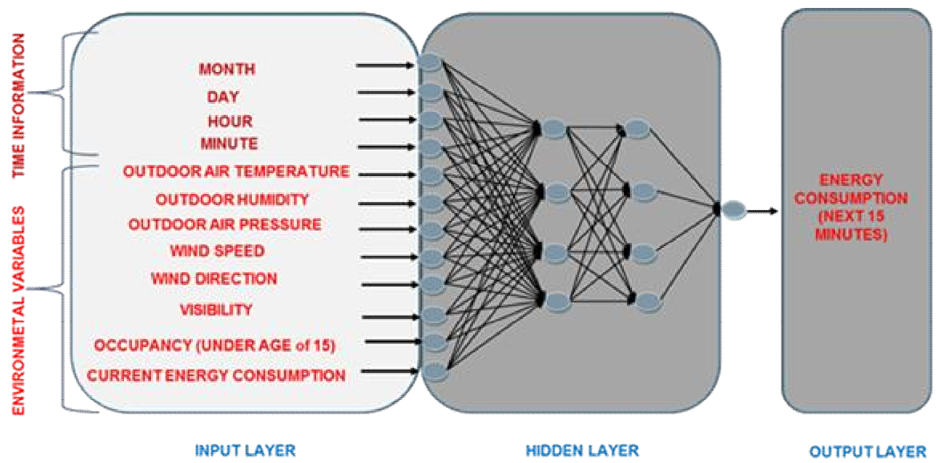

Fig. 2. The proposed ANN topology for each building.

As highlighted in Figure 2, each ANN has external weather conditions to utilize as input and increase correlation between inputs and output, these weather conditions are selected as outdoor weather temperature, outdoor humidity, outdoor air pressure, wind speed, wind direction and visibility. Moreover, one social variable is also included as input of ANN which is the existence of the children under age 15 in the selected building. This variables has been determined through a sensitivity analysis process.

The variables which are related the environmental conditions has a direct impact on the energy consumption such as in highly windy and cold conditions, the energy consumptions tend to go up. Moreover, there is a direct correlation between consumption and the occupants under age of below 15 which generates an expected patterns in the electricity consumption profile. Thus, this property transform the electricity consumption into highly irregular and unpredictable conditions. Finally, time information is also included as month, date, hour and minute in the inputs part of the ANN aligned with the current energy consumption of the selected building. The proposed ANN models for the selected six pilot are utilized to determine the entire districts required electricity demand by aggregation of individuals, shown as in Figure 3. Each building's ANN performs individually to predict electricity demand, which are then aggregated to produce the district electricity demand. The experiments and results for the selected pilot district are presented in the following sections.

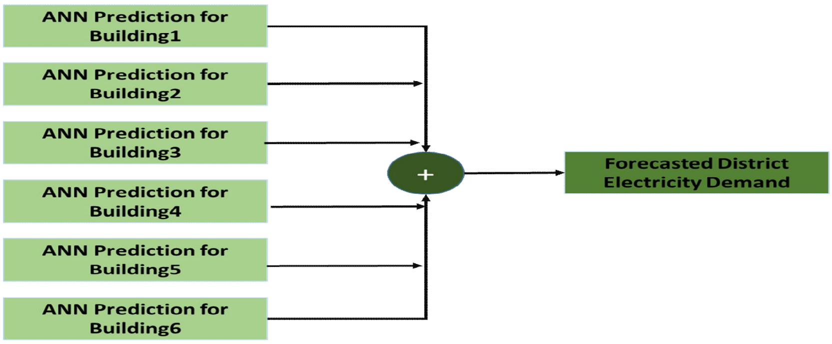

Fig. 3. The proposed forecasted district electricity demand.

4 Experiments

To determine the best performed ANN for each individual building, several experiments were conducted using the Irish Smart Grid data which contains 1.5 years of energy consumption every 30 minutes. The experiments were carried out to determine best performed ANN topology which requires to determine the best performed the learning function type, the number of hidden layer, the number of process element in hidden layers, and transfer function types in both hidden layers and output layer. The maximum iteration number was set to 5000 epochs. To determine the best performed learning function, the following topology was utilized; two hidden layers with 20 number process elements in each hidden layer and logarithmic sigmoid function in both hidden layers and outputs layers. The following learning algorithms were utilized for experiments on the MATLAB platform; Traingd, Trainbfg, Traincgb, Trainlm, Trainscg [7]. The results are presented in Table 1.

Table 1. The experiments for the learning function types.

Learning Function	Error rate						
	Expected	Bldg1	Bldg2	Bldg3	Bldg4	Bldg5	Bldg6
Traingd	0.001	0.031	0.171	0.149	0.094	0.114	0.062
Trainbfg	0.001	0.004	0.201	0.121	0.094	0.329	0.088
Traincgb	0.001	0.006	0.219	0.184	0.051	0.091	0.047
Trainlm	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Trainscg	0.001	0.003	0.167	0.004	0.005	0.002	0.004

*Bldg1,2,3,4,5,6: Building number 1,2,3,4,5,6.

The best performing learning function is found with Levenberg–Marquardt based backpropagation algorithm. Hereafter, this algorithm was utilized as the learning function for the ANN to perform the remaining experiments. The second stage of the experiments was to determine the number of process elements in the hidden layer. To carry out this experiments, two types of hidden layer was tested for each building as one hidden layer and two hidden layers. The results are presented in Table 2.

Table 2. The experiments for the number of hidden layer.

Number of hidden layer	Error rate						
	Expected	Bldg1	Bldg2	Bldg3	Bldg4	Bldg5	Bldg6
1	0.001	0.001	0.002	0.002	0.001	0.001	0.001
2	0.001	0.001	0.001	0.001	0.001	0.001	0.001

There was not any difference between the use of single and double layers, except for buildings 2 and 3, where the use of single layer did not meet the criteria for expected error rate. Therefore, two hidden layers were used for subsequent experiments. In third stage of the experiment, the process is carried out to determine the transfer function types in both hidden layer and output layers. It has been utilized logarithmic sigmoid function (LS), hyperbolic tangent sigmoid (TS) and linear (PL) in both hidden layers and output layers. The results are illustrated as in Table 3.

Table 3. The experiments for the transfer function types.

Transfer Functions [H1H2 O]	Error rate						
	Expected	Bldg1	Bldg2	Bldg3	Bldg4	Bldg5	Bldg6
LS LS LS	0.001	0.001	0.001	0.001	0.001	0.001	0.001
TS TS TS	0.001	0.007	0.089	0.008	0.013	0.007	0.004
PL PL PL	0.001	0.101	0.190	0.150	0.153	0.145	0.127

*H1: hiddenLayer1, H2: Hidden layer 2, O: Output Layer.

According to Table 3, the usage of logarithmic sigmoid function provides the best performed topology. The following experiments will be carried out using this transfer function type in both hidden layers and output layer. The last experiments to determine the best performed topology is to determine the number of process element in the hidden layers. The results are presented in table 4.

Table 4. The experiments for the number of process elements in the hidden layers.

Transfer Functions [H1H2]	Error rate						
	Expected	Bldg1	Bldg2	Bldg3	Bldg4	Bldg5	Bldg6
5 5	0.001	0.073	0.110	0.008	0.103	0.009	0.009
10 10	0.001	0.002	0.048	0.002	0.002	0.008	0.003
20 20	0.001	0.001	0.001	0.001	0.001	0.001	0.001
30 30	0.01	0.006	0.023	0.009	0.009	0.007	0.006

According to the Table 4, the best performed network was found as using 20 process elements in both hidden layers. Based on the entire topology determination process, the performed network utilized to conduct the forecasting process for the district level. According the experimental results, the average forecasting accuracy for each buildings was found as 95.94%, 84.40%, 94.65%, 94.47%, 95.79% and 95.84% by eliminating zero energy consumed days. The results are presented in Figures 4-9.

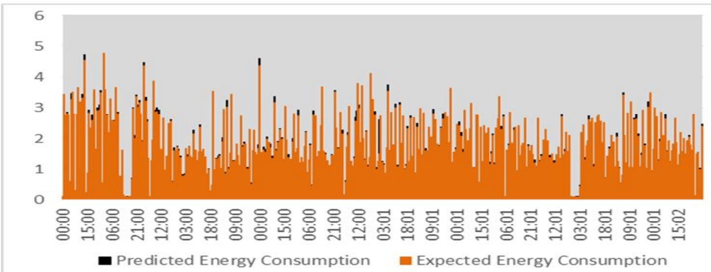

Fig. 4. The electricity demand comparison between forecasted results and expected results for building 1.

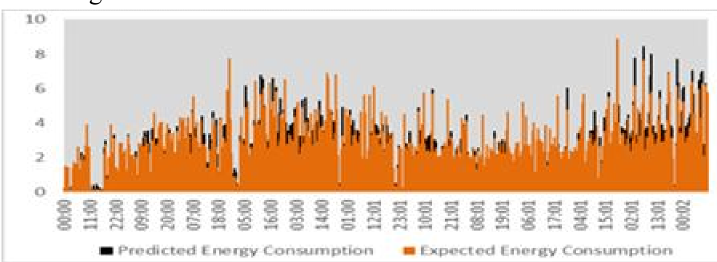

Fig. 5. The electricity demand comparison between forecasted results and expected results for building 2.

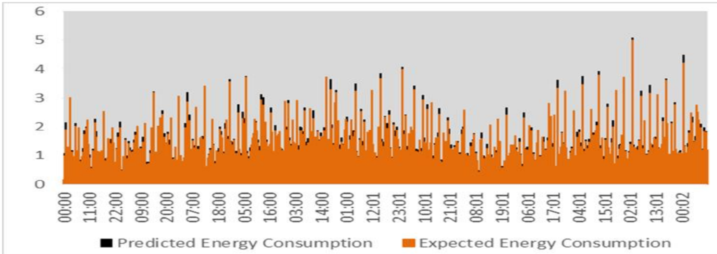

Fig. 6. The electricity demand comparison between forecasted results and expected results for building 3.

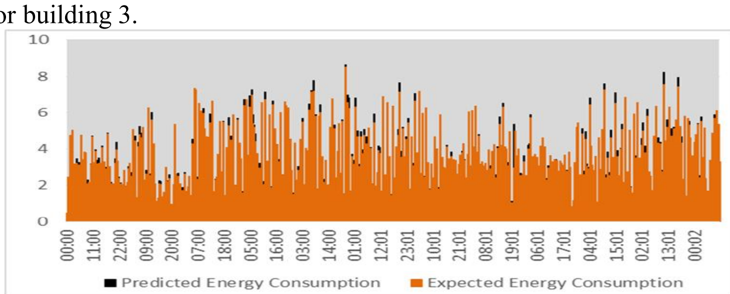

Fig. 7. The electricity demand comparison between forecasted results and expected results for building 4.

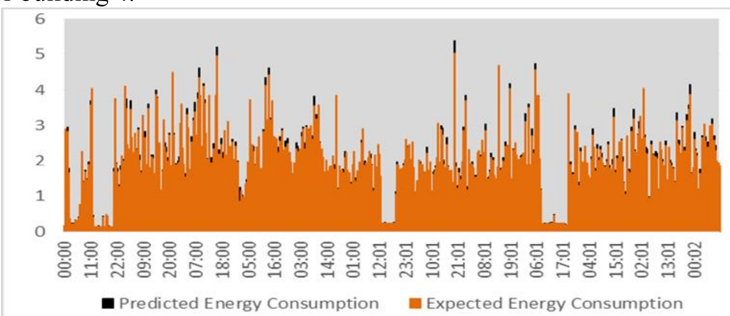

Fig. 8. The electricity demand comparison between forecasted results and expected results for building 5.

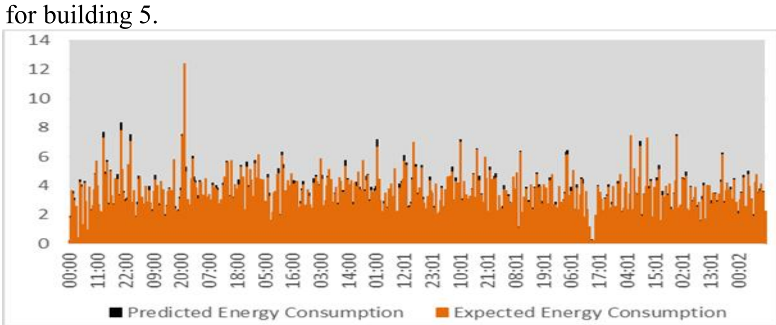

Fig. 9. The electricity demand comparison between forecasted results and expected results for building 6.

Further the average percentage error of the aggregated demand was found as 3.9%. The entire process was integrated under the forecasting interface by Cardiff University, shown in Figure 10.

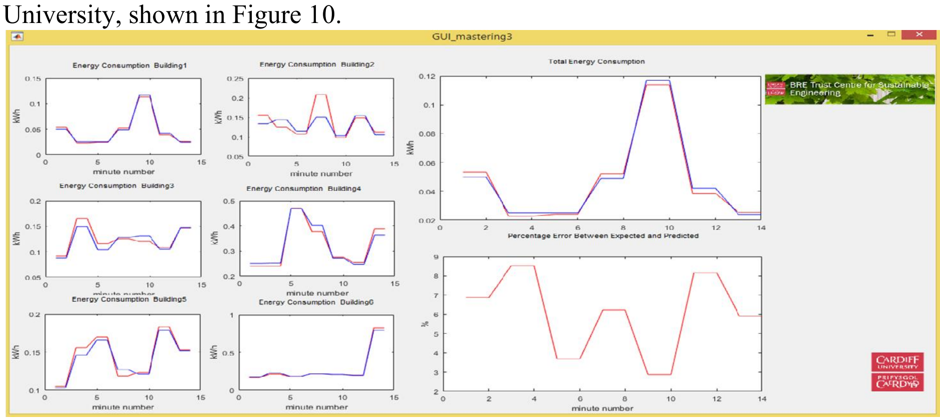

Fig. 10. The forecasting interface.

As highlighted in Figure3, each buildings ANN performs individually to predict the electricity demand for each individual building, then aggregation of entire buildings demand provides the desired demand for the district electricity demand. In the next stage, the experiments and results will be presented for the selected pilot district according to the proposed model.

5 Conclusion

In this study, an ANN based district grid energy demand forecasting model is proposed. To test the performance, the proposed framework, six buildings with different energy characteristic are selected from Irish Smart Grid data [16]. To determine the best performed ANN for each individual building, several different types of ANN topology were tested and presented in the experiments section. According to the results, the district level energy consumption was determined about 4% average percentage error. This figure is also highly related to electricity consumption pattern. As the regular user has a repetitive pattern which allow the intelligent system such as ANN to learn patter quicker with higher prediction rate. However this prediction profile may change with different electricity users such as people who have different professions, ages and income. Further, the electricity consumption behavior is also depends on the different states such as a people in warm regions tend to use electricity for cooling, or people who live is the colder regions tend to use for heating. In some regions, they do not even need to neither of them where they only utilize for their appliances. Therefore energy consumption pattern may derivate from each other, however the main important issue with forecasting is to have a regular pattern to generalize the knowledge from the consumption pattern.

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