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The Comparision of Mid Term Load Forecasting between Multi-Regional and Whole Country Area Using Artificial Neural Network

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Abstract-[1] **Load forecasting is very important for operation of electricity companies such as for operation, unit commitment, and planning. This research presents a comparison of mid term load forecasting between multi-regional area model (6 neural network models of north, north-east, centre, east, south-east, south-west areas in Thailand) with the factors based on regional area and the whole country area with the factors based on whole country area. The data information composes of the peak load, energy consumption, humidity, rainfall, wind speed, consumer price index, and industrial index recorded from year 1997 to 2007 which are given from many resources in the country. This study shows the results in energy consumption demand forecasting and peak load demand forecasting, case study in Electricity Generating Authority of Thailand (EGAT). Artificial Neural network(ANN) is used with have feed forward back propagation algorithm and LM algorithm.. The experimental results show that the multi-regional area forecasting model can reduce the error and improve the forecast accuracy effectively more than that of the whole country area forecasting model in mid term load forecast.**

Index Terms- **Peak load; Energy consumption; Neural network; Forecasting; Multi regional; Whole country.**

I. INTRODUCTION

The electricity is the necessity in daily life and it is one of the main driving factors for country economic. In order to provide sufficient electricity and make the economic grown continuously, the load forecasting is required for the related electricity produrcers. Since the construction of a power plant must take 5-15 years for planning, designing, environmental admitting to constructing step and there are few electric networks of Thailand and neighbour countries, the mid term load forecasting (MTLF) and the long term load forecasting (LTFL) are very important for building up the energy stability in Thailand. Load forecasting can be classified into 4 differential types : Very short term load forecasting having period time in a minute; it is important for real time operation, Short term load forecasting having period time in a minute to three months; it is important for unit commitment and operation, Mid term load forecasting having period time in three months to three years; it is important for fuel reserve planning or unit commitment and Finally, Long term load forecasting having period time in three years to fifteen year; it is important for generation or power plant planning in the future.

In 1987, [1] described about short-term load forecasting survey and comparing load forecasting in short-term , mid-term and long-term. In this paper, each research article has used differential techniques for determining the accurate output value. In [2-8], neural network for short-term load forecasting are used based on historical load and temperature input data. Moreover, some paper use additional input data from day types, humidity, wind speeds and seasons. This method is performed in compared with conventional method. Training network is achieved by supervise learning and back propagation algorithm. Another technique for short-term load forecasting is using fuzzy logic and neural network [9]. In 2004, [10] proposed a short term load forecasting using autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) method based on non-linear load. It is concluded that using both methods can help each other in short-term load forecasting of the system. In 2007, [11] proposed a novel method approach to load forecasting using regressive model and artificial neural network (ANN model) with the case study carried out for Turkey. In this research, two methods are separately performed and compared. It shows that both methods give high accuracy results.. In [12-14], combination of artificial neural network (ANN), Genetic algorithm and Fuzzy logic (Fs) method are proposed for adjusting short-term load forecasting of electric system. Genetic algorithm is used for selecting better rules and back propagation algorithm is also for this network. The papers show that they give more accuracy results and faster processing than another forecasting methods. In 2005, [15] proposed short-term load forecasting for holiday by using fuzzy linear regression method. The proposed algorithm shows good accuracy and the average maximum percentage error of 3.57 % in the load forecasting of the holidays.

There are many algorithm above for load forecasting in statistical methodology like time series, exponential smoothing, autoregressive integrated moving average (Box-jenkins) and there are many algorithm for load forecasting in computation intelligence like fuzzy logic, neural network, genetic, and chaos [1-16].

This paper proposed the comparison between multi regional area of the country forecasting and whole of the country area forecasting with have new factors such as consumer price index, industrial index, and another factors

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like temperature, humidity, rainfall, wind speed for energy consumption load forecasting and peak load forecasting of the country [16].

This paper is organized as following, section II describes about the peak load and energy consumption demand and the forecasting. Artificial Neural Network and data information is presented in section III. In section IV Experimental Results are illustrated. Finally, the conclusions are drawn in section V.

II. Peak Load/Energy Consumption Demand And Forecasting

The mid-term peak load demand as a function of time has complex nonlinear behaviors. It depends on a number of complex factors such as seasonal weather, and national economic growth [9].

A. *Peak load demand*

Monthly maximum demand or peak load demand (Unit in MW) data is form Electricity Generating Authority of Thailand (EGAT) recorded in 1997 to 2007. The correlation between peak load demand and time series established in Fig.1.

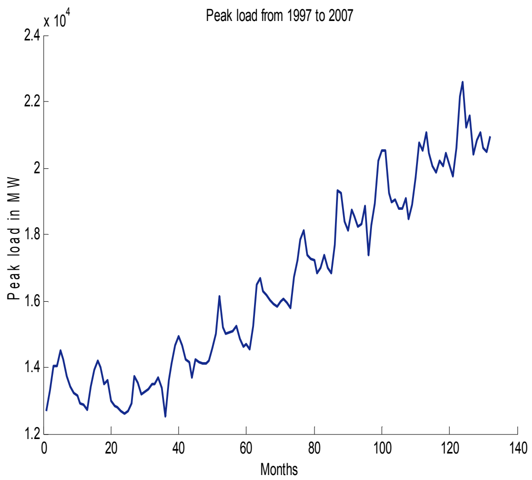


Fig. 1 Monthly peak load of Thailand (MW) recorded from January 1997 to December 2007

B. *Energy Consumption Demand*

Monthly energy consumption demand (Unit in GWh) data is form Electricity Generating Authority of Thailand (EGAT) recorded in 1997 to 2007. Fig.2 shows the correlation between energy consumption demand and time series.

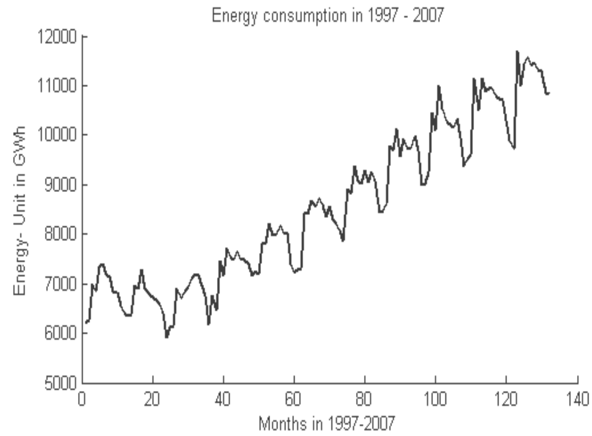


Fig. 2 Monthly Energy consumption of Thailand (GWh) recorded from January 1997 to December 2007

Both peak load demand and energy consumption demand, are consider in the period from 1997 to 2007. They are established as the parameters in this forecasting model.

C. *Samples of the factors correlation*

The samples of the factors correlation show in Table I

TABLE I: the samples of the factors correlation using SPSS program.

	Peak	MaxT	MinT	MeT	Rn	Hd	Ws	CPI	IDI
Peak	1	.128	.074	.106	.007	-.002	.083	.917	.960
MaxT	.128	1	.233	.715	-.200	-.401	.193	-.077	-.056
MinT	.074	.233	1	.776	.790	.704	.204	.013	-.060
MeT	.106	.715	.776	1	.355	.186	.239	-.066	-.097
Rn	.007	-.200	.790	.355	1	.933	.055	.083	-.014
Hd	-.002	-.401	.704	.186	.933	1	-.108	.113	.008
Ws	.083	.193	.204	.239	.055	-.108	1	-.043	.036
CPI	.917	-.077	.013	-.066	.083	.113	-.043	1	.930
IDI	.960	-.056	-.060	-.097	-.014	.008	.036	.930	1

Notations

Peak is Peak load demand
MaxT is maximum temperature
MinT is minimum temperature
MeT is mean temperature
Rn is rainfall or rainy
Hd is Humidity
Ws is wind speed
CPI is consumer price index
IDI is industrial index

In Table I, we can be see that the high correlated values with peak load demand are industrial index which is 96%

and the consumer price index which is 91.7%. Other correlated values can be seen in this table.

III. Artificial Neural Network (ANN) And Data Information

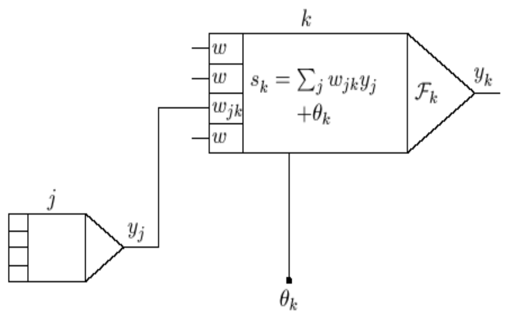
A. *Artificial Neural Network (ANN)*

A framework for distributed representation

An Artificial Network consists of a pool of simple processing units which communicates by sending signals to each other over a large number of weighted connections. A set of major aspects of a parallel distributed model can be distinguished [17]:

1) a set of processing units ('neurons,' 'cells');
2) a state of activation y_k for every unit, which equivalent to the output of the unit;
3) a connections between the unit. Generally each connection is defined by a weight w_{jk} which determines the effect which the signal of unit j has on unit k;
4) a propagation rule, which determines the effective input s_k of a unit from its external inputs;
5) an activation function F_k, which determines the new level of activation based on the effective input $s_k(t)$ and the current activation $y_k(t)$;
6) an external input (bias, offset) θ_k for each unit;
7) a method for information gathering (the learning rule);
8) an environment within which the system must operate, providing, providing input signal and-if necessary-error signals.

Fig.3 illustrates these basics,



- Fig.3 The basic components of an artificial neural network. The propagation rule used here is the 'standard' weighted summation [17]

Processing units

Each unit performs a relatively simple job: receive input from neighbours or external sources and use this to compute an output signal which is propagated to other units. Apart from this processing, a second task is the adjustment of the weights. The system is inherently parallel in the sense that many units can carry out their computations at the same time.

Within neural system it is useful to distinguish three types: *input* units (indicated by an index i) which receive data from outside the neural network, *output* units (indicated by an index o) which send data out of the neural network, and *hidden* units (indicated by an index h) whose input and output signals remain within the neural network.

Connections between units

In most cased, we assume that each unit provides an additive contribution to the input of the unit with which it is connected. The total input to unit k is simply the weighted sum of the separate outputs from each of the connected units plus a *bias* or *offset* term θ_k:

$$s_k(t) = \sum_j w_{jk}(t) y_j(t) + \theta_k(t) \tag{1}$$

The contribution for positive w_{ik} is considered as an *excitation* and for *negative* as *inhibition*. In some cases more complex rules for combining inputs are used, in which a distinction is made between excitatory and inhibitory inputs. We call units with a propagation rule (1) *sigma units*.

Activation and output rules

We also need a rule which gives the effect of the total input on the activation of the unit. We need a function F_k which take the total input $s_k(t)$ and the current activation $y_k(t)$ and produces a new value of the activation of the unit k:

$$y_k(t+1) = F_k(y_k(t), s_k(t)) \tag{2}$$

Often, the activation function is a non-decreasing function of the total input of the unit:

$$y_k(t+1) = F_k(s_k(t)) = F_k\left(\sum_j w_{jk}(t) y_j(t) + \theta_k(t)\right) \tag{3}$$

Paradigms of learning

We can categorise the learning situations in two distinct sorts. These are :

Supervised learning or Associative learning in which the network is trained by providing it with input and matching output patterns. These input-output pairs can be provided by an external teacher, or by the system which contains the network(self-supervised).

9) Unsupervised learning or Self-organisation in which an (output) unit is trained to respond to clusters of pattern within the input. In this paradigm the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather the system must develop its own representation of the input stimuli.

B. *Accuracy of Forecasted (AoF)*

In order to evaluate forecasting accuracy of the whole procedure, the following indices have been calculated (4-5) :

- Mean Square Error (MSE) for each month of forecasting :

$$MSE = \sum_{i=1}^{M} \frac{(Actual_i - Forecasted_i)^2}{M} \tag{4}$$

Where $Actual_i$ is the real value of the monthly parameters (Peak load or Energy demand) in the i^{th} year, and $Forecasted_i$ is the forecasted value in the same year, M is month.

- Mean Absolute Percentage Error (MAPE) give by :

$$MAPE = \frac{1}{M} \sum_{i=1}^{M} \frac{|Actual_i - Forecasted_i|}{Actual_i} \times 100 \tag{5}$$

Where $Actual_i$ is the real value of monthly parameter(Peak load or Energy demand) at the i-th year, $Forecasted_i$ is the forecasted value in the same year, M is month.

C. *Data Information*

This paper proposed the historical information or data for mid term load forecasting as following [16]:

Monthly Peak load demand (MW) and energy consumption demand (GWh) are supported Electricity Generating Authority of Thailand(EGAT) and Information from Ministry of Energy Thailand. Humidity (H), Rainfall (R), Wind Speed (W) are given from Meteorology Department of Thailand (TMD). Current Price Index (CPI) is informed by Ministry of Commerce Thailand. Industrial Index (IDI) including the forecasted values are given from Ministry of Industry Thailand. All data information are recorded from year 1997 to 2007.

IV. Experiments And Results

A. *Experiments*

The whole area of The country model

The whole area of country model has many feature inputs such as average temperature, humidity, rainfall, wind speed, consumer price index, and industrial index of Thailand. It can be seen in Fig. 4. The data can divided into two sets for forecasting. The forecasted value can found by equation 6:

$$y_k(t+1)=F_k(S_k(t))=F_k\left\{\sum_j w_{jk}(t)y_j(t)+\theta_k(t)\right\}_{country} \tag{6}$$

Training set : January 1, 1997 to December 31, 2006.
Testing set : January 1, 2007 to December 31, 2007.

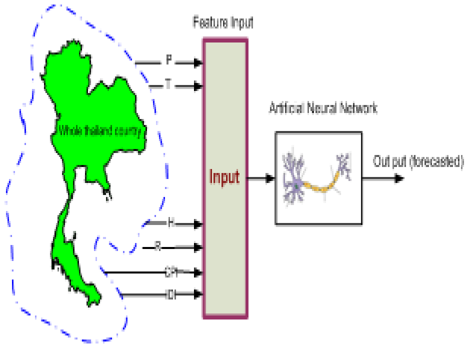
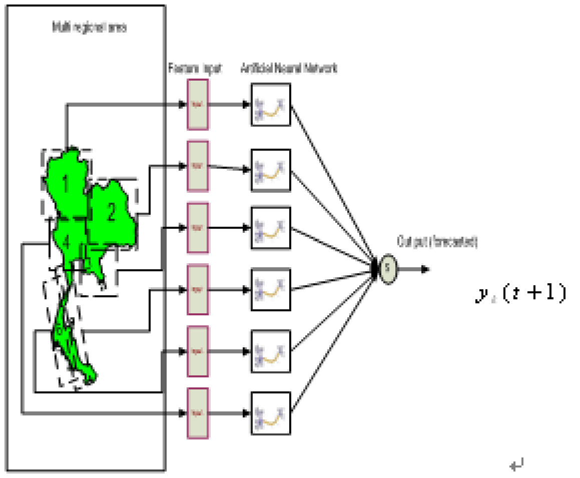


Fig.4 Whole area of the country model

The multi- regional area of the country

The multi-regional area of the country model separates the feature inputs into 6 regional areas based on the regional areas in Thailand as shown in Fig.5. The data can be divided into two sets for forecasting. The forecasted value can found by equation 7:

Training set : January 1, 1997 to December 31, 2006.
Testing set : January 1, 2007 to December 31, 2007.



Note: 1-North, 2-North east, 3-East, 4-Centre, 5-South east, 6-South west.

Fig.5 Multi regional area of the country model

$$y_k(t+1)=\frac{\sum_1^N F_k(S_k(t))}{N_{regional-area}}=\frac{1}{N}\left\{\begin{array}{l}F_k\left\{\sum_j w_{jk}(t)y_j(t)+\theta_k(t)\right\}_{north}+\ldots\\ +F_k\left\{\sum_j w_{jk}(t)y_j(t)+\theta_k(t)\right\}_{south-west}\end{array}\right\} \tag{7}$$

Where dash lines are north-east, centre, east, and south-east regional areas, N is number of regional area.

B. *The Results*

The forecasted values, actual values, and mean absolute percentage errors of the monthly energy consumption and monthly peak load demand by using multi-regional area forecasting model and the whole country forecasting model are shown in Table II and III , respectively.

TABLE II: MONTHLY ENERGY CONSUMPTION MAPE

	Artificial Neural Network (ANN)				
	Multi regional		Whole country		EGAT
Month	Forecated	Pe	Forecated	Pe	Actual(GWh)
January	9798.81	1.06	9082.49	8.30	9904.58
February	9723.40	0.10	9076.23	6.75	9733.23
March	11035.36	5.54	12676.39	-	
				8.50	11683.31
April	10939.00	0.54	10614.46	3.50	10999.45
May	11259.60	1.57	11617.19	-	
				1.55	11439.88
June	11218.89	3.02	11098.28	4.25	11590.90
July	11439.49	-	11104.42	2.55	
		0.39			11395.00
August	11347.32	1.09	11593.13	-	
				1.05	11472.67
September	11373.72	-	11268.68	0.50	
		0.42			11325.31
October	11134.63	1.40	11580.80	-	
				2.55	11292.84
November	10950.84	-	11764.05	-	
		0.99		8.50	10842.45
December	10689.55	1.13	10790.89	2.00	10812.52
MAPE		1.45		4.75	

Note that. EGAT is Electricity Generating Authority of Thailand
PE is Percentage error

TABLE III: MONTHLY PEAK LOAD DEMAND MAPE

	Artificial Neural Network (ANN)		
	Multi regional	Whole country	EGAT

Month	Forecasted	PE	Forecasted	PE	Actual(MW)
January	19701.10	0.27	19276.69	2.42	19755
February	20428.33	0.79	20650.32	-0.27	20593
March	20318.77	8.31	20820.85	6.04	22161
April	21090.54	6.62	21915.14	2.97	22586
May	21299.43	0.02	20066.93	5.49	21234
June	21023.47	2.46	21024.51	2.46	21555
July	20314.68	0.40	21024.51	-3.08	20396
August	20641.05	1.01	20085.89	3.67	20853
September	20277.56	3.72	19397.16	7.90	21063
October	20529.11	0.31	19494.21	5.34	20594
November	20136.23	1.69	20585.05	-0.49	20483
December	20082.77	4.17	20385.84	2.72	20957
MAPE		2.48		4.75	

Note that. EGAT is Electricity Generating Authority of Thailand
PE is Percentage error

The above results show that the forecasting by using multi-regional area model can reduce error and give higher accuracy than that of the whole area model. It is because the factor inputs in regional area are close to the actual factors in that area such as the temperature in the northern area in November-January are much different from the temperature in south-east area. Table II and III shows the monthly results in both forecasting methods. The multi-regional area model can reduce the error of monthly energy consumption in January, February, March, April, June, July, September, October, November and December. Moreover, it can reduce the error of monthly peak load demand in January, May, July, August, September and October.

V. Conclusion

This paper presents the comparison of the mid term load forecasting using Artificial Neural Network with feed forward back propagation algorithm by using multi-regional area model and the whole country model. Case study is in Thailand Country; the Electricity Generating Authority of Thailand (EGAT). This forecasted values are useful for unit commitment, operation, and fuel reserve planning in the power system. The feature inputs used in this paper are peak load, energy consumption, humidity, rainfall, wind speed, consumer price index, and industrial index. The experimental results show that multi-regional area model can reduce error in each month and give more accuracy than that of the whole of the country model.

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