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Enabling External Factors for Consumption Electricity Forecasting using Hybrid Genetic Algorithm and Fuzzy Neural System

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***Abstract*—Forecasting of the future load is important because of dramatic changes occurring in the electricity consumption lifestyle. Several algorithms have been suggested for solving this problem. This paper introduces a new modified fuzzy neural system approach for short term load forecasting. By using two phase on Fuzzy Inference system and Genetic algorithm for optimization, weight can improve the accuracy of electricity load forecasting. The relationship external factors like temperature, humidity, price load, Gross Domestic Product and load is identified with a case study for a particular region. Data for a monthly load of five years has been used. The accuracy algorithm has been validated using Root Mean Square Error (RMSE). The result RMSE is 0.78 it is shown that our proposed method is feasible.**

Keywords*—Electricity load forecasting, hybrid, Genetic Algorithm, Fuzzy Neural System, external factors, RMSE

I. Introduction

Electricity has huge environmental, social, and economic impacts, such as its influence on climate change, poverty reduction efforts, human culture, industrial and agricultural productivity, and ecological and human health [1]. Several parties use electric power, like the household sector, industry, commercial businesses, and public services [2]. Electricity consumption will continue to rise. The increase in demand for electricity requires that the electricity provider can deliver the power needs of consumers so that stability in every sector of community fields can be assured.

Considerate the potential impacts of the external factor on electrical load demand is crucial for global strategic energy plans. Historical data, temperature, humidity, population, price load and gross domestic product (GDP) has various impacts of each forecast factors. The power system on tropics are categorized as dry areas make a huge impact for climate change, which is greatly affected by the weather changes. Population of uncontrolled and unpredictable temperature and extremely changeable humidity can affect the electrical consumption habits in daily life. The relationship GDP factor with electricity consumption showed that income allows can enjoy by residents of an area and the ability of economic resources in producing goods and services in a sector. If the value of GDP of the primary means indicates that the ability of economic resources in the area were high and vice versa when the value of GDP in the region showed that small mean financial capability in the area of small. The aim using the external factors is expected to help increase the accuracy of forecasting electricity consumption [3].

Artificial intelligence has been the major domain of work in many advanced load forecasting. In this paper, we propose our improvement to the previously our research proposed electricity load forecasting [2]. Regression is one of most widely used mathematical techniques. Several regression models for electricity load forecasting have been presented [4], [5]. Neural Networks (NN) has been proved as strong solution for load forecasting that serve minimization by tuning mechanism [6]–[8]. Neural network output is the number of function linear mathematical even nonlinear of its inputs. The inputs may be the outputs of other network layer as well as actual network inputs. On other hand Fuzzy Inference System (FIS) has been successfully implemented.in various forecasting problem [9]–[11].

The forecasting capability of the NN model can be improved by using a combination of neural networks and fuzzy logic. A compound of fuzzy inference system and neural network forms fuzzy neural system (FNS). This system constitue a FIS part and NN part. FIS part serves following purposes:

1. to define membership functions this method adapts itself using NN
2. to corresponding fuzzy rules this maps using fuzzy sub-sets
3. implements defuzzification

NN part serves following purpose:

1. it serves push error by using the tuning mechanism of NN

Furthermore, a promising approach for getting the benefits of both the fuzzy systems and neural networks by merge them into an integrated system. Due to local minima problem of the implemented conventional local optimization techniques because the convergence of learning is usually stagnant and may not confirm. The convergence of learning can be improved by using a global optimization technique such as genetic algorithm. This paper is aimed to develop modified fuzzy neural system for load forecasting. The ANN model accuracy will be improved by adopting a genetic algorithm based optimization procedure for finding the optimal weights of the model. Fuzzy inference

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system using two phased, in order to reduce rule that be used at fuzzification phase. Due to the method of fuzzy logic system, rule phase plays an important role in the result of prediction.

II. LOAD FORECASTING MODEL

In this paper, model two fuzzy inference system phase are considered the block diagram of the proposed forecasting model is shown in Figure 1. The data of these eight inputs are fed to the fuzzy logic the system is divided into two stages which outputs the load proportional to these eight parameters. Where the division parameter two stage FIS is based on the effect on electricity consumption. When a parameter is changed, the power consumption will change as well; it is considered a parameter is "Positive" and the rest parameter “Negative” that mean this parameter if considered in electricity consumption tends to reduce the burden on electricity consumption. Although the parameters in this category experienced an increase in peak period less affected the electrical load. However, the load is not just depending on the historical data but also depends on external factor such as temperature, humidity, population, price load and Gross Domestic Product. In this paper uses historical data is denoted "t" is actual data, the "t-1" one month earlier, "t-2" six months earlier, "t-3" is one year earlier, temperature denoted by "temp", Gross domestic product symbolized "GDP", humidity denoted "Hum", Price load denoted "Price", Population denoted "Pop". For that reason, the output of fuzzy logic system is fed to the neural networks model for training and comparing a set of past load to predict the future load. The modelling procedure has been applied on the date presented in Fig. 2(a-f).

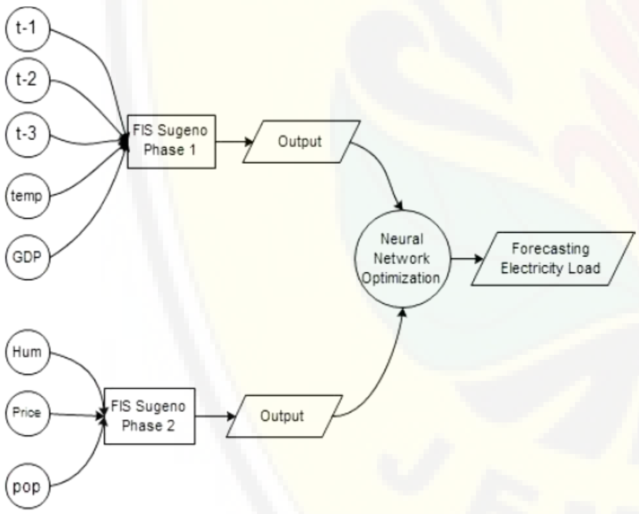
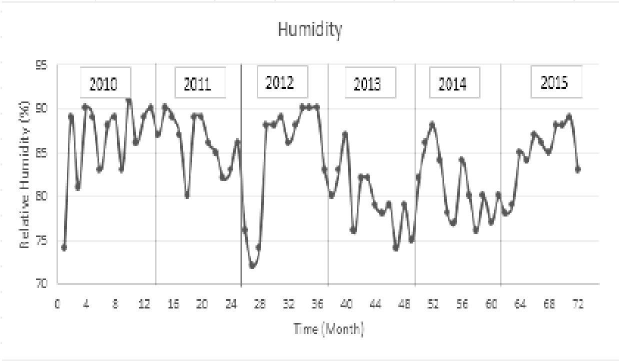
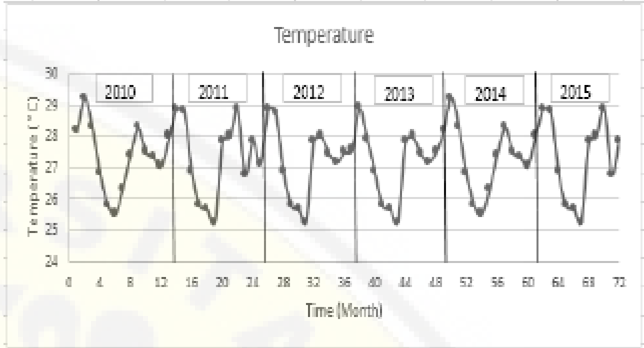


Fig 1. Block diagram of the load forecasting model.



(a)



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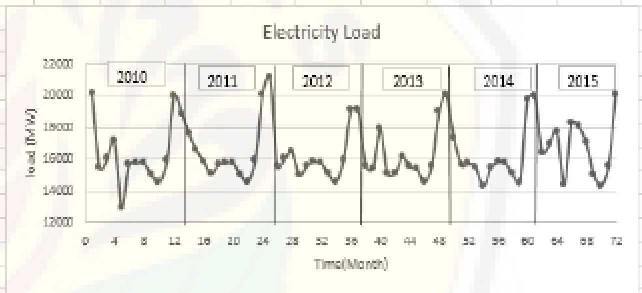

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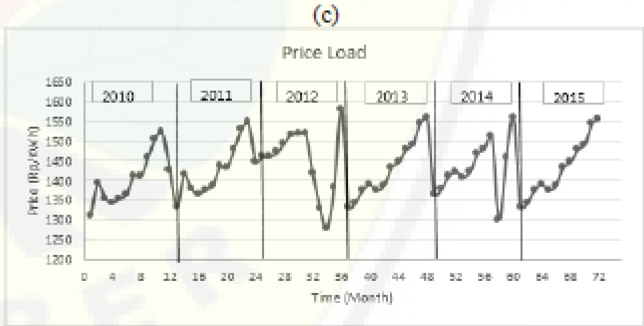

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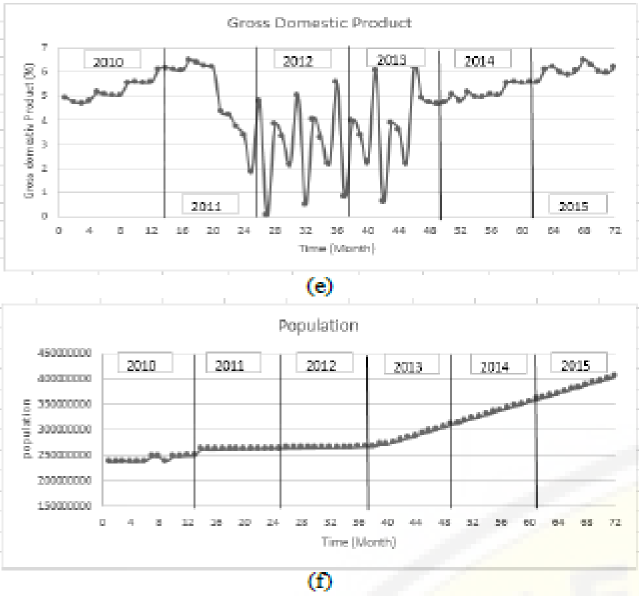

Fig 2(a-f). Monthly variation of humidity temperature, demand, price load, gross domestic product and population

III. Fuzzy Inference System

The main processes of the fuzzy inference system include: fuzzification, knowledge base, decision making and defuzzification. In the fuzzification part, the parameter is represented as a variable input. The parameters used as input variables are historical load data, temperature, humidity, GDP, price and population. In the first stage of fuzzification the temperature and load has been categorized into low, and high. For each membership function, the input variables, where μ is the degree of membership and x is the value of the input to be converted into a fuzzy set, the example are described in equation 1 and equation 2.

$$\mu\, low\,(x) = \begin{cases} 1 & x \le 10 \\ \frac{20 - x}{10} & 10 < x < 20 \\ 0 & x \ge 20 \end{cases} \qquad (1)$$

$$\mu\, high\,(x) = \begin{cases} 0 & x \le 10 \\ \frac{x - 10}{10} & 10 < x < 20 \\ 1 & x \ge 20 \end{cases} \qquad (2)$$

In Figure 3 there is an example on determined triangular membership temperature and domain divided into two fuzzy subsets label as “low” and “high” where the fuzzy subsets’ high are limited [20 - 35] and fuzzy subsets’ low are limited [5 - 10].

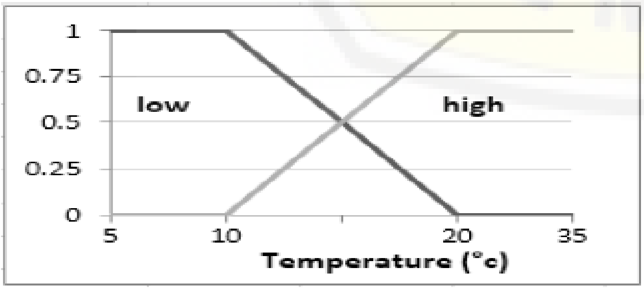

Fig 3. The example of membership function “Temperature”

IV. Neural Networks

Neural Network model will “learn” the relation between these two inputs from FIS phase. We using single hidden layer ANN model shown in Figure 4 is used to represent the fuzzy logic output.

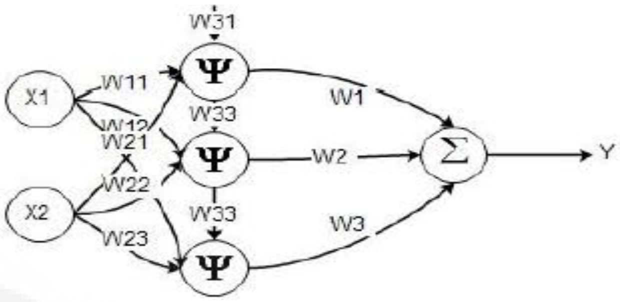

Fig 4. Single hidden layer NN

In Figure 4, forecasting load represent as Y, the output of the fuzzy inference system as input represents X2 and X1. W1i, W2i and W3i are the input weights and W1, W2, and W3 is the output weight. An optimization technique can be used in training the neural network model and finding the optimal values for the input and output weights. Here, a genetic algorithm based optimization procedure has been developed.

V. Hybrid Algorithm

Hybrid GAs and Fuzzy Neural System focuses on hybrid with two jobs. First, the use of Genetic Algorithms on neural network is used to avoid local optimum on neural network. Implement of GA is present in the input and output weights NN. Secondly, FIS in Fuzzy Neural System uses two stages where its goal to reduce the rule to be faster in the computing side. Separation rule into two phases based on the relationship of positive and negative with the use of electricity. The steps of the implemented genetic optimization are presented in Figure 5 and it can be summarized as:

a. Randomly, generation of initial population of individuals. Each individual consists of 11 variables (8 input weights and 3 output weights). The generated values of these weights are within -1 and 1. The current of generation number one will be the parents of the next generation individuals and the optimization will continue over Nmax generation.

b. Calculating the corresponding error between the actual and simulated values of the output for each individual as follows:

- Computing Y in (1) using the values of the input and output weight in the individual over the entire values of the X1and X2.
- Determining the total error between the simulated Y and the correlative actual one as follows:

$$Error = \frac{1}{M}\sum_{m=1}^{M}(Y_{act} - Y_{sim})^2 \qquad (3)$$

Where M is the total number of the actual data, Yact is the actual data and Ysim is the corresponding simulated one.

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c. Classifying the individuals of the selected population and their errors to reject some of the maximum error individuals in the population.

d. Recombining the selected individuals to perform crossover reproduction by using double-point crossover routine.
e. Mutating, the reproduced offspring from the crossover process
f. Continuous step on no two to determine the error of each reproduced individual.
g. The next step is reinsertion. Reinsertion replaces the most error individuals in the parent with individuals in the new reproduced population.
h. The generational counter is incremented, and the steps from c to g are repeated until generation no. = Nmax.
i. When the number of generational counter is equal to Nmax or the minimum error is less than a fixed threshold value εs, the algorithm stretch the last generation and stops.
j. The minimum error individual will be chosen and the values of its variables will be considered as optimal values for the network model weights.

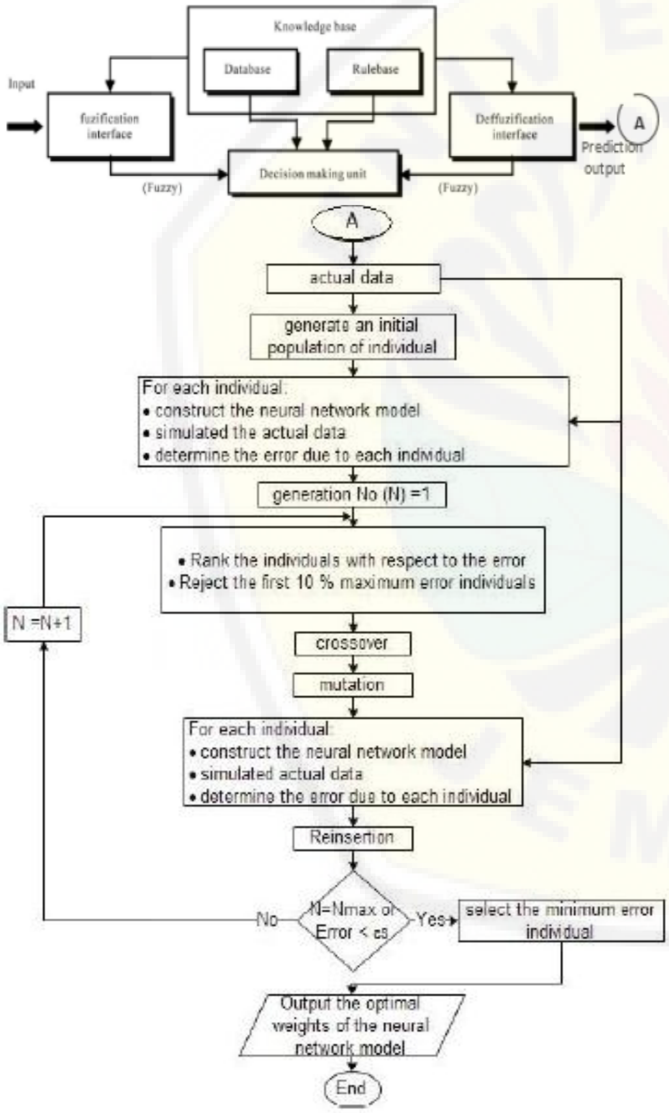

Fig 5. Flowchart proposed method

VI. Experimental Analysis and Result

This procedure has been applied to the actual data of historical data, temperature, humidity, price load, GDP, and population (see Fig. 2) of 4 years from 2010 to 2015. The historical data, temperature, humidity, price, GDP, and population as input to Fuzzy inference system which gain a measured load. This value in addition to the historical load are then input to the NN model.

We proposed using two phase Fuzzy Inference system. The 'if-then' design rules for the fuzzy inference system depends on the number of membership functions used in each input variable using the system (e.g. our fuzzy inference system uses eight input variables in which each entry contains two membership functions; the total number of fuzzy-rules is 2^8= 256. If we use two phase fuzzy it will reduce it. Fuzzy phase 1 have five parameter input (t-1, t-2, t-3, temp, and GDP) so number of rule is 2^5= 32 and Fuzzy phase 2 have three parameter input (Hum, Price and Pop) so the number of fuzzy rule is 2^3=8 and total from two phase is 40. Thus, we only need to use the number of the fuzzy rule is 40. By reducing the amount of this rule makes it very helpful in the process of computing because it will create a powerful and fast execution time.

The modelling procedure of NN is started by random initial population which generating a uniformly distributed of 2000 individuals. Each individual consists of 11 variables (input and output weights). The maximum number of generations is set to 100 and εs is defined to be equal to 0.001. The average error of the individuals will stop when asymptotically approaches values very close to the minimum error and finally the procedure is stopped after small number of generations when εs is reached. The simulation time, using Netbeans IDE 8.1, 3 GB RAM and 2.13 GHz computer.

The powerful convergence capability is demonstrated of the developed procedure and its robustness of exploring the search space and capturing the region of the global minimum. We use data from 01 January 2010 until 31 December 2015. In this paper we use 48:24 as training and testing data.

For accuracy testing, how well the performance of our proposed method estimate the error forecast. Because more appropriate unbiased estimators applied to see how far the model can forecast the values of electricity load, error measure of accuracy is employed. For this reason, the models are evaluated by the square root of the mean square error (RMSE)[12]. The result our forecast show on Table 1.

Figure 6 is the result of a plot of training data for forecasting electricity load using two methods of comparison that is FIS and Neural Network. FIS and Neural Network chosen due to confirm the successful performance of our proposed method is essentially the integration of FIS and Neural Network. The actual data with the red line, modified FNS with a blue line, FIS with a purple line and the green line is NN. There looks proximity actual line data and our proposed method, this happens because the results of the forecasting method we go well.

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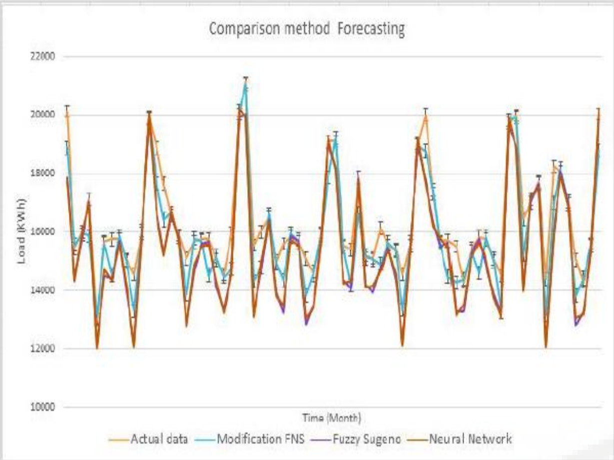

Fig 6. Comparison between actual data, proposed method, Fuzzy Inference system and NN

TABLE I. RESULT FORECASTING LOAD

Time (Month in 2014- 2015)	Actual Data	Hybrid	Fuzzy Inference System	Neural Network
Jan 2014	20102.2	18872.2	17867.2	17756
February	15442.5	15553.5	14442.5	14342
March	16003	15933	15843	16077
April	17111.1	15881.1	17031.1	16920
May	13001.2	13112.2	12107.2	12007
June	15663	15593.25	14482	14716.1
July	15749.2	14519.69	14429	14318.2
August	15750.4	15861	15670	15579
September	15050.7	14980	13975	14209
October	14542.8	13312.8	12201	12090
November	15955	16066	15976.4	15876
…………	….	….	…..	…..
Dec' 2015	20750	20420	20670	20503
RMSE	-	**0.779**	**55.24**	**22.982**

In Table 1 illustrates that the value of the electric load forecasting using Modified FNS produces the smallest RMSE value error is 0.78, while the Fuzzy Inference System generates values error is 55.24 and 22,987 for Neural Network. This occurs because the Modified FNS feasible in integrating fuzzy inference system and neural network with the help of Genetic Algorithm as the technique that can be used in training the neural network models and finding the optimal values for the input and output weights. Fuzzy Inference System method generates the forecasting accuracy ugliest error due to weakness is depending on the location of the determination rule and membership function. For the neural network method, the weaknesses depend on a number of hidden layer, neurons, and the epoch is very noteworthy because its a strong impact on the forecast that will be produced.

All the weaknesses of the Fuzzy Inference System and Neural Network above can be solved by Modified FNS. On our proposed method, there is a division of FIS into a two phase. This do to avoid the use of the rule that too much because it would be bad for forecasting and computing. For additions determinant of weight with Genetic Algorithms is very helpful in overcoming weakness of Neural Network.

The same testing data is applied to assure the efficacy of this optimized Neural Network weight in FNS. The root mean square error of 0.78 reflects the superiority of the optimized results in this regard. The overall decrease in the RMSE of more than 20 compare with Neural Network result reflects that the GA based approach for the optimization of NN in FNS architecture is authenticated.

VII. CONCLUSION

The problem arises when forecast the electric load in the future using external factors such as temperature, humidity, price, and GDP. The problem determination of optimized Neural Network weight can be solved by using genetic algorithm and reduce rule on fuzzy inference system where the division parameter two stage FIS is based on the effect on electricity consumption. It makes more agile and accurate in forecasting using many input parameters on Fuzzy Inference System. A considerable reduction in root mean square error (RMSE) is observed after by hybrid GAs and Fuzzy Neural System and the result is modified FNS topology and retraining this optimal network structure produce the lowest accuracy of the method of comparison is equal to 0.78 it is proved that modified FNS is a good forecasting precision with fast running time, thus verifying that our proposed scheme is feasible.

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