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A HYBRID METHOD FOR LOAD FORECASTING IN SMART GRID BASED ON NEURAL NETWORKS AND CUCKOO SEARCH OPTIMIZATION APPROACH

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ABSTRACT

Load balancing is one of the most challenging goals in smart grid systems. Obviously, to response this challenge, a selfish user's behavior necessitates the use of incentive compatible mechanisms. In the mechanisms, the incentives should be provided in a manner to motivate consumers to cooperate for regulation of demand and supply. Dynamic pricing is one of the best mechanisms in which the price is being adjusted dynamically according to make a balance between supply and demand. In the balance, the consumer's demand for energy through financial incentives is adjusted. To determine and announce the appropriate electricity price, there should be a precise forecast for energy usage. This paper develops two neural networks for each influential factors based on the situation such as weather related or historical loads criteria. Afterwards, the outputs of neural networks are aggregated with the use of Induced Ordered Weighted Averaging Operator (IOWA). The argument ordering process is guided by mean square error. Also the cuckoo optimization algorithm is applied on artificial neural networks to improve the accuracy of them. The experimental result show that the precision of aggregated load forecasting based upon IOWA operator is improved significantly.

Keywords: Smart Grid, Artificial Neural Network, Data Fusion, Cuckoo, OWA operator

1. INTRODUCTION

Smart grid system is the integration of power grid with smart network connection. The purpose of this system is to provide a more reliable, environmentally friendly and economically efficient power system (Amin and Wollenberg, 2005; Fan et al., 2013). The main challenge of a smart grid is how to improve the efficiency of energy distribution and consumption. Forecasting the future consumption in smart grid is much more complex than power grid, due to the need of forecasting in both micro grid and Demand Side Management (DSM) aspects. Hipper et al. (2001) indicates that electric demand forecasting models can be categorized into three categories (Hippert et al., 2001): (a) Very short-term load forecasting (VSTLF), (b) Short-term load forecasting (STLF) and (c) Medium-term and long-term load forecasting (MTLF, LTLF). To model Load forecasting in smart grid, there are several categories in the literature: Time Series (Guan et al., 2013), (Box et al., 2011), Regression Models (Bunn and Farmer, 1985; Taylor and Buizza, 2003), State Space and Kalman filtering technology (Park and Lee, 1991), as well as artificial intelligence techniques.(Hsu and Chen, 2003) . During recent years, researchers tried to improve the accuracy of electricity load forecasting. To do this, the first and simplest approach looks at historical load data as a time series and takes advantage of them to forecast future (Vemuri et al., 1973).

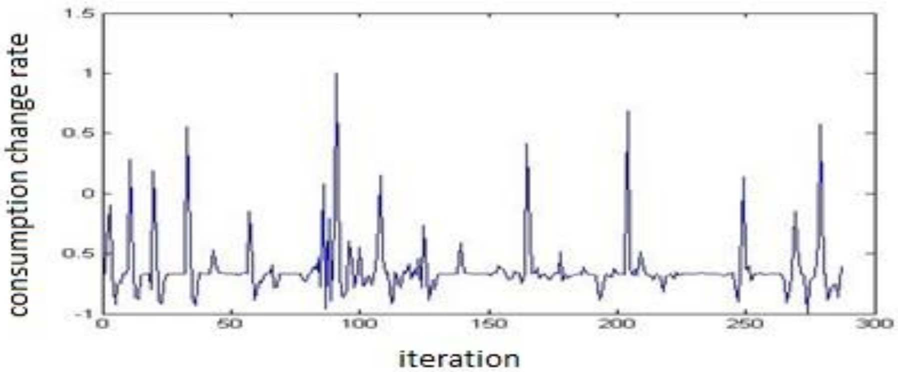

Figure 1 Normalized Consumption Change

The main disadvantage of this model is that it ignores the other factors that influence electricity load. Mbamalu proposed Autoregressive (AR) model that consider seasonal factors (Mbamalu and El-Hawary, 1993). Researchers found out that forecasting with multi variable approach is more accurate than the univariate AR model. State space and Kalman filtering technology treat the periodic component of the load as a random process and use 3–10 historical data to establish the periodic load variation for estimating the dependent variables (Load or temperature) of the power system.(Brown, 1983; Gelb, 1974) The disadvantages of these approaches is difficulty of avoiding observation noise. Artificial Neural Network (ANN) is the popular artificial technique for load forecasting in recent decades. There are different types of ANN such as multi-layer perceptron, RBF neural network, Artificial Neuro-Fuzzy. Regression models set up a cause effect relation between electricity load and other independent variables.

Micro grid is a network of different energy source such as wind or water turbine, solar panel located at the distribution network side which supply energy for a finite area. The networks of micro grid can either both conjunct with the grid or isolate autonomously (Asano et al., 2007). In a power grid management, one of the main problems is forecasting the future consumption. Data load of a micro grid can have more high frequency changes than the one in conventional power systems due to its lower inertia. (Fig.1) Thus, forecasting method needs to be more optimized to have an accurate short term load forecasting. Control of a micro grid can be considerably different than the traditional power systems, because of the different characteristics of its supply and demand. (Asbury, 1975)

There are several applied load forecasting models in the literature in which use artificial neural networks. The instability of renewable energy and changing the importance of different influential factors on the load consumption necessitates us to aggregate different methods. Here we combine neural network methods with induced ordered weighted averaging operator (IOWA) considering several influential factors on load consumption to cover so called instability.

The rest of article is as follows. Consumption forecasting along with different applied method are discussed briefly in section 2. The article continues with describing the induced ordered weighted averaging operator in section 3. Section 4 talks about influencing forecasting factors. Next section describes our new approach. A numerical experiment is presented in section 6. Finally conclusion is drawn in section 7.

2. CONSUMPTION FORECASTING TOOLS

As it is obvious from the term ’smart grid’, being able to estimate the future responses of different elements of the system and adapting the whole system toward the most potential efficiency is one of the most important promises which should be delivered. Forecasting the power consumption is one of the fundamental problems in smart grid research area. Regardless of Micro grids’ size, forecasting future peak time is crucial for efficient communication between them. Researchers are carrying out a scientific study to find a solution in order to forecast consumption of consumers in a specific date and time. There are two important tools in artificial intelligent techniques: (a) Artificial Neural Network (ANN); (b) Support Vector Machine (SVM). Since the RBF neural network and ANFIS are the most important techniques employed in chaotic time series forecasting, we use these method.

2.1. Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are a mathematical models designed based on nature of brain. Similar to a human's brain, ANNs use neurons in their structure. The basic structure consists of:

Input layer: This layer gets the inputs, multiplies them in a weight and sends them to the next layer.
Middle layer(s) (Hidden layer(s)): The number of hidden layers and neurons are arbitrary. The number of hidden layers has trade-off; therefore they should be chosen carefully in order to return an appropriate output.

Output layer: Another group of neurons creates the outside world through its output.

There are different type of neural networks such as Multi-Layer Perceptron (MLP), RBF neural network, General regression neural network (GRNN), time-delay neural network, and Adaptive Neuro-fuzzy inference system (ANFIS). Since ANFIS and RBF are applied for data analysis in this paper, they are described briefly here.

2.2. Radial Basis Function (RBF) neural network

The RBF neural network consists of three layers; an input layer, a nonlinear hidden layer and a linear output layer. The RBF neural network has a feed forward structure (Fig.2).

The input layer collects the inputs similar to other neural networks. The hidden layer consists of the number of neurons that apply a non-linear transformation to the input, and the output is a summation function. So we denote the input as x and output as y(x). The output is like equation (1):

$$y(x) = \sum_{i=1}^{M} w_i \exp\left(-\frac{\left(\|x - c_i\|^2\right)}{2\sigma^2}\right) \qquad (1)$$

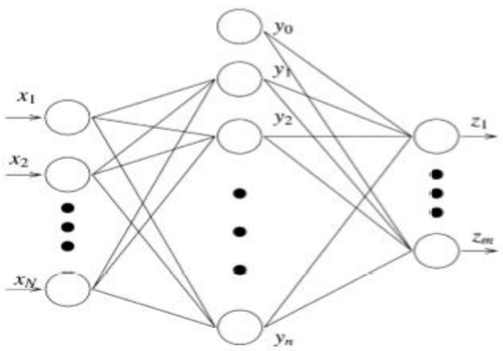

Figure 2 RBF Neural Network Structure (Hwang and Bang, 1997)

2.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is one of the most useful neural networks to solving approximate problems. (Buragohain and Mahanta, 2008) ANFIS is a hybrid model, which uses neural network and fuzzy logic to find the relation between inputs and outputs (Jang, 1993). The fuzzy model which is used in ANFIS is Takagi-Sugeno. ANFIS has the ability to approximate the non-linear function. Therefore ANFIS network is known as a global estimator, as this model combines artificial neural network and fuzzy inference system. ANFIS has 5 layers (Fig. 3) which is described below:

Input layer: Like every neural network, this layer get the input data and send them to the second layer.

Fuzzification layer: Due of this layer is to fuzzify the input data, so every input factors can connect to membership functions.

Fuzzy rules: Fuzzy rules are located here. The number of neurons in this layer is equal to the number of rules being defined.

Then part: In this layer output of each rule is inserted.

Output: All outputs are combined here by an aggregation function.

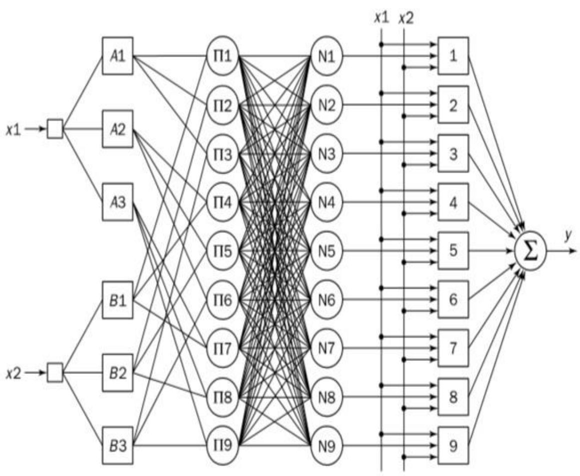

Figure 3 ANFIS Neural Network Structure (Negnevitsky, 2005)

3. INDUCED ORDERED WEIGHTED AVERAGING OPERATOR FOR FUSION

Instability of renewable energy is a challengeable problem in smart grid, in one aspect it could be effect on the behavior of consumers, so to predict the consumers' behavior, aggregation of different predictors could be a good technique. The Ordered Weighted Averaging (OWA) operator was first presented by Yager in 1988 (Yager, 1988). The classic definition of OWA operator of dimension *n* is a function

$$F : R^n \to R$$

that has an associated *n* vector

$$W = [w_1, w_2, ..., w_n]^T$$

such that

$$w_i \in [0,1]$$
$$\sum w_i = 1$$

furthermore

$$F(a_1, a_2, ..., a_n) = \sum w_i b_i \quad (2)$$

where b_j is the *j*-th largest of a_j.

In 1999 Yager presented a new type of OWA operator which is called Induced Ordering Averaging (IOWA) operator (Yager and Filev, 1999). The elements were sorted based on their values in OWA while IOWA operator introduces a new approach of ordering in which the elements are ordered based on the induced variable correlated to them. In particular, let

$$Y < y_1, ..., y_n >$$

be the inducing variable, so:

$$OWA(< x_1, y_1 >, ..., < x_n, y_n >) = \sum_{i=1}^{n} w_i x_{\xi(i)} \quad (3)$$

$$s.t. \; w_i \in [0,1]$$

$$\sum_{i=1}^{n} w_i = 1$$

Where the notation $\xi(.)$ denotes the $< x_i, y_i >$ ordered in a way that $y_{\xi(1)} > \ldots > y_{\xi(n)}$.

Generally inducing variable is information about the elements. Mean Squared Error (MSE) could be considered as induced variable in fusion of multiple neural networks. Since lower values of MSE are more desirable the approach of ordering MSE variables increasingly is been selected in this work. To determine OWA operator weights Y. Hwang et al. (1997) suggested a model which produce as equally important OWA operator weights as possible for a given orness degree , which required to solving this optimization problem:

$$\text{Minimize} \sum_{i=1}^{n-1} (w_i - w_{i+1})^2$$

$$orness = \alpha = \frac{1}{n-1} \sum_{i=1}^{n} (n-i) w_i \qquad (4)$$

$$\sum_{i=1}^{n} w_i = 1, 0 \le w_i \le 1$$

4. FACTORS THAT INFLUENCE LOAD FORECASTING IN SMART GRID

Electricity load is dependent on different factors. Hernández et al. (2013) used weather variables as a factor that affects load forecasting. In other articles also the weather variable, mostly used as an effective factor (Chandler and Hughes, 2013; Hernandez et al., 2013). Daneshi et al. (2008) in addition to weather, get other variables such as: customer information, energy prices, and regional development of the country. Guan et al. (2013) also use calendar values (time, month, etc.), and consumption values for the last hour as an effective factor.

5. PROPOSED METHOD BASED ON NEURAL NETWORK AND INFORMATION FUSION

In smart grid the instability of renewable energy is a major challenging problem. This instability affects the smart consumer's consumption thus the methods of forecasting the demand could be combined to cover this instability.

Since each technique has both advantage and disadvantage, the fusion of them could cover their disability in some situation where they cannot works appropriately. The important factors which influence the consumption value may change in different times and places. The changing importance of each factor and the instability of renewable energies, which are a part of efficient smart grid system, are affecting consumer's consumption in a way that in order to cover this instability, forecasting methods should be combined with methods such as IOWA. Thus we apply IOWA to address this issue. The process flow of the model is illustrated in Fig. 4.

As mentioned in the first section, there are some models in the literature which use multivariable approaches to forecast the load consumption. This paper is applying ANN on each variable and is combining them by the IOWA operator while the other state-of -the-art algorithms use this variable as an input of ANN (Hernandez et al., 2014). Our modeling process consists of two main stages: a training phase and a forecasting phase.

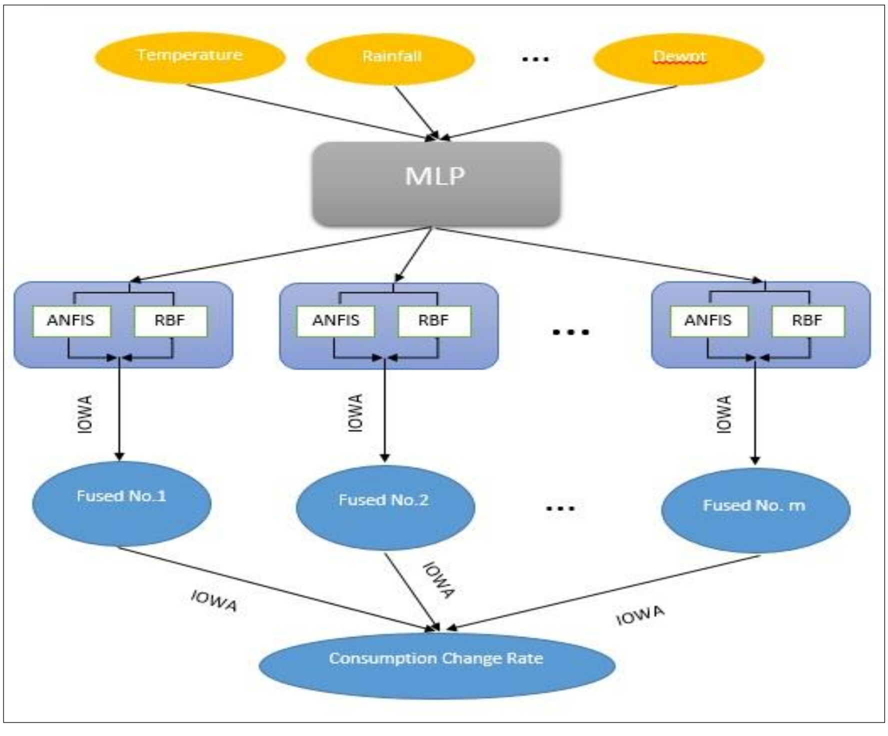

Figure 4 Process flow diagram

5.1. Training phase

In literature, iteration interval is usually considered between 15 to 60 minutes in short term forecasting. Here we divide each hour into 12 iterations so every iteration is in 5 minutes. The estimation could be more accurate by considering iteration interval shorter than 5 minutes but it imposes computing complexity and rapid power price change which suffers customer comfort.

There is a trade-off between temperature, wind, rain, humidity, last amount of usage, Dew point (Dewpt), rain fall, and solar intensity are the factors which are considered eligible to feed MLP. The most influential factors (results of the first MLP) are fed into the next group of ANNs. In this stage two neural networks of ANFIS and RBF are created for each factor. Their inputs are the last three iterations of each factor. For example, for variable temperature the input of each ANFIS and RBF is: $temp_{i-2}, temp_{i-1}, temp_i$and the outputs is: $change\_rate_{i+1}$, which is the predicted change of consumer's consumption. On both ANFIS and RBF, the CUCKOO optimization algorithm(see (Yang and Deb, 2009)) is applied to train much faster and accurately. CUCKOO optimization pseudo code is described in Fig 5. After training of ANNs, the weights vector for IOWA operator is calculated by equation 4.

5.2 Forecasting phase

This phase consists of 3 sub-phases which are described below:

Step 1: Defining the importance of each factor: In this stage some factors are considered to be influencing the electricity consumption. By applying Multi-Layer Perceptron (MLP) find the most influential factors. Since the activation function which is used in this MLP has a positive output, so would be expected the variable which have higher weights than average weight be the most influential factors. In this step m factors that have the most effect on electricity usage will be find.

Step 2: Generating Consumption Change Percentage: Two neural networks, ANFIS and RBF, get the resulted data from first step. An ANFIS and RBF is created for each factor extracted from first step. These inputs are like a time series for each variables, and the output is the consumption change percentage. The CUCKOO algorithm is applied on ANFIS and RBF to find the best architecture much faster. It's obvious that there will be 2*m* NNs combined.

Step 3: Aggregating ANFIS and RBF results using IOWA: The output of ANFIS and RBF for each variable is aggregated using IOWA operator. Then we will have *m* aggregated factor.

Step 4: Final Fusion: In this step all *m* aggregated factors, are fused once more.

6. NUMERICAL EXPERIMENT

The algorithm is applied on data borrowed from (Barker and Mishra and Irwin and Cecchet and Shenoy and Albrecht, 2012) that is average household electricity usage every second for three different homes which are non-aggregated. The first step is to aggregate data and calculate electricity usage of every home per iteration. Another part of mentioned data is weather information, which consists of temperature, humidity, Pressure, wind speed, rainfall, and solar intensity.

Cuckoo psdeudo-code

Generate initial population of N host nests, $h_(i)i, i = 1, \dots, N$
while $fmin < MaxGeneration$ **do**
Get a cuckoo randomly be Levy flights evaluate its quality
    [A] Choose randomly a nest j among N
    if $F_i > F_j$ then **then**
        Replace j by the new solution.
    end if
    A fraction (pa) of worse nest is abandoned and new ones are built.
    Keep the best solution
    Rank the best solution
end while

Figure 5 Cuckoo search algorithm

6.1. Finding the most influential factor

As mentioned in previous section the first step is to find the most influential factors. For this purpose, one MLP with seven inputs, which consists of temperature, wind, rain, humidity, last amount of usage, Dewpt and solar was created. This MLP has 2 hidden layers with 8 neurons in layer one and 2 in layer two. The summation of the weights of each input is calculated and if it is larger than the average of weights, it is chosen as an influential factor. This is one of the advantages of this method, since in different months or different regions, influential factors are variable. In other word, the region or time of the year affects the importance of each weighted factor. For instance, in a dry season or dry region in summer in which the amount of rain is not considerable, the model ignores the impact of rainfall factor.

According to table 1, the most influential factors in consumers' behavior are temperature, last consumption and solar values. Therefore the model is adaptable based on the sudden climate changes.

6.2. Creating ANFIS and RBF

Considering extracted factors in previous step, two ANFIS and RBF neural networks, generated. Their inputs are the last three iterations of each factor. For example for variable temperature the input of ANFIS is: and the output is: which is predicted change of consumer's consumption by the influence of temperature changes. CUCKOO search algorithm is applied on ANFIS and RBF neural network to find the best weights in less iteration.

Table 1 Summation of weights of each variable

	Wind	*Temp*	*Dewpt*	*Last Cons.*	*Rain*	*Humidity*	*Solar*
Sum	-3.4984	-0.4760	-3.9918	4.4122	-3.7305	-4.7754	0.8174
Total Avg.	-1.1265						

Then calculated change rates of ANFIS and RBF, are aggregated by IOWA fusion operator. As the number of results for each variable is two, so with different orness degree, theseweights are calculated. Table 2 shows the calculated weights and MSEs of aggregated RBF and ANFIS for each variable. According to table 2 the best results are obtained by orness=0.9. The graph in Fig.6, presents the influence of fusion on the value of MSE by assuming the orness degree equal to 0.9. Horizontal axis of the graph has the values 1, 2 and 3, which are last consumptions, solar and temperature, in order. The vertical axis represents the MSE for each factor with different neural network. It is clear when looking at the graph, by fusion the output of ANFIS and RBF, the MSE value is decreased.

6.3. Fusion of calculated change rates

Now there are three different consumption change rates, which are calculated by the influence of three factors, thus, these factors are combined by IOWA fusion operator and oreness degree equal to 0.9. In this case by solving the equation 4, weights vector is equal to ⟨0.812, 0.136, 0.052⟩. Fig. 7 shows the influence of fusion on the value of MSE**.** This chart shows the MSE value reduction by fusion of the outputs of three predictors, temperature, solar, and last consumptions, which was expected.

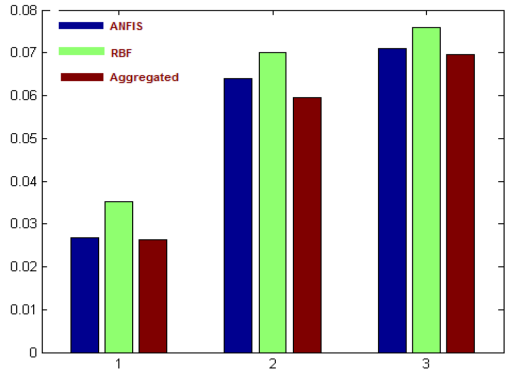

Figure 6 influence of fusion on MSE

7. CONCLUSION

In smart grid system there are several factors that influence on the users' load consumption. The importance of these factors may be changed in different times and places. Another consideration is the instability of renewable energies which are affecting on the user's consumption.

Table 2 weights with different orness degrees

Orness Degree	*0.9*	*0.5*	*0.1*
Weights	<0.9,0.1>	<0.5,0.5>	<0.1.0.9>
Last Cons. MSE	0.02638	0.028863	0.0337
Solar MSE	0.05962	0.06260	0.06820
Temp. MSE	0.06974	0.0707	0.0744

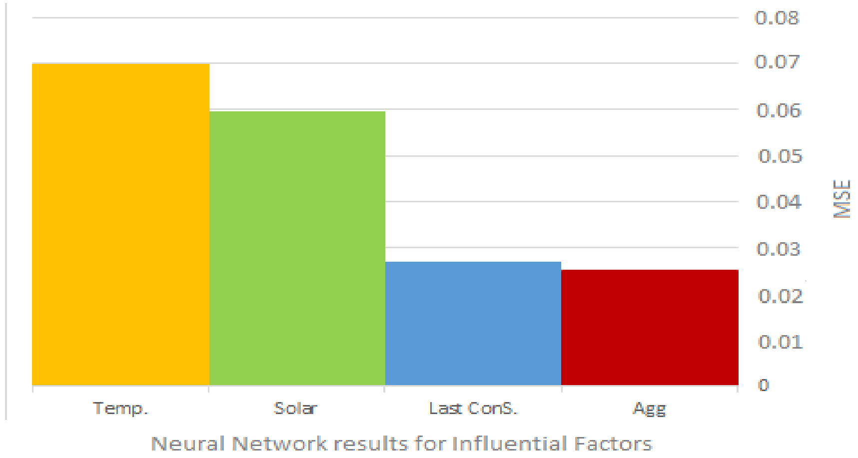

Figure 7 Influence of fusion on MSE

In order to cover this instability, forecasting methods could be fused together. In this paper two optimized neural networks (ANFIS and RBF), by cuckoo optimization algorithm, for each influential factor such as historical loads or weather data are implemented. The optimized neural networks produce a prediction of users' consumption as the outputs. These outputs based upon induced ordered weighted average (IOWA) are aggregated. The MSE value is selected as an induce variable for IOWA operator. Experimental result shows that the precision of aggregated load forecasting based upon IOWA operator in comparison with non-hybrid methods is improved significantly and also the model is adaptable based on the region in a way that it could manipulate weights of each factor, to result in more accurate power consumption forecast.

REFERENCES

Amin, S. M., & Wollenberg, B. F. 2005. Toward a smart grid: power delivery for the 21st century. *Power and Energy Magazine, IEEE*, *3*(5): 34-41.

Asano, H., Hatziargyriou, N., Iravani, R., & Marnay, C. 2007. Microgrids: an overview of ongoing research, development, and demonstration projects. *IEEE Power Energy Magazine*, 78-94.

Asbury, C. E. 1975. Weather load model for electric demand and energy forecasting. Power Apparatus and Systems, IEEE Transactions on, 94(4): 1111-1116.

Barker, S., Mishra, A., Irwin, D., Cecchet, E., Shenoy, P., & Albrecht, J. 2012. Smart*: An open data set and tools for enabling research in sustainable homes. *SustKDD, August*.

Box, G. E., Jenkins, G. M., & Reinsel, G. C. 2011. Time series analysis: forecasting and control (734). John Wiley & Sons.

Brown, R. G. 1983. *Introduction to random signal analysis and Kalman filtering*. John Wiley & Sons.

Bunn, D., & Farmer, E. D. 1985. Comparative models for electrical load forecasting.

Buragohain, M., & Mahanta, C. 2008. A novel approach for ANFIS modelling based on full factorial design. *Applied Soft Computing*, *8*(1): 609-625.

Chandler, S., & Hughes, J. G. 2013. Smart grid distribution prediction and control using computational intelligence. In *Technologies for Sustainability (SusTech), 2013 1st IEEE Conference on* : 86-89.

Daneshi, H., Shahidehpour, M., & Choobbari, A. L. 2008. Long-term load forecasting in electricity market. In *Electro/Information Technology, 2008. EIT 2008. IEEE International Conference on* : 395-400.

Fan, Z., Kulkarni, P., Gormus, S., Efthymiou, C., Kalogridis, G., Sooriyabandara, M.,& Chin, W. H. 2013. Smart grid communications: overview of research challenges, solutions, and standardization activities. *Communications Surveys & Tutorials, IEEE*, *15*(1): 21-38.

Gelb, A. 1974. *Applied optimal estimation*. MIT press.

Guan, C., Luh, P. B., Michel, L. D., Wang, Y., & Friedland, P. B. 2013. Very short-term load forecasting: wavelet neural networks with data pre-filtering. *Power Systems, IEEE Transactions on*, *28*(1): 30-41.

Hernández, L., Baladrón, C., Aguiar, J. M., Calavia, L., Carro, B., Sánchez-Esguevillas, A., & Gómez, J. 2012. A study of the relationship between weather variables and electric power demand inside a smart grid/smart world framework. *Sensors*, *12*(9): 11571-11591.

Hernandez, L., Baladron, C., Aguiar, J. M., Carro, B., Sanchez-Esguevillas, A. J., Lloret, J., ... & Cook, D. 2013. A multi-agent system architecture for smart grid management and forecasting of energy demand in virtual power plants. *Communications Magazine, IEEE*, *51*(1): 106-113.

Hernandez, L., Baladron, C., Aguiar, J. M., Carro, B., Sanchez-Esguevillas, A. J., Lloret, J., & Massana, J. 2014. a survey on electric power demand forecasting: Future trends in smart grids, microgrids and smart buildings. *Communications Surveys & Tutorials*, *IEEE*, *16*(3): 1460-1495.

Hippert, H. S., Pedreira, C. E., & Souza, R. C. 2001. Neural networks for short-term load forecasting: A review and evaluation. *Power Systems, IEEE Transactions on*, *16*(1): 44-55.

Hsu, C. C., & Chen, C. Y. 2003. Regional load forecasting in Taiwan—applications of artificial neural networks. *Energy conversion and Management*, *44*(12): 1941-1949.

Hwang, Y. S., & Bang, S. Y. 1997. An efficient method to construct a radial basis function neural network classifier. *Neural networks*, *10*(8): 1495-1503.

Jang, J. S. R. 1993. ANFIS: adaptive-network-based fuzzy inference system. *Systems, Man and Cybernetics, IEEE Transactions on*, *23*(3): 665-685.

models. In *Proceeding of the 8th power industrial computing application conference* (1): 31-37.

Wang, Y. M., Luo, Y., & Liu, X. 2007. Two new models for determining OWA operator weights. *Computers & Industrial Engineering*, *52*(2): 203-209.

Yager, R. R. 1988. On ordered weighted averaging aggregation operators in multicriteria decisionmaking. *Systems, Man and Cybernetics, IEEE Transactions on*, *18*(1): 183-190.

Mbamalu, G. A. N., & El-Hawary, M. E. 1993. Load forecasting via suboptimal seasonal autoregressive models and iteratively reweighted least squares estimation. *Power Systems, IEEE Transactions on*, *8*(1): 343-348.

Negnevitsky, M. 2005. *Artificial intelligence: a guide to intelligent systems*. Pearson Education.

Park, J. H., Park, Y. M., & Lee, K. Y. 1991. Composite modeling for adaptive short-term load forecasting. *Power Systems, IEEE Transactions on*, *6*(2): 450-457.

Taylor, J. W., & Buizza, R. 2003. Using weather ensemble predictions in electricity demand forecasting. *International Journal of Forecasting*, *19*(1): 57-70.

Vemuri, S., Hill, D., & Balasubramanian, R. 1973. Load forecasting using stochastic

Yager, R. R., & Filev, D. P. 1999. Induced ordered weighted averaging operators. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, *29*(2): 141-150.

Yang, X. S., & Deb, S. 2009. Cuckoo search via Lévy flights. In *Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on* :210-214.