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A Computing Model of Artificial Intelligent Approaches to Mid-term Load Forecasting : a state-of-the-art- survey for the researcher

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***Abstract*—This article presents the review of the computing models applied for solving problems of mid-term load forecasting. The load forecasting results can be used in electricity generation such as energy reservation and maintenance scheduling. Principle, strategy and results of short term, midterm, and long term load forecasting using statistic methods and artificial intelligence technology (AI) are summaried, Which, comparison between each method and the articles have difference feature input and strategy. The last, will get the idea or literature review conclusion to solve the problem of mid term load forecasting (MTLF).**

***Index Terms*-Artificial Intelligent, Mid-term load, Forecasting, state-of-the-arts**.

I. Introduction

The electricity is the necessity in the 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 producers. Since, the construction of a power plant must take 5-10 years from planning, designing, environmental admitting to constructing step and there are few electric networks of Thailand and neighbor countries, the midterm load forecasting (MTLF) and the long term load forecasting (LTFL) are very important for building up the energy stability in Thailand [1,2].

Electricity load forecasting is not only significant for investment planning of three electricity authorities (Electricity Generating Authority of Thailand (EGAT), Metropolitan Electricity (MEA), and the Provincial Electricity Authority (PEA)) but also it is useful for estimating the financial statement of three electricity institutes. Figure1 shows the peak load profiles of the MEA and PEA classified by types of electricity consumers. The accuracy forecasted values make the proper investment for three electricity authorities. If the forecasted values are too high, the exceeding investment is obtained and it will push this expenses to consumers. However, if the forecasted values are too low, the inadequate investment is occurred and it will cause electricity deficiency in the country.

The forecasted electricity demands are defined as two values: the peak value (Maximum load demand) and energy [1]value (Electric energy demand).

The peak value is used in planning for new electricity plants while the energy value is used in planning for fuel providing. In the past, each electricity authority used the different methods to find these values.

Forecasting of the energy value

- The MEA and PEA uses the econometric model with Error Correction Model of Engle-Granger method or the econometric method with auto-Regressive Distributed Lag (ARDL) for monthly forecasting. The forecasting variables effected to electric load demands are electricity bill rate, GDP and temperature. Since, there are no monthly GDP data, they used the money quantity that circulate in people hand and the deposit reserve call of people in bank system instead adding with the specific losses in the distribution systems. The loss values in the distribution systems of the MEA and PEA are respectively 3.64% and 5.20% of the electricity demand taking from EGAT.
- Direct customers of EGAT use the direct inquires method from electricity consumers.
- The EGAT uses combining energy values from the MEA, the PEA and direct customers adding with the loss values in the generation system and transmission system to be the energy value of the system. The specific loss is about 5.10 % of energy value of the system.

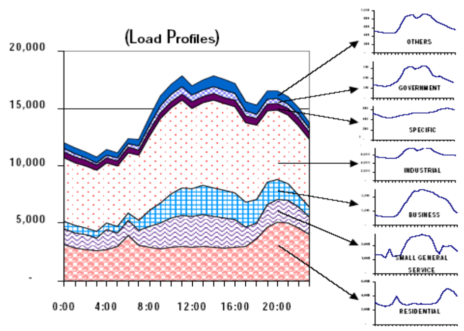

Figure.1: The use of Load Profile to find peak values of the MEA and the PEA[2].

Forecasting of the peak value

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- The MEA and PEA use the character of load profile of each customer to calculate energy value and adjust this value to be equal to the forecasted energy value of each type of customers. The over all peak value can be obtained by adding every load profiles of all customers as illustrated in Figure1.

- The direct customers of the EGAT use the principle of load profile by adjusting the load profile of each customer to be equal to the forecasted value and adding all load profiles to get the over all peak value.

- The EGAT adds all the load profile from The MEA and PEA as well as the direct customers to find the peak value. At the same time, this method can determine the peak value of the MEA, PEA and the direct customers in the same system (Coincident Peak) [2].

Beside the mentioned methods, the expert systems [3,4,5,6,7] such as the artificial intelligent (AI) are frequently used for the system that required training and making decision based on the massive data. In the past, many artificial intelligence (AI) and Expert system (Es) methods such as artificial neural network (ANN), Fuzzy logic (Fs) and Genetic algorithm (GA) are proposed for the electricity load forecasting in short-term, mid-term and even long-term forecasting.

This paper presents a survey for a state of the art of load forecasting methods including input classifications, algorithm approaches and output determinations. The reviewed papers are covered in short-term, mid-term and long-term load forecasting. However, in last few sections, there will be emphasized on mid-term load forecasting. Load forecasting classification and paper reviewed are presented in section II. In section III, the mid-term load forecasting concepts are explained in details. The experimental and results analysis are described in section IV. Finally, the conclusion with some comparison are in section V.

II. Load Forecasting Classification And Paper Reviewed

Load forecasting results have been used for operation planning of electric system as well as maintenance and fuel reserved planning [8].

The load forecasting can be classified into 3 different types according to the forecast period.

1. Short-term load forecasting,
2. Mid-term load forecasting,
3. Long-term load forecasting

In each load forecasting, period of time, forecasted values and aims of forecasting are noticeably different and they are comparably described in Table 1.

TABLE I. Types of load forecasting [8]

Forecast problem	Short term	Medium term	Long term
Time horizon	1/4–24 h	1 day–few weeks	Few months–year
Forecasted value	Load curves	Load curves	Energy required
Accuracy	Exact load curves	Error ≪ Capacity	Exact energy
Time step	1/4–1 h	1 h	1 h
Operation	Economic dispatch	Unit commitment	Reserve planning
Planning	Unit commitment	Reserve planning	Capacity expansion

Because of the difference of time period, forecasted values and aims of each load forecasting type, researchers in the past proposed many different algorithms and methods in order to obtain the precise load forecasting values. Next, relative papers and research topics of each load forecasting type are briefly concluded.

In 1987, [9] 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 [10-16], 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 [17]. This paper presents that the neuro-fuzzy method that gives more accuracy results compared to one of the neural network method. In [18-19], types of input data using in fuzzy logic and neural network algorithms are historical load and weather. The case study is Electric company in China (Hang zhou Electric Power Company) In this paper, the principle of fuzzy rough sets is used to help neural network in forecasting. In [20], fuzzy logic with back propagation algorithm (BP) is used for short-term load forecasting in the uncertainty of the data input case. In this paper, the network composes of 51 inputs and 24 outputs and it is simulated by MATLAB . [21] presents short-term load forecasting by combining neural network and genetic algorithm with the case study in Taiwan while [22] presents the implementation of genetic algorithm method for fastening computation and increasing forecasting accuracy. The time period of this load forecast value is in 24 hours. In year 2001, [23] presents load forecasting model using the principle of wavelet decompositions to bring to more accuracy in electric load forecasting. In year 2006, [24] presents short-term load forecasting using fuzzy logic algorithm and input data of time and temperature. The input variable ‘time’ has been divided into eight triangular membership functions. The membership functions are Mid Night, Dawn, Morning, Fore Noon, After Noon, Evening, Dusk and Night. Another input variable ‘temperature’ has been divided into four triangle membership functions. They are Below Normal, Normal, Above Normal and High. The ‘forecasted load’ as output has been divided into eight triangular membership functions. They are Very Low, Low, Sub Normal, Moderate Normal, Normal, Above Normal, High and Very High. The case studies have been carried out for the Neyveli Thermal Power Station Unit-II (NTPS-II) in India. In 2004, [25] proposes 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, [26] proposes 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 [27-29], combination of artificial neural network (ANN), Genetic algorithm and Fuzzy logic (Fs) method are propsed 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 other forecasting methods. In 2005, [30] proposes 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. [31], in 2006, proposes a novel hybrid load forecasting algorithm, which combines the fuzzy linear regression method and the general exponential smoothing method with the analysis of temperature sensitivities. [32], in 2006, proposes the development of load forecasting which combines the fuzzy logic, neural network and chaos and another algorithm as shown in Figure 2. The proposed algorithm shows good accuracy or better than conventional method. [33] proposes an approach based on combined regression method and fuzzy inference system that developed for load forecasting. In addition, the fuzzy inference system makes a load correction inference from historical information and past forecast load errors from a multi linear regression model to infer a forecast load error. The effectiveness of the proposed approach to the short term load forecasting problem is demonstrated by practical data from the Taiwan Power Company. Paper [34] presents the development of a neuro-expert system for medium term load forecasting, back propagation algorithm is slightly modified and is used to train the artificial neural network. The proposed algorithm is tested on the practical 66/11 kV primary distribution system of Mysore, Karnataka State, South India.

TABLE II. SUMMARY OF SHORT TERM LOAD FORECASTING CLASSIFIED BY ALGORITHM.

Reference	Algorithm
[10],[11],[12],[13],[14],[15],[16],[23],[60]	Artificial Neural Network
[17],[18],[19],[20]	Artificial Neural Network + Fuzzy logic
[21],[22]	Artificial Neural Network + Genetic
[24]	Fuzzy logic
[25],[59]	ARIMA+ Artificial Neural Network
[26]	Regression+ Artificial Neural Network
[27],[28],[29]	ANN + GAs + Fuzzy
[30],[33]	Fuzzy logic +Regression
[31],[32]	Hybrid
[55]	Support Vector Machine (SVM)

**ARIMA = Autoregressive Integrated Moving Average [25]*

TABLE III. SHORT TERM LOAD FORECASTING CLASSIFIED BY TYPE OF INPUT.

Reference	Input
[10],[11],[13],[17],[18],[19], [20],[23],[24],[25]	Historical load Temperature
[16]	Humidity
	Rainfall
[12],[14],[15],[27],[28],[29],[30],	Wind speed
[31]	Season
	Weekday-mon-friday
	Weekend- sat-sunday
	Special day

Form Table 2 ,it can see that the methods of load forecasting are mainly classified by algorithms. However, preceding article interests do not absolutely give the importance with algorithms. yet, they will also study in different kinds of the input variables in short term load forecasting such as temperature and load in the past etc. Other input variables of short term load forecasting are summarized in Table 3.

The pre-processing methods are used in some articles for selecting inputs before forecasting process. Many and different input data are chosen or grouped before the forecasting [17], [55], [42] The preprocessing methods are summarized in Table 4.

The previous summaries are the guidelines for midterm load forecasting that will be described in Section III.

TABLE IV. SHORT TERM LOAD FORECASTING CLASSIFIED BY INPUT SELECTION METHODS

Reference	Pre-processing
[17],[55]	Self-Organizing map
[13]	Graphical modeling for selection input variable
[57]	Input dimension reduction
[42]	Fuzzy clustering

III. THE MID-TERM LOAD FORECASTING CONCEPTS

The articles of mid term load forecasting are summarized into 3 classification topics .

A. Data Inputs

1) I nput classification

Historical load inputs and meteorological data such as monthly maximum temperature, minimum temperature are used in [35-37] and [39, 40]. Economic variables are also included in [38]. The historical load data are collected from Electricity Generating Authority of Thailand (EGAT). Temperature data are provided from Meteorological Department and economic data are presented by the government of Thailand.

2) Input improvement

Articles [13, 17, and 42] proposed the input improvement or input selection for preprocessing of load forecasting. Many researchers used grouping data technique for decreasing complication of data and calculation time of the network. The preprocessing methods are for example Self-Organizing Map and Data mining.

B. Artificial Intelligence technology methods and other method for load forecasting

1) Expert systems (Es)

Article [34], proposes neuro-expert for electric mid term load forecasting. The principle of Heuristic Rules is used for sorting out complex data can decreased the time and memory in training network.. Back propagation algorithm neural network is used for forecasting.

2) Artificial Neural Network (ANN)

[34-38] used Artificial Neural Network (ANN) approach to forecast electrical demand load, by using the data supporting from the government. The forecasting can be performed the results in yearly (to 15 years), weekly (to 3 years) and hourly (to 24 hours). ,Many groups of researchers used this forecasting approach for electricity mid term load forecasting. Also this method can be used for electricity peak load forecasting of distribution system [37]. By using the relationship of learning data in the past, present and the future of temperature, the network can forecast a daily peak load, total load of day and electricity monthly load consumption. However, in [38], historical load, economic and population variables are added for demand load forecasting by using neural network, time lagged feed forward network (TLFN).

3) Fuzzy logic (Fs)

In [42], principle of fuzzy logic is integrated with another method, The fuzzy logic method is used to manage the data-tolerance. In several articles used it for separating the input data [42]. Some articles use it in repeating process of forecasting in order to get the best answer. [17-19],[28-29].

4) Genetic algorithms

In [48-49], genetic algorithms are used for electric load demand forecasting. In [48], it is used together with neural network for load forecasting. This article is hourly load forecasting,. It is used as a base for monthly load forecasting, which duration time is 45 day and 49 day ahead by using historical data in 2005. In this method genetic algorithm is used to seek the initial weight of the neural network without random initial weight. It will give the network getting the results faster.

5) Support Vector Machine (SVM)

Support vector machine (SVM) is presented in [50] for electric load forecasting. This method used historical data in the past , present and the future in the weather and load, in 2001 to forecast load in 31 days ahead. This method is similar to neural network unless the support vector machine (SVM) can be used to separate input data before going to forecasting process.

6) Statistics

[51-53] proposes the methods of load forecasting by using the principle of mathematic or statistic such as Physical series algorithm [52] Autoregressive [51] and Non-linear regression [53]. Statistics method is suitable for linear type of data. for example humidity, heat or temperature or meteorological parameter and historical monthly load [51].

C. The adaptation of output forecasting

In 1995, L.D.Voss, M.M.A.Salama, and J.Reeva [56] developed the forecasting technique to load forecasting by using neural network and output filter correction as shown in Figure 3 . In this article, MA Filtering is used to improve the output.

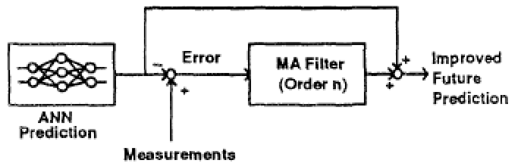

Figure.2: Load forecasting adaptation, MA Filtering [56]

IV. THE EXPERIMENTAL RESULTS AND ANALYSIS

The articles mentioned previously can be comparably summarized in different points of view based on MAPE in Table 5-8. However, the comparison can not tell that which one of the method gives the best accuracy or which one is the best method. It is because each research technique is performed in different objectives and using different data. The forecasting will focus on the output error that can be determined as

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{X_k^R - X_k^F}{X_k^R}\right|.100 \qquad (1)$$

Where

X_k^R is actual load of monthly load in k-th year

X_k^F is parameter of forecasted in same year

N is number of test set

TABLE V. ACCURACY FOR EACH TYPE OF INPUT

Reference	Type of input	Accuracy
[24]	Historical load , temperature	MAPE < 2%
[38]	Historical load, temperature, GDP, CPI, HIS, population	Can decrease error
[40]	Historical load , temperature, humidity, wind speed, Rainfall	MAPE < 2%

** GDP = Gross Domestic Product, CPI =Current Price Index, HIS = Housing*

TABLE VI. PRE-PROCESSING

Reference	Pre-processing	Algorithm	Accuracy
[41]	Knowledge based	ANN+ Knowledge base	MAPE 2.29 %
[48]	Fuzzy clustering	Fuzzy+ANN	MAPE 1.568 %
[55]	Self-Organizing map	SVM	MAPE (w) 1.65% (s) 2.42%

** SVM = Support Vector Machine*

TABLE VII. ALGORITHMS

Reference	Input	Algorithm	Accuracy
[24]	Historical load , temperature, day type	Hybrid	MAPE 1.60%
[37]	Historical load , temperature	ANN+hidden adj	2 hidden best results
[46]	Historical load , day type	Hybrid+GA	MAPE 2.80%

** GA= Genetic algorithm, adj = adjust, Hybrid = more than a algorithm*

TABLE VIII. FILTERING OUTPUT

Reference	Input	Algorithm	Output	Accuracy
[56]	Historical load Weather Economic Populatio n	ANN+MA Filtering	Peak Monthly Load	Avg. error decreased from 3.24% to 1.26% Peak error decreased from 9.55% to 4.81%

** MA = Moving Average*

Table 5-8 show accuracy for each type of input, pre-processing, algorithm, and filtering output. The next, presents the article preceding of the forecasting from international research.

V. CONCLUSION

Mid term load forecasting (MTLF) becomes an essential tool for today power systems, mainly in those countries whose power systems operate in a deregulated environment. This kind of load forecast is useful for many applications such as maintenance scheduling and development of cost efficient fuel purchasing strategies. In the past load forecasting are performed using the principle of artificial intelligence technology. Each method uses difference input and gives difference accuracy depending on the complexity of input.

The artificial intelligence technology is used as a decision part in mid term load forecasting. It has ability to work with non-linear data. Moreover, it can be effectively performed in complicate forecasting model for continuous data or signal. This technology will help the conventional method (statistical) in the complexity problems based on the value of the variable between the variable input and nonlinear correlation by training of data, learning process.

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