Radial Basis Function (RBF) Neural Network for Load Forecasting during Holiday

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***Abstract*—Providing solution for short term load forecasting is a major challenge remained for researchers due to the nature characteristics of load which are non-linear, probabilistic and uncertainty. As the statistical assumption may fail to estimate the load profile precisely, the intelligent techniques play important role to provide alternative solutions. This paper discusses the variant of artificial neural network called radial basis function (RBF) neural network for short term load forecasting. The method is recently attracted attention due to structure simplicity and high identification performance. The RBF method is an artificial neural network model motivated by locally-tuned response biological neurons that provide selective response characteristics for some finite range of the input signal space. The estimation process is carried out with 4 previous peak load holiday to predict the peak load of the next holiday using data of the year 2005-2011 in Makassar City, Indonesia. The validation results show that the proposed method can offer very accurate forecasting results, indicated by small mean absolute percentage error (MAPE) for the estimation task of the year of 2012 and 2013 in comparison to conventional least square polynomial approximation method.**

Keywords- short term; load forecasting; intelligent methods; RBF; neural network.

I. Introduction

The high accuracy of load forecasting method is highly needed in the corridor of emerging operation of power system. Poor peak load estimation leads to defective scheduling and allocation of back up generation units which may affect the reliability condition of the system and power system security. In addition, the real-time load forecasting is really essential for the market participants under deregulated electricity market. In this respect, the short term load forecasting (STLF) greatly influences the system marginal price. In fact, the load characteristics are unique, non-linear and uncertainty. They are unique because the load profile will be never obtained similar to the previous conditions.

The peak load during holidays is totally different from the weekdays and so on. Their non-linearity comes up with dynamic behavior of customers and they are affected by environmental conditions, such as wind speed, precipitation, atmospheric pressure, temperature and humidity. Consequently, these two characteristics drive the load profile in the uncertainty condition; therefore the probabilistic solution based on statistical assumption may fail. The main problem of probabilistic methods such as linear regression, auto-regress moving average (ARMA) and auto-regress integrated moving average (ARIMA) is the limited capability to work in every possible condition because they are highly dependent on the historical data which is singular by locations and complicated mathematical equations [1]. Therefore, the diversity and integrating methods for load forecasting are a major challenge remained for researchers.

Diversification methods for short term load forecasting is still necessary discussed in order to approach the simplicity and high accuracy methods. Recently, the intelligent methods and their hybrid combinations play important roles to deal with the uncertainty conditions of load profile and provide alternative solutions for short term load forecasting. Hinojosa and Hoese proposed fuzzy inductive reasoning and evolutionary algorithm for load forecasting one day ahead based on temperature variations [2]. The proposed method can improve the accuracy of forecast result by optimizing the linear and non-linear correlation between variables. Chen at. al attempted to forecast the tomorrows load taking a similar day-based wavelet neural network method [3]. In this method, the wavelet decomposition and separate neural networks are utilized to capture the features of load at low and high frequencies. The numerical testing is also confirmed with high accuracy prediction even under the nature of high frequency load. Another application of wavelet transform combined with feed forward neural network called adaptive wavelet neural network is used for an accurate and efficient short-term load forecasting [4]. Similar to Chen's work, this method also deals with the noisy nature related to loss of high frequency information. A satisfactory improvement of the forecasting accuracy is also achieved by quantum neural network model considering the effective input variables set related to the most influential causes with maximum correlation degree to load profile [5].

The eminences of the intelligent methods over the conventional methods are basically the simple computational technique and algorithm, simplicity structure and high accuracy performance without the necessity to solve any non-linear mathematical equations. For instance, the fuzzy set and fuzzy logic solve the non-probabilistic information and uncertainty by manipulating data through the rule base and adjusting the membership function. Therefore, this method is suitably used to solve and model complex systems with non-linear and non-exact characteristics [6]. In case of artificial neural network models, they are capable to handle the nonlinear model of large multivariate data sets and they reported very reliable to forecast the load profile, especially in short term forecasting. Even though, the modeling process of artificial neural network requires good knowledge to define the appropriate level of model complexity and choosing the input variables [7].

Most of the proposed methods have investigated the weather and environmental factors as the most influential factors affecting the future load profile. Taylor introduced the triple seasonal methods for online short-term load forecasting by modeling the intraweek and intraday seasonal cycles in intraday load data [8]. Fay and Ringwood concerned about the weather forecast error that lead to defective estimation of load profile and present a new technique for minimizing the consequences of this degradation [9]. The weather historical data such as wind speed, precipitation, atmospheric pressure, temperature and humidity is highly considered as the influenced factors to the load behavior [10]. However, the weather approach and its implication is less necessary because the actual data of peak load several days before the estimated time is basically unpredictably changed and they already represent the accumulating power demand affecting not only by weather conditions. In fact, the fluctuation of weather condition does not change the load dramatically for short term estimation in the specific region condition, such as in Makassar City of Indonesia. Moreover, mining the historical data from meteorological measurement is time-consuming and it is very difficult to have the similar meteorological category and features with the forecasting day. The large amount of data may force the proposed method to experience slow computational speed [11].

The paper discusses the applications of radial basis function (RBF) neural network for short term load forecasting. The proposed method is an artificial neural network model motivated by locally-tuned response biological neurons. These nerve cells have response characteristics which are selective for some finite range of the input signal space. The origin formulation of the RBF neural network was developed in order to produce deterministic mapping of data by exploiting links with traditional function approximation. This approach attempts to introduce the notion that the training of neural network could be described as curve fitting. Recently, the RBF method seems very reliable and is showing high accuracy and stability for short, medium and long term load forecasting by utilizing virtual instruments and taking the environmental factors as variables [10]. In this paper, the environmental factors are not taken into account as the variables for both proposed method. The proposed methods were tested only with the actual peak load data of 4 days of previous holiday to predict the peak load at the time of holiday. This work motivated by Kim et.al which emphasizes that the load profile during holiday is totally anomaly from the ordinary weekdays during a year [12]. The data range between 2005 and 2011 is used as the reference to estimate the peak load of 13 days of public holiday in Makassar City of Indonesia for the estimation task of the year 2012 and 2013. The performance of both methods is measured by the mean average percentage error (MAPE). More detailed explanations about the proposed method are presented in the next section.

II. Radial Basis Function (RBF) Neural Network

Approach to the short-term load forecasting is the use of the radial basis function (RBF) neural network. The structure of RBF model is very simple with three layers; input, hidden and output. At glance, it is pretty similar to the three layered feed forward neural network (TFFN), except for the activation function and the algorithm. In the TFFN method, the sigmoid function is commonly used as the activation function between layers, while the RBF utilizes radial basis and linear functions between input and hidden layers and between hidden layer and output layer, respectively. In terms of the algorithm, the TFFN uses the back propagation algorithm for adjusting the weights and during the training process. Meanwhile, the number of hidden layer in the RBF method is updating sequentially until the error goal is reached. For this reason, the training process in the RBF network is fast and the network structure is directly confirmed. The high accuracy of this method during the validation process is also convincing.

In the training process of artificial neural network, we consider the peak load during holiday is some kind of periodical data. It means there is actually implicit data relation between the peak load of previous holiday and the next holiday. Therefore, for radial basis function (RBF) neural network, four inputs of previous year of selected holiday (H-1, H-2, H-3 and H-4) are arbitrarily selected to predict the peak load holiday (H*) as a single output. For instance, to predict the peak load during New Year event of 2012, then the inputs of H-1, H-2, H-3 and H-4 are considered as the peak load during New Year events on 2011, 2010, 2009 and 2008, respectively. Similar approach is taken for prediction the load during holiday in the following year. Basically, the number of input may larger than the taken assumption. However, there is significant trade-off between complexity of neural network structure and the accuracy level. In this case, it is possible to have better accuracy but ends up with large complex neural network. The structure and training error for each predicted peak load during holiday can be seen in Table I. It seems than simpler structure with small number of hidden node can be obtained for some cases of predicted due the simplicity correlation between the input data and the target output. However, all cases cannot be forced to convergence in the same structure because their random nature of data.

During the training process, the input vector which will result in lowering the network error is used to create a new hidden neuron. If the current error after the neuron insertion is low enough, the training stops. In this study, the parameter of training process: the mean squared error goal (GOAL), spread of radial basis functions (SPREAD), maximum number of neurons (MN) and the number of neurons to add between displays (DF) are 0.003, 1.0, 25, 1, respectively. The outcomes of the training process are the number of the hidden neurons that represent the structure of RBF neural network and the training error that represents the accuracy of the confirmed structure.

TABLE I: STRUCTURE OF TRAINING ERROR

Predicted holiday (H*)	Number of hidden nodes	Training error
H1	9	0.00025
H2	8	0.00019
H3	6	0.00024
H4	6	0.00028
H5	5	0.00031
H6	6	0.00030
H7	8	0.00022
H8	8	0.00018
H9	7	0.00019
H10	6	0.00026
H11	7	0.00021
H12	9	0.00019
H13	8	0.00022

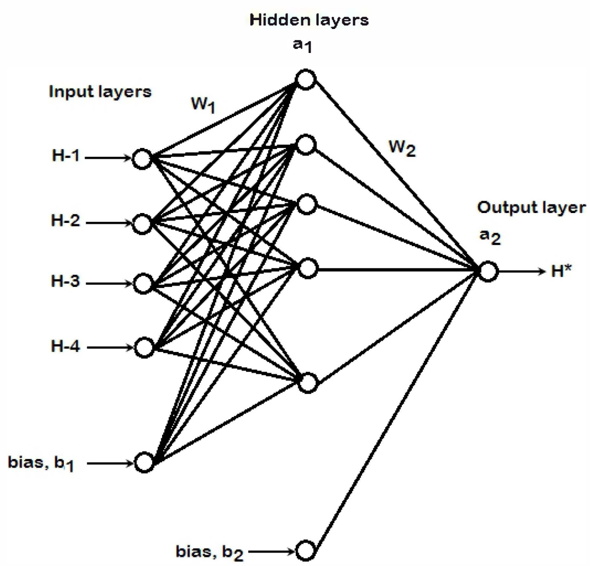

Figure 1. RBF structure

The RBF structure for one forecasted peak load holiday is shown in Figure 1. Therefore, there are 13 similar structures with different number of hidden nodes for the overall study. The algorithm of RBF neural network is elaborated as follows. In the RBF structure, the *Euclidean* distance weight function (‘*dist*’) is applied for input signals processing before preceding them to the '*radbas*' activation function in hidden layer. The mathematical equation in this stage is formulated as follows:

$$a_1(n) = radbas \quad [dist \ (w_1(n,1)(H-1) + w_1(n,2)(H-2) + w_1(n,3)(H-3) + w_1(n,4)(H-4)).b_1(n,1)] \qquad (1)$$

where a_1 is the active nodes in hidden layer, n is the number of nodes number in hidden layer, w_1 is the weight matrix between input and hidden layers and b_1 is the bias connected to each nodes in hidden layer.

After this process, the output layer a_2 is calculated by simply applying the '*purelin*' activation function in output layer. The mathematical equation is stated for this condition as:

$$a_2(m) = purelin[(\sum_{n=1}^{n} w_2(m,n).a_1(n)) + b_2] \qquad (2)$$

where a_2 is the active nodes in the output layer, m is the number of nodes in output layer, w_2 is the weight matrix between hidden and output layers and b_2 is the bias connected to output layer.

The last stage of construction the RBF neural network is the validation process. The proposed RBF structure is tested with different input signals other than data used in the training process. The purpose of this stage is to evaluate the accuracy of network to respond in different signals conditions.

III. SIMULATION RESULTS AND DISCUSSION

Following Indonesian National holidays during a year, there are 13 official holidays in Makassar city which their names are shown Table II. The data characteristics are identified with random changes annually and the pattern is different between one holiday and the others. It means that the electricity demand is possibly reduced in the following years by comparing the previous years. For example, the peak load in 2006 is lower the peak load in 2005 during New Year holiday, as this trend is similar in 2009 and 2010 compared to the previous year’s peak load. The pattern of peak load also occurs in other holiday. If the peak load reduced in the current year, it is possibly increased in the next year. Nevertheless, the rate growth is never more than 25%.

TABLE II: PEAK LOAD DURING HOLIDAY FROM 2005 TO 2011

Year / Holidays	H1 (MW)	H2 (MW)	H3 (MW)	H4 (MW)	H5 (MW)	H6 (MW)	H7 (MW)	H8 (MW)	H9 (MW)	H10 (MW)	H11 (MW)	H12 (MW)	H13 (MW)
2005	352.51	325.99	333.88	335.33	328.03	338.25	340.39	369.30	326.87	330.64	300.55	324.23	325.40
2006	303.28	340.84	345.37	358.40	345.50	336.49	387.79	327.44	339.41	349.43	342.51	355.86	382.10
2007	335.52	344.60	352.97	398.87	357.34	365.28	349.42	358.89	361.24	363.05	313.32	349.00	349.06
2008	326.05	362.34	374.62	367.32	356.23	334.40	351.08	391.57	376.91	360.56	382.18	368.94	430.64
2009	390.77	420.78	388.15	388.39	408.82	416.53	411.60	410.32	406.67	400.90	368.71	417.55	388.14
2010	390.29	416.82	435.20	423.05	435.51	434.66	407.90	443.22	419.19	416.92	443.66	454.05	460.96
2011	440.38	464.09	435.77	436.67	477.19	463.38	467.37	456.02	477.39	452.90	369.11	418.62	414.83

TABLE III: FORECASTED PEAK LOAD DURING HOLIDAYS IN THE YEAR OF 2012

Holiday	Name of Holiday	Actual power (MW)	Forecasted power (MW)	MAPE (%)
H1	New year	581.24	580	0.0164
H2	Chinese new year	509.27	510	0.0110
H3	Birthday of the prophet Muhammad SAW	508.03	505	0.0462
H4	Silent day	536.71	535	0.0246
H5	Good Friday	522.81	520	0.0416
H6	Birthday of Buddha	518.90	515	0.0583
H7	Ascension	517.71	520	0.0339
H8	Isra Miraj of the prophet Muhammad SAW	529.99	525	0.0731
H9	Independence day	534.33	530	0.0628
H10	Islamic Idul Fitri	555.14	550	0.0719
H11	Islamic Idul Adha	541.42	540	0.0202
H12	Islamic new year	549.54	545	0.0641
H13	Christmas	580.04	575	0.0674

The average demand growth during holiday from 2005 to 2011 is about 7%. Several factors influence to the pattern of peak load during holiday in Makassar city, for instance the mobility of people leaving the city to the hometown, the temporary close of some business area and government office and people are leaving home for recreational activities. Due to the unpredictable random peak load pattern, the conventional method owned by the utility is not giving satisfaction to predict how much power should be available to the forthcoming holiday. For this reason, the diversity method based intelligent techniques by means the artificial neural network must be proposed and tested for this short term load forecasting cases.

The performance index for RBF neural network method is introduced to measure the accuracy between the forecasted and actual values. In this study, the mean absolute percentage error (MAPE) as in (3) is used. The smallest MAPE indicates the highest accuracy performance. The main reason of using absolute error to the measure the performance index is the data characteristic is discontinuity between one holiday and other holidays. It means no correlation between the peak loads; nevertheless our proposed prediction method is still able to perform accurately.

$$\text{MAPE} = \frac{\sum_N \left|\frac{P_a - P_e}{P_a}\right|}{N} x 100\% \quad (3)$$

where P_a is the actual power, P_e is the forecasted power and N is the number of data evaluation.

TABLE IV: FORECASTED PEAK LOAD DURING HOLIDAYS IN THE YEAR OF 2013

Holiday	Name of Holiday	Actual power (MW)	Forecasted power (MW)	MAPE (%)
H1	New year	576.70	575	0.0227
H2	Chinese new year	556.73	552	0.0659
H3	Birthday of the prophet Muhammad SAW	549.11	550	0.0124
H4	Silent day	551.37	555	0.0503
H5	Good Friday	559.91	565	0.0693
H6	Birthday of Buddha	546.73	545	0.0244
H7	Ascension	560.06	555	0.0701
H8	Isra Miraj of the prophet Muhammad SAW	560.06	565	0.0673
H9	Independence day	572.52	570	0.0340
H10	Islamic Idul Fitri	545.06	540	0.0721
H11	Islamic Idul Adha	559.01	564	0.0681
H12	Islamic new year	592.95	590	0.0385
H13	Christmas	576.41	575	0.0189

To validate the performance of RBF neural network for short-term load forecasting, the historical data of daily peak load during holidays in Makassar city, Indonesia for 7 years measurement between year 2005 and 2011 is used. Then, the study is more specifically focused on the peak load data of 4 days of previous selected holiday (H-1,…,H-4) to predict the peak load of the next selected holiday (H*). Two scenarios are set for the verification process. The first scenario is to forecast the peak load holidays in the year of 2012 using the historical data in the year of 2008-2011. Then, the second scenario is to forecast the peak load holidays in the year 2013 using the historical data in the year of 2009-2012. These forecasting results are shown in Table III and IV, consecutively.

The actual data in 2012 and 2013 as the comparison parameter is obtained from the data base of utility calculated using conventional least square polynomial approximation method. However, the local utility does not have the actual peak load data for public holidays especially for H9 to H13 in 2012 and the lack of actual peak load information for all public holidays in 2013. Therefore, they may attempt to approach the unavailability forecasted data information by using simple conventional prediction method by means the least square polynomial approximation method. The main problem of this conventional method is the sort of data must be complete during certain period of years. Meanwhile, our proposed method is only using some partial information of the previous peak load in the previous four consecutive years.

TABLE V: SUMMARY RESULTS OF PERFORMANCE INDEX

Performance index (MAPE)	RBF	
	2012	2013
Minimum (%)	0.0110	0.0124
Maximum (%)	0.0731	0.0721
Average (%)	0.0455	0.0472

The accuracy of the proposed method for short term load forecasting task is explained as follows. The estimation results by means the performance index in Table V show that the peak load forecasting using RBF method yields low error (min: 0.011, max: 0.07, average: 0.05) for load estimation in 2012. They have similar trend in terms of high accuracy for the case in 2013. The results indicate that RBF neural network method offers simple structure and algorithm with high accuracy estimation. This method is very useful for the operator to set different scenarios because the forecasting method is only depending on the training process with very simple adjustment to reach the best structure.

IV. CONCLUSION

Diversification and integrating methods for the short term load forecasting have been concerned to find the robust solution. It is due to the nature characteristic of the load which are unique non-linear, probabilistic and uncertainty. For this reason, the paper has discussed the implementation of RBF neural network method for the load forecasting during public holidays in Makassar City of Indonesia. Despite the weather and environmental conditions are considered as the most influential factors for the customers' behavior, they are not significantly affecting the short period load forecasting. In this work, only the peak load during the holiday and four days before holiday are taken into account without the necessity to assess the external factors that may change the load characteristics.

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