PI-controlled ANN-based Energy Consumption Forecasting for Smart Grids

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Abstract: Although Smart Grid (SG) transformation brings many advantages to electric utilities, the longstanding challenge for all them is to supply electricity at the lowest cost. In addition, currently, the electric utilities must comply with new expectations for their operations, and address new challenges such as energy efficiency regulations and guidelines, possibility of economic recessions, volatility of fuel prices, new user profiles and demands of regulators. In order to meet all these emerging economic and regulatory realities, the electric utilities operating SGs must be able to determine and meet load, implement new technologies that can effect energy sales and interact with their customers for their purchases of electricity. In this respect, load forecasting which has traditionally been done mostly at city or country level can address such issues vital to the electric utilities. In this paper, an artificial neural network based energy consumption forecasting system is proposed and the efficiency of the proposed system is shown with the results of a set of simulation studies. The proposed system can provide valuable inputs to smart grid applications.

1 INTRODUCTION

The traditional power grid in many countries suffers, amongst others, from huge maintenance costs because of the system's age, from scalability issues because of the globally increasing demand for more power along with the expense of building new power stations and from lack of efficient system monitoring that could increase the overall performance by acting proactively in preventing damages. Therefore, the Smart Grid (SG) solution has been presented as an evolutionary system for power generation and distribution. A SG is a modernized power transmission and distribution network which uses robust two-way data communications, distributed computing technologies and smart sensors to improve reliability, safety and efficiency of power delivery and use (Gungor et al, 2010; Gungor et al, 2011). SGs use renewable energy production, smart meters and modern communication technologies for effective system monitoring, thus succeeding in addressing many of the requirements of a modern power grid system while significantly increase its performance.

Using a sophisticated information processing and communication technology infrastructure, the SG is able to fully use and benefit from its distributed power generation system, while maximizing the whole system's energy efficiency. Consequently, the SG is also considered as a data communication network which, by supporting many power management devices, achieves seamless and flexible inter-operational abilities among different advanced system components that leads to an efficient performance. The power system infrastructure is comprised of all the devices found on existing electrical grids, as described above, with the additions of smart meters and sensors deployed throughout the grid to detect outages and measure critical performance metrics that should be forwarded to the backhaul system's detection and decision data centres. This infrastructure generally includes the power generation, transmission and distribution system and the customer premises.

At the core of a SG, Advanced Metering Infrastructure (AMI) lies. Basically, AMI is a two-way communications network between customer premises and the backhaul of the SG and consists of smart meters, advanced sensors and monitoring

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systems that collect and distribute information between the connected devices in order to enable the gathering and transfer of energy usage information in near real-time. Since the amount of collected data is huge and the collected data is important, the utility communication infrastructure is expected to be scalable and provide high bandwidth capabilities and low latency (Sood et al, 2009; Tuna et al, 2013). Although SGs can address their current challenges with their smart metering and AMI, forecasting tools can help them further optimize their operations. Because the complexity of challenges has been growing and a SG is a data-rich environment with many data inputs from several applications. Basically, forecasting is a data-intensive numeric discipline and used by utilities for various planning, investment and decision-making purposes. Using forecasting tools which manage large quantities of usage data from new inputs from smart meters, the utilities can determine how their customers will use energy and try to understand when their customers will change their behaviour in response to personal economic conditions, demand response programs, government initiatives, and whether and climate change concerns. In this way, the utilities can plan their operations. Finally, among many important questions that can be answered by forecasting tools, from the return on investment view, the key question is "what types of pricing programs are likely to produce the largest benefits?".

Several modelling techniques have been proposed for demand forecasting. They can be classified into nine main categories (Alfares and Nazeeruddin, 2002; Gajowniczek and Zabkowski, 2014; Chan et al, 2012), namely multiple regression, exponential smoothing, iterative reweighted least-squares, adaptive load forecasting, stochastic time series, ARMAX models based on genetic algorithms, fuzzy logic, artificial neural networks, and expert systems. In comparison with the other techniques, artificial neural networks (ANNs) are better at solving forecasting problems due to their hidden layers and ability to learn (Gajowniczek and Zabkowski, 2014). They are able to identify hidden trends thereby finding the trends in time series and use them to produce more accurate results. Therefore ANNs are very popular and attractive for practical applications.

There are many studies in the literature that deal with the models/techniques for demand forecasting. In (Javed et al, 2012), autonomic demand side management is presented as a paradigm to provide demand side management and demand response in micro-grids. Liu *et al.* in (Liu et al, 2012) mainly focus on a hybrid model with parameter optimization for load forecasting of micro-grids. A design problem in a setting where several agents can generate estimates of independent future demands at a cost is investigated in (Egri and Vancza, 2013). In the proposed approach, an aggregator agent elicits the forecasts and based on this information, optimises a procurement decision. Schachter and Mancarella define the functionality required for developing a short-term load forecasting module for demand response applications and propose an algorithm to provide high forecasting performance (Schachter and Mancarella, 2014).

In this study, a forecasting approach for SGs is proposed. The approach is based on the use of the back propagation neural network algorithm which is a multilayer feed-forward network trained according to error back propagation algorithm. Using the proposed approach, SG operators can estimate future demand from the past and respond with their purchases. This also allows them to offer electricity generated from renewable sources. The rest of the paper is organized as follows. Section 2 presents the details of the artificial neural network based forecasting approach for smart grid and focuses on its implementation. Section 3 presents the evaluation results. Finally, the paper is concluded in Section 4.

2 ARTIFICIAL NEURAL NETWORKS FOR DEMAND FORECASTING

ANN is basically a parallel distributed processor consist of simple processing units that has an inherent trend for storing experiential knowledge and making it available for use (Haykin, 2008). Multilayer feed-forward neural networks are generally used based on minimization of an error function and back propagation (BP) learning is the common training method used in these networks. BP learning uses the gradient descent procedure to train the connection weights (Fazayeli et al, 2008). Multilayer feed-forward neural networks consist of a layer of input units, one or more layers of hidden units, and one output layer of units. Every layer has neurons and is connected with next layers. Each connection between nodes has a weight associated with it. The trend of on-line learning for the supervised training of multilayer perceptrons has been further raised by the development of the back propagation algorithm. BP algorithm can be described using the following equations.

$$o_j = f(net_j) = f(x) \text{ then } net_j = \sum_j^i w_{ji} o_i + \theta_j \quad (1)$$

$$E_p = \frac{1}{2} \sum_{j \in out.} (t_{pj} - o_{pj})^2 \quad (2)$$

$$\left.\begin{aligned} \delta_{pj} &= (t_{pj} - o_{pj}) \\ \Delta_p w_{ji} &= -\varepsilon\left(\frac{\partial E_p}{\partial w_{ji}}\right) \\ \Delta_p \theta_j &= -\varepsilon\left(\frac{\partial E_p}{\partial \theta_j}\right) \end{aligned}\right\} \quad (3)$$

where j is the layer number and i is neuron number, o_j is neuron output, net_j is weighted sum, θ_j is bias, w_{ji} is weight, ε is learning rate, δ_{pj} represents error value in layer j, t_{pj} is target output and o_{pj} is actual output. Equation (2) is used to estimate the entire error in the output layer for the pth sample pattern, the error that is eventually minimized by variating the weights and biases using gradient descent (3).

Levenberg-Marquardt algorithm, one of the most important optimization method (Roweis, 2009), was used for the development the proposed NN. This technique, due to Levenberg (Levenberg, 1944) and Marquardt (Marquardt, 1963), is a sequence of the following two methods (Ranganathan, 2004):

I. the Gauss-Newton's method approaches rapidly near to a global or local minimum but sometimes may deviate;
II. the Gradient descent method certainly approaches through a proper selection of step size parameter but does slowly.

The block diagrams and the architecture of the developed ANN are shown in Figure 1 and Figure 2, respectively.

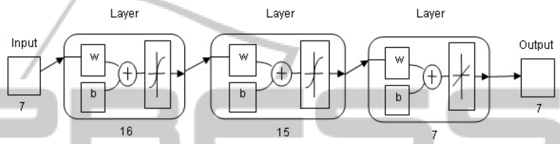

Figure 1: The structure of the proposed multilayer NN model prepared using Neural Network Toolbox of MATLAB.

Proportional-Integral-Derivative (PID) controller and its alternatives P, PI and PD are the one of the best popular controllers used in nearly all control

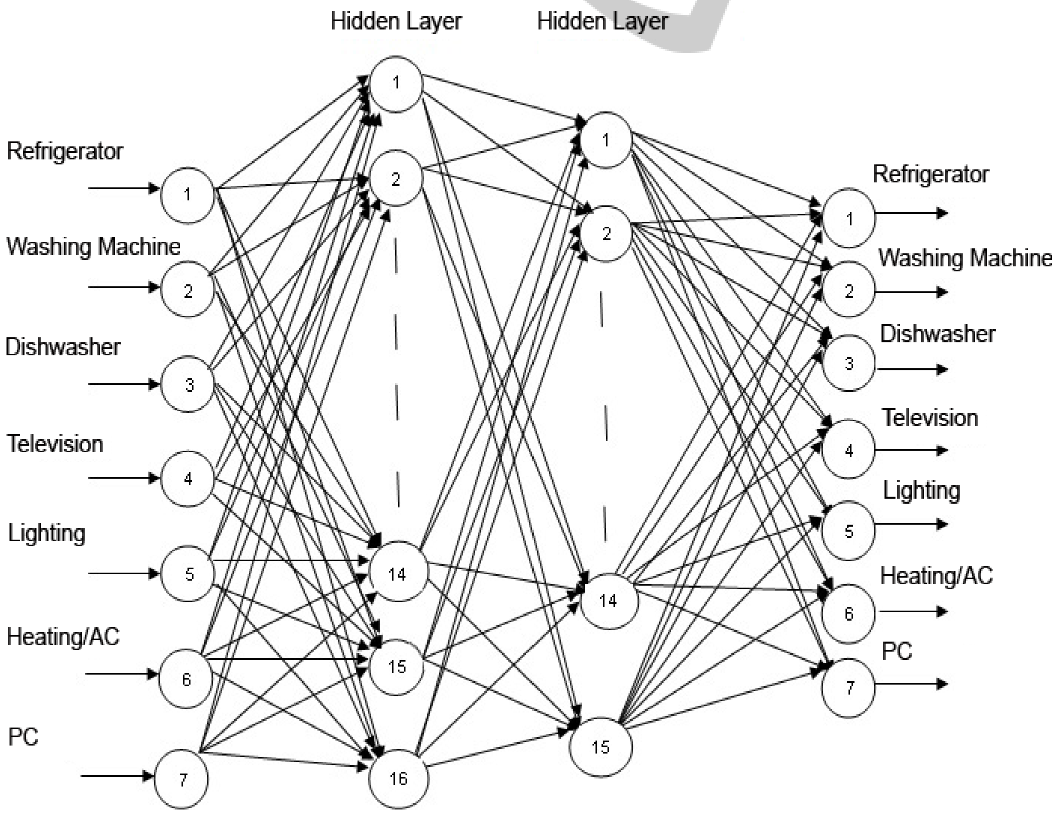

Figure 2: Architecture of the system for energy consumption load forecast.

applications. Base of the popularity is from its simplicity. The tuning method of Ziegler-Nichols (Ziegler and Nichols, 1942) is implemented widely in the industrial process area. The reproduction of the PID gains relies on the presence of a process time delay. The control system proposed in this paper is based on neural networks. To improve the performance of the system, PI controller is added to the system. Figure 3 illustrates the block diagram of the closed loop system.

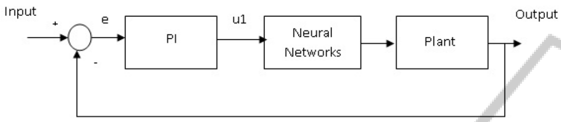

Figure 3: Block diagram of the closed loop system.

The block diagram shows that a PI controller is linked with the neural network controller system in closed loop. Then, the PI controller becomes:

$$U_1(t) = K_p e(t) + K_I \int_0^{\tau} e(\tau) d\tau \tag{4}$$

where *e(t)* is the closed loop error function. The basic action of the proportional gain is to determine the system response time or bandwidth. The integral gain improves steady-state and low frequency trajectory following by adding stiffness against disturbances and steady state errors.

3 PERFORMANCE EVALUATION

In recent years, different load forecasting methods have been developed and implemented. Artificial neural network based methods are popular in smart grid applications. This study focuses on comparing a house's neural network based energy consumption load forecast and PI+Neural Network energy consumption load forecast. There are 7 inputs in this house. These inputs include refrigerator, washing machine, dishwasher, television, lighting, heating/air condition and computer. The dataset is collected hour by hour for 1 week. Table 1 lists the partial dataset. The simulated results were observed using MATLAB Neural Network Toolbox (MathWorks, 2014) and they were compared with their actual datasets. The improved NN model is a 1-input layer, 2-hidden layers (including 16 and 15 nodes, respectively) and 1-output layer. As already explained, the Levenberg-Marquardt optimization algorithm was used since it presents certain advantages over BP (Michailidis et al, 2014).

Table 1: Partial data set.

		Inputs							Outputs						
		RG	WM	DW	TV	Light.	H/AC	PC	RG	WM	DW	TV	Light.	H/AC	PC
1	00:00	50,0	0,0	0,0	0,0	50,0	200,0	0,0	50,0	0,0	0,0	0,0	51,0	200,0	0,0
2	01:00	50,0	0,0	0,0	0,0	50,0	200,0	0,0	49,0	0,0	0,0	0,0	50,0	196,0	0,0
3	02:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	51,0	0,0	0,0	0,0	0,0	203,0	0,0
4	03:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	50,0	0,0	0,0	0,0	0,0	201,0	0,0
5	04:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	50,5	0,0	0,0	0,0	0,0	198,0	0,0
6	05:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	50,0	0,0	0,0	0,0	0,0	199,0	0,0
7	06:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	51,0	0,0	0,0	0,0	0,0	197,0	0,0
8	07:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	49,5	0,0	0,0	0,0	0,0	202,0	0,0
9	08:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	49,0	0,0	0,0	0,0	0,0	200,0	0,0
10	09:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	50,0	0,0	0,0	0,0	0,0	204,0	0,0
11	10:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	49,0	0,0	0,0	0,0	0,0	199,0	0,0
12	11:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	48,5	0,0	0,0	0,0	0,0	200,0	0,0
13	12:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	51,5	0,0	0,0	0,0	0,0	201,0	0,0
14	13:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	50,0	0,0	0,0	0,0	0,0	205,0	0,0
15	14:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	49,5	0,0	0,0	0,0	0,0	200,0	0,0
16	15:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	50,0	0,0	0,0	0,0	0,0	199,0	0,0
17	16:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	51,0	0,0	0,0	0,0	0,0	202,0	0,0
18	17:00	50,0	0,0	0,0	0,0	0,0	200,0	0,0	50,5	0,0	0,0	0,0	0,0	201,0	0,0
19	18:00	50,0	0,0	0,0	0,0	50,0	200,0	20,0	49,0	0,0	0,0	0,0	48,0	200,0	19,0
20	19:00	50,0	50,0	0,0	150,0	50,0	200,0	20,0	50,0	49,0	0,0	149,0	49,0	203,0	21,0
21	20:00	50,0	50,0	0,0	150,0	50,0	200,0	20,0	49,0	50,0	0,0	151,0	51,0	199,0	20,0
22	21:00	50,0	0,0	0,0	150,0	50,0	200,0	20,0	48,5	0,0	0,0	150,0	50,0	197,0	18,0
23	22:00	50,0	0,0	0,0	150,0	50,0	200,0	20,0	51,0	0,0	0,0	152,0	51,0	198,0	21,0
24	23:00	50,0	0,0	0,0	0,0	50,0	200,0	0,0	50,0	0,0	0,0	0,0	48,0	200,0	0,0

The comparison of the training dataset with the corresponding ANN result and PI+ANN result for Refrigerator (RG), Washing Machine (WM), Dishwasher (DW), Television (TV), Lighting (Light.), Heating/Air Conditioning (H/AC) and Computer (PC) are given in Figures 4-10, respectively. Before being entered into the ANN model, the input dataset was normalized for more reliable results and then rescaled to the original dataset. The activation functions used for the neurons of the proposed ANN model were tangent-sigmoid functions for the two hidden layers and linear transfer functions for the output layer. The performance of the NN model and PI+NN model and regression between target and NN output and between target and PI+NN output are shown in Figure 11 and Figure 12, respectively.

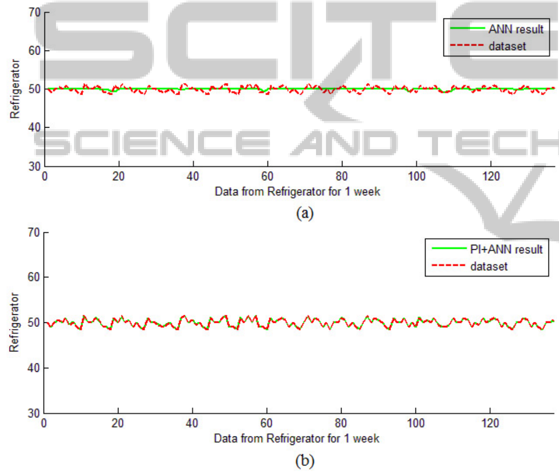

Figure 4: a) ANN result for Refrigerator, (b) PI+ANN result for Refrigerator.

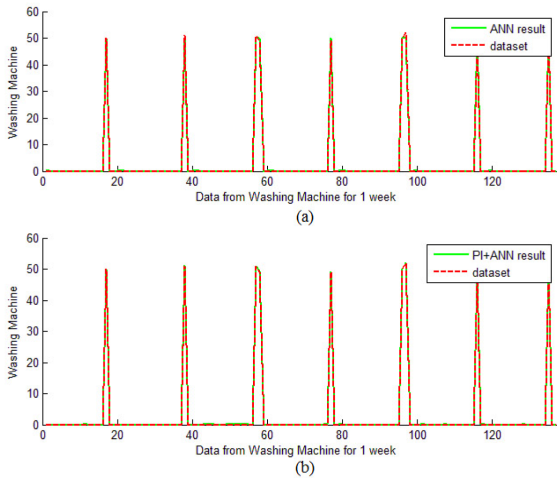

Figure 5: (a) ANN result for Washing Machine, (b) PI+ANN result for Washing Machine.

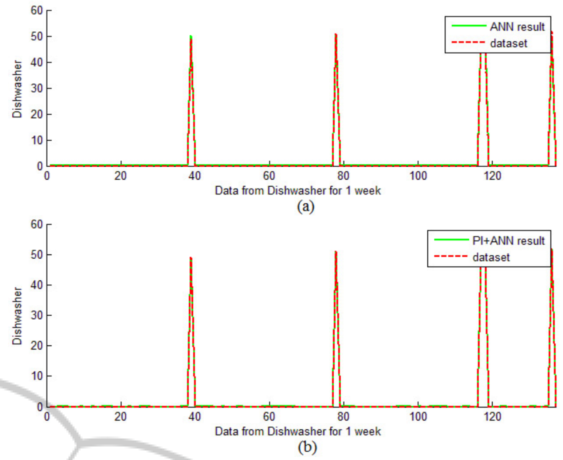

Figure 6: (a) ANN result for Dishwasher, (b) PI+ANN result for Dishwasher.

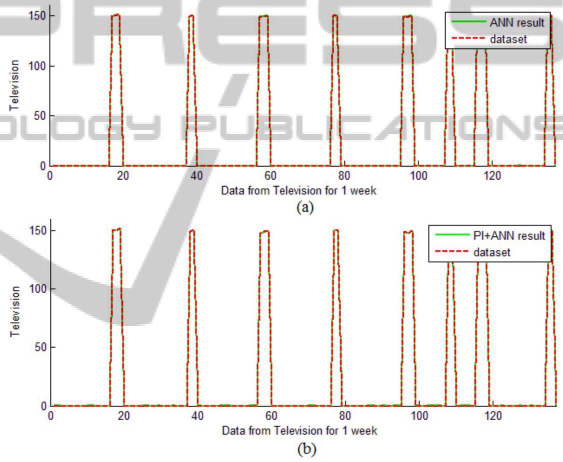

Figure 7: (a) ANN result for Television, (b) PI+ANN result for Television.

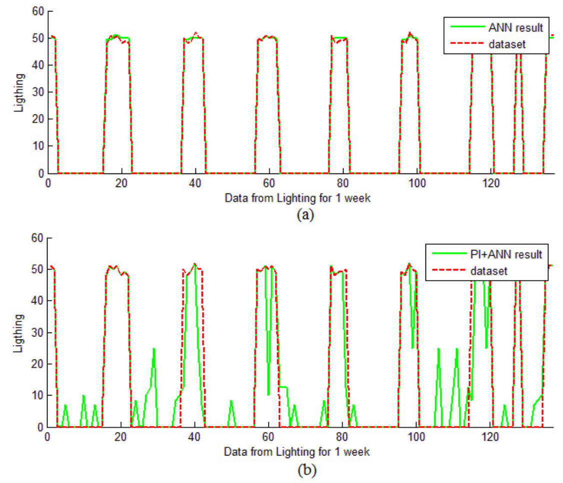

Figure 8: (a) ANN result for Lighting, (b) PI+ANN result for Lighting.

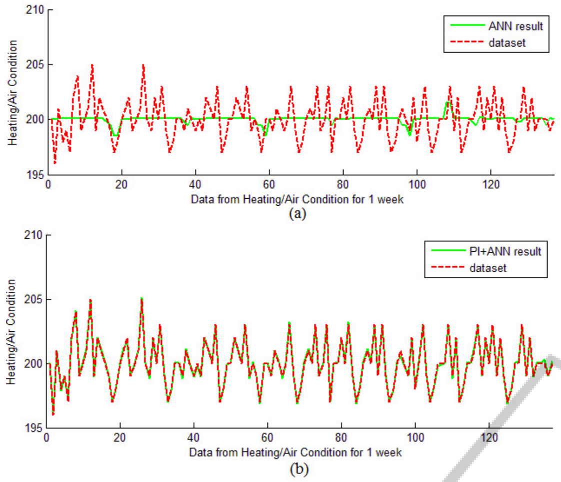

Figure 9: (a) ANN result for Heating/Air Condition, (b) PI+ANN result for Heating/Air Condition.

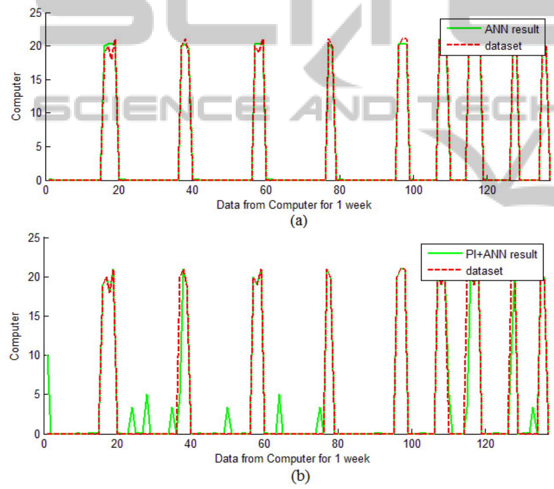

Figure 10: (a) ANN result for PC, (b) PI+ANN result for PC.

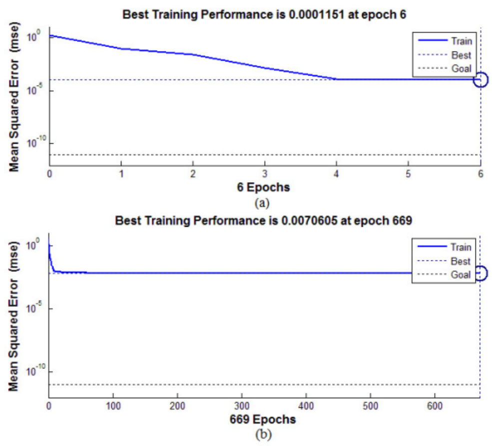

Figure 11: (a) ANN performance result, (b) PI+ANN performance result.

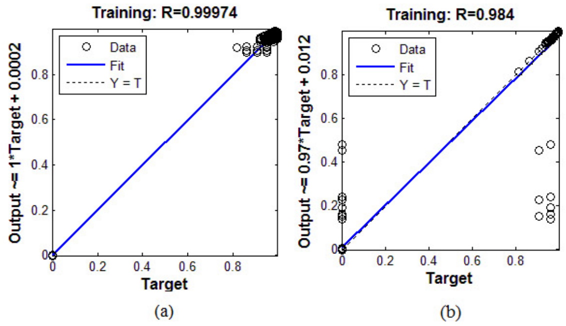

Figure 12: (a) ANN regression, (b) PI+ANN regression.

4 CONCLUSIONS

To be able to meet emerging economic and regulatory realities, the electric utilities must be able to determine and meet demand, interact with their customers and implement new hardware and software technologies. Although the transformation from the traditional power grid to the smart grid brings many advantages and helps them realize these, they still need to use forecasting tools to further optimize their operations from the return on investment view. For this purpose, in this paper, an energy consumption forecasting approach for smart grids has been presented. Based on the data input received from smart meters, the proposed approach enables the electric utilities to forecast electricity demand. In addition, it provides a valuable input to many smart grid applications.

REFERENCES

Gungor, V. C., Bin, L., Hancke, G. P. 2010. Opportunities and challenges of wireless sensor networks in smart grid. *IEEE Trans. Industrial Electronics*, 57(10), 3557-3564.

Gungor, V. C., Sahin, D., Kocak, T., Ergut, S., Buccella, C., Cecati, C., Hancke, G. P. 2011. Smart Grid Technologies: Communication Technologies and Standards. *IEEE Transactions on Industrial Informatics*, 7(4), 529-539.

Sood, V. K., Fischer, D., Eklund, J. M., Brown, T. 2009. Developing a communication infrastructure for the smart grid. *IEEE Electrical Power and Energy Conference (EPEC 2009)*, 1-7.

Tuna, G., Gungor, V. C., Gulez, K. 2013. Wireless Sensor Networks for Smart Grid Applications: A Case Study on Link Reliability and Node Lifetime Evaluations in Power Distribution Systems. *International Journal of Distributed Sensor Networks*, 2013(2013), Article ID 796248, Available from: doi: 10.1155/2013/796248 [Accessed 3rd March 2015].

Alfares, H. K., Nazeeruddin, M. 2002. Electric load forecasting: literature survey and classification of methods. *International Journal of Systems Science*, 33(1), 3-34.

Gajowniczek, K., Zabkowski, T. 2014. Short term electricity forecasting using individual smart meter data. *Procedia Computer Science*, 35, 589-597.

Chan, S.C., Tsui, K.M., Wu, H.C., Hou, Y., Wu, Y.-C., Wu, F. F. 2012. Load/Price Forecasting and Management of Demand Response for Smart Grids: Methodologies and Challenges. *IEEE Signal Processing Magazine*, 29(5), 68-85.

Javed, F., Arshad, N. Wallin, F., Vassileva, I., Dahlquist, E. 2012. Forecasting for demand response in smart grids: An analysis on use of anthropologic and structural data and short term multiple loads forecasting. *Applied Energy*, 96, 150-160.

Liu, N., Tang, Q., Zhang, J., Fan, W., Liu, J. 2014. A hybrid forecasting model with parameter optimization for short-term load forecasting of micro-grids. *Applied Energy*, 129, 336-345.

Egri, P., Vancza, J. 2013. Efficient Mechanism for Aggregate Demand Prediction in the Smart Grid. *LNAI*, 8076, 250-263.

Schachter, J., Mancarella, P. 2014. A Short-term Load Forecasting Model for Demand Response Applications. *Proc. 11th International Conference on the European Energy Market (EEM)*.

Haykin. S. O. 2008. *Neural Networks and Learning Machines*, Prentice Hall. New York, 3rd edition.

Fazayeli, F., Wang, L., Liu, W. 2008. Back-Propagation with Chaos. *IEEE Int. Conference Neural Networks & Signal Processing*, 5-8.

Roweis, S. 2009. *Levenberg-Marquardt optimization*. [Online] Available from: http://www.cs.nyu.edu/?roweis/notes/lm.pdf [Accessed 3rd March 2015].

Levenberg, K. 1944. A method for the solution of certain non-linear problems in least squares. *Quarterly of Applied Mathematics*, 2, 164-168.

Marquardt, D. 1963. An algorithm for least-squares estimation of nonlinear parameters. *SIAM Journal on Applied Mathematics*, 11(2), 431-441.

Ranganathan, A. 2004. *The Levenberg-Marquardt Algorithm*. Honda Research Institute, USA.

Ziegler J.G., Nichols B. 1942. Optimal setting for automatic controllers. *Trans ASME*, 64, 759-768.

MathWorks. 2014. Neural Network Toolbox, [Online] Available from: http://www.mathworks.com/products/neural-network/ [Accessed 2nd March 2015]

Michailidis, E. T., Tuna, G., Gezer, G., Potirakis, S. M., Gulez, K. 2014. ANN-Based Control of a Multiboat Group for the Deployment of an Underwater Sensor Network. *International Journal of Distributed Sensor Networks*, 2014 (2014), Article ID 786154, Available from: doi: 10.1155/2014/786154 [Accessed 3rd March 2015].