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Building electrical energy consumption forecasting analysis using conventional and artificial intelligence methods: A review

Mohammad Azhar Mat Daut[a,b], Mohammad Yusri Hassan[a,b,*], Hayati Abdullah[a,c], Hasimah Abdul Rahman[a,b], Md Pauzi Abdullah[a,b], Faridah Hussin[a,b]

[a] Centre of Electrical Energy Systems (CEES), Institute of Future Energy, Universiti Teknologi Malaysia (UTM), 81310 Johor Bahru, Johor, Malaysia
[b] Faculty of Electrical Engineering, Universiti Teknologi Malaysia (UTM), 81310 Johor Bahru, Johor, Malaysia
[c] Faculty of Mechanical Engineering, Universiti Teknologi Malaysia (UTM), 81310 Johor Bahru, Johor, Malaysia

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ABSTRACT

It is important for building owners and operators to manage the electrical energy consumption of their buildings. As electrical energy is the major form of energy consumed in a commercial building, the ability to forecast electrical energy consumption in a building will bring great benefits to the building owners and operators. This paper provides a review of the building electrical energy consumption forecasting methods which include the conventional and artificial intelligence (AI) methods. The significant goal of this study is to review, recognize, and analyse the performance of both methods for forecasting of electrical energy consumption. Compared to using a single method of forecasting, the hybrid of two forecasting methods can possibly be applied for more precise results. Regarding this potential, the swarm intelligence (SI) method has been reviewed to be hybridized with AI. Published literature presented in this paper shows that, the hybrid of SVM and SI methods has indeed presented superior performance for forecasting building electrical energy consumption.

1. Introduction

The pattern of population rate around the world is growing rapidly every year [1]. This rise also affects the electrical energy consumption for accommodation, country advancement and others. With regard to these advancements, adequate energy is needed to supply the worldwide energy demand, while ensuring the safety of Mother nature [2]. Therefore, the electrical energy consumption is necessary to be forecasting to achieve energy conservation and reduce negative impact on Mother Nature.

Research on electrical energy consumption forecasting has evolved into many methods that can be roughly categorized into artificial intelligence (AI) -based methods [3–5] and conventional methods [6,7]. Between these two methods, the AI methods are currently more popular than the conventional methods due to their ability to solve nonlinear problems. Generally, the time scale of this forecasting can be divided into three categories which are short-term load forecasting (STLF) (1 h up to 1 week), medium-term load forecasting (MTLF) (1 month up to 1 year) and long-term load forecasting (LTLF) (1 year and above) [8].

Even though the conventional method has not become a priority as AI method, this method is still applied in the forecasting analysis. This is important to achieve accurate result of forecasting. Previously, conventional methods such as stochastic time series and regression-based approach had been widely applied before the emergence of AI method. Basically, these conventional methods are capable of achieving satisfactory result when solving linear problems. The idea of stochastic time series is based on reliable forecasting that can be accomplished by extending the pattern of the time series in the future, while the regression-based approach is based on biological phenomena [9].

The artificial neural network (ANN) used to be popular in the last few decades. Essentially, this approach is inspired from the biological brain due to the power of brain that can adapt with the learning process. The ANN approach involves two phases which are the learning phase and the recalling phase. In the learning stage, the ANN is trained until it has learned the tasks. Usually at this learning stage, it will be done in an offline mode, while at the recalling stage, the ANN is used to solve the task. Thus, the learning process is divided into two types; supervised and unsupervised. The supervised learning is essentially based on the training pattern that was given to the method together with the teaching or targets [10,11]. The unsupervised learning involves learning without teaching or targets [12,13]. Although this

* Corresponding author at: Centre of Electrical Energy Systems (CEES), Institute of Future Energy, Universiti Teknologi Malaysia (UTM), 81310 Johor Bahru, Johor, Malaysia.
E-mail address: yusrihutm@gmail.com (M.Y. Hassan).

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method has been widely used by researchers in the field, there are some advantages and disadvantages that need to be acknowledged when this method is applied.

Recently, the support vector machine (SVM) has been very popular among researchers, due to the fact that the use of this method can solve the nonlinear problems while using small quantities of training data. This SVM is related to the supervised learning methods applied for categorization and regression and being introduced by Cortes and Vapnik [14] in 1995. This approach ranks very high in the context of accuracy and can solve nonlinear problems using small quantities of training data. The SVM is based on the structure risk minimization (SRM) with the idea to minimize the upper bounds of error of the object function [15].

Although both methods can be used to solve nonlinear problems, there still some spaces for improvement in the forecasting performance of these methods. Thus, the hybrid method was introduced in the electrical energy consumption forecasting field. The hybrid method is a combination of two methods [16,17]. Compared to single method, the hybrid method has better potential in solving problems for load forecasting. There are two types of hybrid methods that have been reported in the literature; a hybrid between a conventional method and an AI method, and a hybrid between two AI methods [18,19]. The combination between two AI methods is interesting due to the ability of the AI methods to perform better than the combination of one conventional method and one AI method.

At present, this method is applied for building energy consumption forecasting and suitable for all types of building [20–24]. The most frequent type of buildings that have been considered in building electrical energy consumption forecasting are office, residential, and engineering buildings with varying room sizes [25]. The energy consumption behaviour of these buildings is influenced by many factors, such as weather conditions, indoor conditions and human occupancy in the building [23,26–28]. Among all these factors, weather condition is the major forecasting factor that may change the indoor conditions and activities in the building electrical energy consumption. For example, the ambient temperature, cloud cover, humidity and solar radiation predominantly affect the non-residential load patterns due to the adjustment of the comfort and lighting levels by the occupants [29–31].

Due to the complex nature of the building's energy behaviour, it is difficult to accurately forecast the electrical energy consumption of a building. The accuracy of the forecasting method will be the focus in this research study. This paper aims to provide a review of the existing methods for forecasting electrical energy consumption of buildings. The consumers as well as the building owners and operators will benefit from the results of this research study. The methods studied in this research work include the ANN, SVM and hybrid methods. The combination of the Particle Swarm Optimization (PSO) [32] and Ant Colony Optimization (ACO) [33] is widely reported in the literature.

This paper is organized as follows: Section 2 will describe the conventional methods for electrical energy consumption forecasting, Section 3 will review the artificial intelligence methods in relation to the previous research works, Section 4 explores the hybrid model using AI methods, and finally, Section 5 presents the conclusion of the study.

2. Overview of conventional methods

In the load forecasting field, the quantitative forecasting technique is more suitable to use due to the availability of time series data to forecast future loads. However, the time series analysis and regression based method have been more widely explored.

2.1. Stochastic time series

In time series analysis, there are four components to fit the models which are seasonal, trending, cyclical, and irregular. This method can give a positive response accurately in some conditions, normally when the set of data is large and complex. Furthermore, the steps must be followed with caution to get an accurate time line throughout data collection.

This method has been used for many years in fields like electrical systems, signal processing and energy. The most common type of method that is always explored in this approach is Autoregressive and Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA).

In the stochastic time series, autoregressive (AR) is the first method to be introduced in this family. This method has been used by researchers [34] since 1996, when load profile was modelled by assuming the load as being a linear combination with the previous load. The following year [35], the autoregressive model was introduced with an optimum threshold stratification algorithm. In this algorithm, the minimum parameter was used to conduct the experiment to make an improvement on the forecast accuracy.

The combination of autoregressive with the moving average (ARMA) had been introduced since 1951. This method can be done by a recursive scheme or by using the maximum-likelihood approach which is basically a non-linear regression algorithm. In 1992, researchers [36] conducted load forecasting by presenting a new time-temperature methodology. In this research, the actual time series of monthly peak demands were decomposed to the deterministic and stochastic load components. Some modifications were carried out by using the weighted recursive least squares (WRLS) with the ARMA model to update the parameters [37]. Chen and Wang [38] used the available forecast error to update the ARMA method for the load forecasting. The derivation of error learning was adapted from the minimum mean square error (MSE). The results showed that the adaptive scheme outperformed the conventional ARMA method.

The ARMA has evolved and has been upgraded, known as autoregressive integrated moving average (ARIMA). Transformation needs to be performed if the process is non-stationary. The transformation can be performed through differencing processes. The first research was conducted [39] to forecast the growth of the system load. The ARIMA method was used to produce the non-weather cyclic component of the weekly peak load. The real time load forecasting by using ARIMA model was also conducted [40].

Since the time series method has been upgraded from ARMA to ARIMA, the application of the method may also be different from the previous version. The ARMA method is normally used for stationary stochastic processes [6]. With some improvement, ARIMA has been developed for use for non-stationary stochastic processes [41]. The difference between stationary and non-stationary processes is that stationary process has constant variance and mean over time, while non-stationary process is the opposite. Both ARMA and ARIMA use load and time as the main inputs to forecast. In the energy consumption forecasting, the weather and time of the day are used as the major inputs to predict the future load.

2.2. Regression based approach

The regression based approach has been applied in this field for two decades. The benefit of this relationship method is that the variable between the dependent and independent can be determined by using the regression based approach. Generally, the use of this method can be classified into two; linear regression (LR) [42] and multiple regressions (MLR) [43]. However, the LR is the simpler method when compared to MLR.

Basically, LR can be classified into two variables; dependent (response) and independent (predictor) variables. In the forecasting field, the dependent variable can be represented as the demand or price of electricity. These variables are mostly dependent on the production. As for the independent variable, it is usually related to the weather, such as temperature, humidity or rainfall. However, in MLR, the least square estimation is applied to estimate the regression coefficient. For MLR, the load will be classified as independent variable [44].

Moghram and Rahman [45] conducted a research by using regression based approach and compared it to other methods to evaluate 24-h load forecasting. In 1990 [46], regression model was used to fit the data and check the seasonal variations. Haida and Muto [47] performed the transformation techniques based on the regression model for daily peak load forecasting. The regression model was used to forecast the load and learn the pattern to forecast the residual load. In another research work [48], two trend-processing techniques were introduced. The importance of this approach is the reduction of errors in the transitional seasons.

2.3. Discussion on conventional methods

In the past, conventional methods have been widely used in load forecasting. Basically, time series is popular for electrical energy consumption forecasting, while regression based approach is widely applied in statistical techniques. In the stochastic time series, there are two important methods which are ARMA and ARIMA. Both of these models use time and load as the input parameters. For the regression based approach, the relationship between the load and other factors such as weather and the economy may influence the pattern of forecasting.

Although the conventional methods are easy to develop and use, these methods cannot deal with the nonlinear pattern and they lack flexibility [25]. The conventional methods involve various factors such as weather conditions, indoor conditions and human occupancy in the building, which may cause the non-linear pattern. If the pattern of these factors is similar every day, it would not affect the error of electrical energy consumption forecasting. However, if there are changes in these factors, they may cause higher error in forecasting. It should be noted that this nonlinearity is the major problem that may affect the forecasting performance. Thus, the conventional method requires some modifications such as by integration with other methods in order to improve the method.

3. Artificial intelligence methods

Nowadays, most researchers prefer to use artificial intelligence (AI) methods in the forecasting field, especially in electrical energy consumption forecasting. This section will review previous works carried out using the artificial intelligence methods, which cover artificial neural network (ANN) and support vector machine (SVM). In addition, majority of researchers prefer using the short-term load forecasting (STLF) and Mean Absolute Percentage Error (MAPE) as the reference to compare the performance of various methods in the electrical energy consumption forecasting field.

3.1. Artificial neural network

According to Damborg, El-Sharkawi [49], the ANN has the potential to predict the dispatch of power in the power system. There are several famous types of ANN models which are widely used, such as back-propagation neural network and feedback neural network. The advantages and disadvantages of the ANN method have been reviewed by Ahmad, Hassan [50], as shown in Table 3.1.

Generally, the strength of the ANN method is that it can solve nonlinear problems and is a very effective approach to this complex application, consequently becoming popular in the forecasting of electrical energy consumption of building. However, the ANN method needs training data input and it may be time consuming. In 1995, Islam and Al-Alawi [51] predicted the monthly electric load and energy for fast growing utility by using neural network. In this study, the weather variables like temperature, humidity, wind speed, brightness of the sun, global radiation, precipitation and vapor pressure had been selected to be tested for the correlation factor, R^2 and to find out their contribution to load forecasting. The mean absolute percentage error (MAPE) had been used to differentiate between the two methods, which were the neural network (NN) and socioeconomic (SE) model. The NN model showed a better performance with a MAPE value of 7.32% compared to the SE model with a MAPE value of 35.60%.

Table 3.1
Advantages and disadvantages of artificial neural network [49].

Pros	• Able to deal with non-linear pattern • Can solve the problem even there have some failures element on the Neural Network • No need supervision and can learn by without any programmed • Can be applied and implemented in any type of application without any problem
Cons	• Require the training time to operate the Neural Network • Should be emulated the architecture of Neural Network • Require a long time for the large number of network

González and Zamarreño [52], in 2005, studied the feedback NN model for the prediction of hourly electrical energy consumption of an office building. They selected temperature, hour, day, input load and output load at the database for the load prediction. They then referred previous research work to compare the MAPE coefficient of the electric load forecasting for the building. Electrical energy consumption forecasting of building for tropical region was carried out by Yalcintas and Akkurt [53] using neural network in 2005. In the study, the testing result of neural network performance had shown its superiority compared with the training result, owing to the lower correlation value, R^2 than the training results.

Karatasou, Santamouris [54], in 2006, proposed the feed forward NN (FFNN) as a medium to forecast the building energy consumption. In the study, the set of data had been divided into two. The first data set A consisted of the following input: temperature, solar radiation, humidity ratio and wind speed while data set consisted of hourly values of electrical power consumption, ambient temperature and humidity. This data was important in order to extend the prediction horizon to 24, hence to compare the accuracy. In carrying out this research, they had differentiated the research work into two parts, which were the single-step, which was dependent on the historical data, while the other part, the multi-step, was designed independently, as shown in Table 3.2. It was observed that the single–step gave a very accurate prediction with a lower value of MAPE when compared to each other, for both data sets.

Mai, Chung [55], in 2014, used the radial basis function of neural network to forecast the electrical consumption for a large office building in China, which produced an outstanding performance for the building electrical energy consumption forecasting. In this research, three different scenarios were studied, which were cold, cool and hot weather. Nonetheless, in order to get better comparison, four different types of evaluation criteria, which were MAPE, RMSE, mean bias error (MBE) and R^2, were used in this research work.

Chae, Horesh [56] introduced an hourly electrical energy consumption forecasting for a commercial office building by using artificial neural network with Bayesian regularization. In this analysis, the ANN was compared with another nine methods such as linear regression, standard ANN and simple model, and the correlation coefficient, R^2, which showed that the neural network with Bayesian regularization had better performance than the other methods.

Neto and Fiorelli [57] studied an institutional building and compared two different methods which were physical principle (EnergyPlus) and a simpler ANN model simulation in the building load forecasting, focusing on electrical energy consumption. They were particularly interested in applying the different parameters such as weather, temperature and occupancy to both models to determine which would be better for forecasting electrical energy consumption of building. Escrivá-Escrivá, et al. [4], proposed another ANN method

Table 3.2
Performances of different 1- and 24-step forecasters [53].

Step	Forecasting	RMS		MAPE		CV		MBE	
		A	B	A	B	A	B	A	B
Single	Next Hour	15.25	1.10	1.50	2.57	2.39	2.97	0.37	0.13
	Within 24-h	16.49	1.16	1.42	2.72	2.6	3.02	0.24	0.18
	Within 24-h (with Multiple-step error)	52.97	16.43	5.59	24.35	8.48	16.43	4.92	14.15
Multi (24)	Next 24-h	34.20	6.76	3.67	13.39	5.47	12.58	−0.05	1.24

Table 3.3
Result of multiple simulations at the UPV as a function of the selection criteria in EU's method [4].

Selection criteria	1	2	3	4	5	6	7	8	9
MAPE	5.10	5.16	5.81	6.42	8.65	10.82	6.04	5.08	12.17

based on the building end-users in 2011. In the study, they [4] selected the input variables such as weather conditions, calendar, type of the day and unpredictable factors, using the weighted MAPE and Energy Mean Error (EME) to evaluate the accuracy of the method with the 9 types of different criteria, as shown in Table 3.3. It was found that the best value of MAPE for the first criteria was 5.10 compared to the other criteria. This was because criteria 1 was used by considering the days being too close to the day of prediction. Extending this research in 2013, Roldán-Blay, Escrivá-Escrivá [58] improved the ANN method by applying the time temperature curve to forecast the electrical energy consumption forecasting.

In 2016, Deb, Eang [22] applied ANN to forecast the daily electrical energy consumption of a cooling system of a building. In this section, the occupant is the most important factor that affects the electrical energy use. Thus, the forecasting models were tested using this factor at the institutional building, which has a high potential on the occupancy schedule. Other than the office and institutional buildings, residential building can also be considered as one of the buildings that need electrical energy consumption forecasting. In order to forecast the energy consumption for residential building, Mihalakakou, Santamouris [59] tested the neural network system with the additional meteorological parameters as input. The inclusion of air temperature and solar radiation in this forecasting was intended so that the neural network would be able to forecast the energy consumption for a residential building.

For the same type of building, Aydinalp, Ismet Ugursal [60] showed that the neural network forecasting was better compared to the engineering models. In this research, two types of neural network were used to forecast the space heating and hot water energy consumption. With the greater value of R^2 and lesser value of CV, it was found that the neural network had a better performance than the engineering models. Yu, Li [61] applied the back propagation neural network to analyse the electrical energy consumption of a residential building in China. The model analysed the data from 1998 to 2006 by using the 16 indicators that might affect the energy consumption. The small error between the actual and forecasted values indicated that this back propagation neural network model is reliable.

The ANN technique particularly shows its strength in the forecasting of the building electrical consumption. Looking at the accuracy of this technique, it indicates that the ANN has the potential to result in a minimum percentage of error compared to the previous method. For the analysis of nonlinear problems, this technique is applicable to be used in getting a better accuracy [62]. The ANN method is also widely applied in other fields such as controlling the heating of a solar building [63], controlling the hydronic heating system [64,65], estimating the temperature in a building [66], forecasting the power load of heavy industry and commodity gain [67] and modelling the building heating energy demand [68].

3.2. Support vector machine

The most powerful and recent technique in load forecasting is Support Vector Machine (SVM). Both methods of ANN and SVM can solve the nonlinear problems, but SVM only requires a small quantity of data to do it. Hence, this method is popular among researchers in the nonlinear problem field. The first researcher who discovered the use of the SVM model for short term load forecasting was Mohandes [69] in 2002. In the study, it was observed that the performance of the SVM model showed a better result than the auto-regression model, by using the same data and weight parameter.

Three years later, Dong, Cao [70] studied load forecasting of four commercial buildings in Singapore. In particular, they used the SVM method to forecast the energy consumption of the buildings. In the study, three types of input had been chosen, which were the mean outdoor dry-bulb temperature, relative humidity and global solar radiation. They observed that the performance of the SVM based on the Coefficient of Variance, CV and Means Square Error, MSE for all buildings was better than the other methods of ANN and genetic programming. In the same year, Hong, Jian-Hua [71] also used the SVM in combination with OPC technologies to predict the online daily load. Authors have used the previous hourly load as the input to predict the next day load output and be conducted for two weeks. The next day, forecasting was done efficiently through the SVM with a combination of OPC with an average of MAPE of 4.04% and an average of MSE of 4.82%, thus showing a satisfactory performance with the ODLF which was used in JSY2000.

Ying-Chun, Dong-xiao [72], in 2006, presented a SVM model for short-term load forecasting in predicting energy consumption. They found that the SVM model has high potential to give a better performance than ANN model by using the MAPE parameter. In the study, they stated that the maximum and mean of MAPE achieved by the SVM in one year were 4.32% and 2.89%, respectively. Hence, it was shown that the SVM has a better accuracy than the ANN and this approach can also be done in the shortest time. There are other superior performances that the author had stated such as that the SVM method can easily capture the load patterns of electricity data and use the structural risk minimization.

In Guangzhou, China, the energy consumption of a cooling system in an office building had been forecasted using the SVM method [73] in 2009. The aim of their research was to forecast the energy consumption of the cooling system in the office building during the summer season. Outdoor dry-bulb temperature, relative humidity and global solar radiation were used as the input parameters during this research. The SVM method was then compared with the Back-Propagation NN (BPNN) in [73], as shown in Table 3.4.

The LSSVM had been applied by Wu and Niu [74], in 2009. In their research work, the LSSVM was validated by the nonlinear relationship between loads and influencing factors, collected in the Inner Mongolia of China, which covered the whole year of 2008 starting from January 1st to December 31th. The LSSVM had shown the capability to solve the nonlinear problem and high potential to be used to forecast the

Table 3.4
Comparison of the prediction errors of SVM model and BP model (unit: %) [73].

Model	Parameter	Training Sample July	Testing Sample			
			May	June	August	October
SVM	RMSE	0.006	1.146	1.157	1.168	1.182
	MRE	0.005	1.001	1.008	1.011	1.016
BP	RMSE	0.008	2.302	2.321	2.223	2.365
	MRE	0.007	2.008	2.021	1.922	2.024

Table 3.5
Evaluation indices between BPNN and LSSVM [76].

Predictor	Evaluation Indices			References
	RME (%)	MARE (%)	RMSE (%)	
BPNN	0.79	4.18	11.84	
LSSVM	0.45	1.65	5.56	

next day load effectively. Xuemei, Jin-hu [75] proposed the LSSVM model to forecast the cooling load for an office building in China. They used three types of evaluation indices, which were relative mean error (RME), mean absolute relative error (MARE) and RMSE of BPNN and LSSVM. Their results indicated that LSSVM had lower values than the BPNN, as shown in Table 3.5.

Qiong, Peng [77] had conducted a study on 59 residential houses in China to predict the energy consumption in a year by using the SVM method. In the study, three methods had been chosen to be compared with SVM, which were back propagation (BPNN), radial basis function neural network (RBFNN) and general regression neural network (GRNN). During the process to differentiate between the methods, RMSE and MRE had been selected as weight parameters. The first result for the training sample, SVM and GRNN method had shown a better result than the two other methods with a value of 0.008 for RMSE and 0.006 for MRE. However, it turned out that after the testing sample had been done, the SVM method had performed even better than GRNN and the two other methods with the RMSE of 2.395 and MRE of 1.895.

In 2009, a cooling load forecasting had been conducted by Hou and Lian [78] using the SVM. In this research, the performance forecasting of SVM had been compared with the ARIMA, and the result showed that the SVM had superior performance than ARIMA, as illustrated in Fig. 1 and Fig. 2. Xinhui, Liang [79], in 2010 forecasted the future 24 h by using the back propagation neural network (BPNN) and SVM in the power system. By using 15 days of historical load data with the temperature and date type of data, the results showed that the SVM has good performance in forecasting, as summarized in Fig. 3.

This SVM is also widely applied in other fields. In 2011, Zhou, Shi

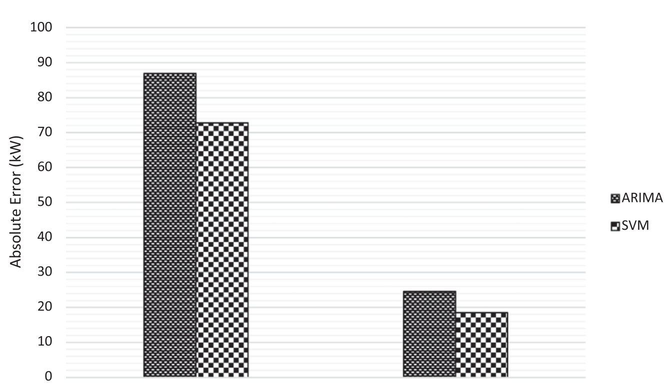

Fig. 1. The Absolute error analysis between ARIMA and SVM [78].

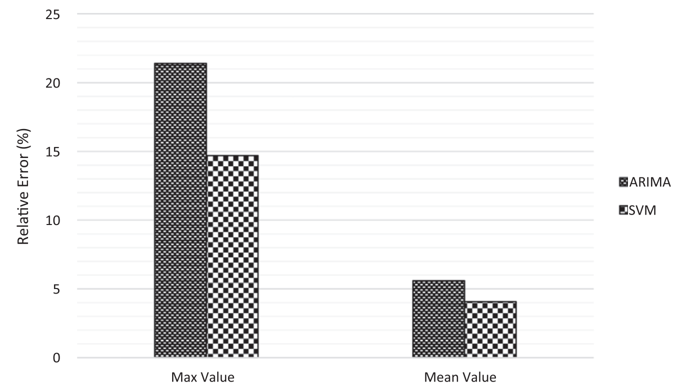

Fig. 2. The relative error analysis between ARIMA and SVM [78].

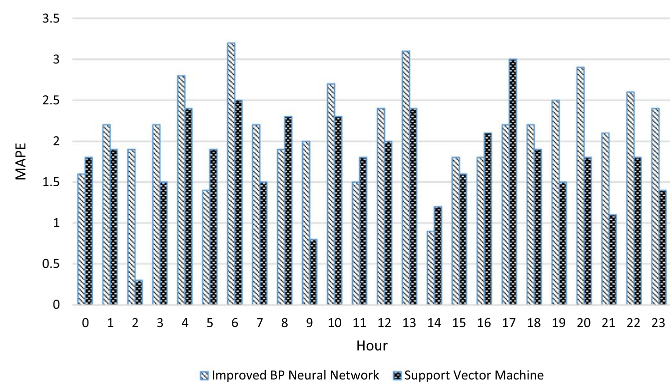

Fig. 3. Comparison MAPE of ANN and SVM [79].

[80] presented the results of fine tuning of LSSVM using three types of SVM kernel, which were linear, Gaussian and polynomial in forecasting the wind speed. Their research was able to differentiate the four seasons; spring, summer, autumn and winter. In the study, the LSSVM model could only perform better in the winter, spring and autumn due to the wind speed being higher compared to during summer.

Zhang, Niu [81], in 2013, developed online LSSVM to optimize the gravitational search algorithm (GSA) for predicting the heat rate of a turbine. The SVM, LSSVM and ordinary least squares (OLS) with optimization GSA had been compared with the proposed model in this study. The outcome exhibited that the online LSSVM with optimization GSA outperformed the other methods.

3.3. Discussion on the artificial intelligence methods

A modern type of forecasting had also been developed. Artificial Intelligence (AI) has shown its capabilities and it has been proven that this method is better than the conventional methods in the forecasting field. One of the strengths of this method is that it can deal with the nonlinear patterns. ANN and SVM are under the AI families. Generally, the principle of ANN is based on the empirical risk minimization (ERM) while SVM is structural risk minimization (SRM). The SVM has been developed as an alternative way to overcome the over-fitting problem that occurs in most cases in ANN. The over-fitting problem occurs in ANN due to the large number of input data [82]. Zhao and Magoulès [25] discussed the comparison between conventional and artificial intelligence methods as reviewed in the literature [25]. Research studies on AI methods are summarized in Table 3.6 and Table 3.7.

Based on this table, it can be observed that the type of methods of forecasting and the time interval has great impact on the forecasting performance. In this case, several time intervals had been applied like per minute [56], per hour [4,52–55,58–60,71,73,76], per month

Table 3.6
Summary of input data used in artificial intelligence methods.

References	[51]	[52]	[53]	[54]	[55]	[56]	[4]	[58]	[22]	[59]	[60]	[61]	[70]	[71]	[73]	[76]	[77]
Type Of Building																	
Residential										•	•	•					•
Non- Residential	•	•	•	•	•	•	•	•	•				•	•	•	•	
Time Interval																	
Per Minutes						•											
Per Hour		•	•	•	•		•	•		•	•			•	•	•	
Per Month	•								•				•				
Per Year												•					•
Electrical Load																	
Historical Load	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Weather Data																	
Temperature	•	•		•		•	•	•	•		•			•	•	•	
Dry Bulb Temperature			•			•							•				
Dew Point Temperature			•														
Wet Point Temperature			•														
Air Temperature										•							
Humidity	•		•	•	•	•							•		•	•	
Wind Speed			•	•		•			•								
Wind Direction			•			•											
Brightness of Sun	•																
Precipitation	•					•											
Vapor Pressure	•																
Global/Solar Radiation	•			•	•				•	•			•		•	•	•
Sky Condition						•											
Indoor Data																	
Ambient Temperature				•	•												
Electric Usage						•		•			•						
Occupancy									•		•	•					
Other Data																	
Thermal Index																	•
Calendar							•							•			
Size of House											•						
The Living Standard												•					
Social Development												•					
Urban Construction and Development												•					
The Natural Condition												•					
Heat Transfer																	•
Size of Building													•				•

[22,51,70] and per year [61,77]. The most significant data for describing the forecast of electrical energy consumption of building should be presented in per hour. This is important due to the significant changes of data that could happen in the next hours. In fact, the collected data per minute does not show much change in the trend of the data. Thus, it will increase the number of training data and gets more complex. Data collected per month and per year are also not appropriate to be used to forecast electrical energy consumption of building. This is because it cannot capture the daily energy consumption in building that is needed to be used to manage the electrical energy consumption.

4. Hybrid methods

Hybrid method has been introduced by researchers as a new approach in the electrical energy consumption forecasting field. The hybrid method should give the best performance as it combines the advantages of the both conventional and AI methods. From the literature, it can be seen that the artificial intelligence methods have the potential to give better results in terms of the accuracy when compared to the conventional methods.

4.1. Swarm intelligence with AI method

Swarm Intelligence (SI) was introduced by Bonabeau, Dorigo [83], inspired by the behaviour of insects and other animals, such as particle swarm optimization (PSO) from bird, ant colony optimization (ACO) from ant and artificial bee colony (ABC) from bees. In comparison with the evolutionary algorithm (EA) and other single methods, this SI is one of the newest branches of meta-heuristic based method. By using approximate and non-deterministic strategies, this swarm intelligence can perform excellently to explore and exploit in searching the space to find the nearest optimal solutions [84]. Generally, there are two necessary fundamentals in this SI, which are self-organization and division of labour. Self-organization is to ensure that the interactions are executed on the basis of purely local information without any relation, while the division of labour is to enable the swarm to respond to changing conditions in the search space [85].

The previous section has described two methods, ANN and SVM, which are widely applied in the forecasting of electrical energy consumption of building. Based on the principle of each method and previous examples, both methods are capable of solving problems in this field. However, Foucquier, Robert [86] noted that ANN and SVM can be classified as the black box approach. This black box approach has disadvantages due to the unknown internal architecture and usage of the trial and error process [87]. Also, when the data set of forecasting is very large, it may affect the stability of forecasting. Thus, this AI method has been introduced to be hybrid with SI to increase the performance of forecasting. Since SI is good in searching method, this

Table 3.7
Summary of performance of artificial intelligence methods.

Method	Features1	Evaluation Indices						Ref.
		MAPE	Relative Error (%)	R^2	CV	RMSE	MBE	
ANN	The actual and forecasted monthly peak load for 1991	7.32	–	–	–			[51]
	The average of MAPE for analysed the period	1.945	–	–	–			[52]
	Testing Result	–	–	0.8832	-`			[53]
	Forecasting performance (Data Set A)	1.42	–	–	2.39	15.25	0.24	[54]
	Forecasting performance (Data Set B)	2.57	–	–	2.97	1.10	0.13	
	Scenario A	0.0578	–	0.973	–	0.1643	–	[55]
	Scenario B	0.0729	–	0.975	–	0.1578	–	
	Scenario C	0.00572	–	0.977	–	0.1511	–	
	Weekday (21)	–	–	–	8.74	–	–	[56]
	Weekend (8)	–	–	–	11.16	–	–	
	Weekday (19)	–	–	–	13.76	–	–	
	Weekend (10)	–	–	–	26.74	–	–	
	Multiple simulation at the UPV of the selection criteria (8) in EU's method	5.08	–	–	–	–	–	[4]
	Multiple simulation at the UPV	4.76	–	–	–	–	–	[58]
	Previous five days energy class	–	–	0.9794	–	–	–	[22]
	Prediction results with 20 class divisions	–	–	0.9712	–	–	–	
	The actual and forecast result of energy consumption	–	−8 to 15	–	–	–	–	[59]
	Domestic Hot Water (DHW)	–	–	0.871	3.337	–	–	[60]
	Space Heating (SH)	–	–	0.908	1.871`	–	–	
	Life energy consumption forecast error	0.14	–	–	–	–	–	[61]
SVM	Building A	−2.72	–	–	2.69	–	–	[70]
	Building B	3.44	–	–	2.39	–	–	
	Building C	0.68	–	–	1.28	–	–	
	Building D	−1.89	–	–	0.99	–	–	
	The load forecasting of 2 weeks	4.04	–	–	–	–		[71]
	May	–	–	–		1.146		[72]
	June					1.157		
	August					1.168		
	October					1.182		
	The accuracy predictor	–	–		–	5.56		[73]
	The prediction error	–	–		–	2.395		[76]

Table 4.1
Day load forecasting precision analysis of PSO -NN [90].

Model	Error < 2%		Error < 3%		Error < 4%	
	Number	%	Number	%	Number	%
9th	18	75	23	95.8	24	100
10th	17	70.8	21	87.5	24	100
11th	18	75	21	87.5	24	100
12th	17	70.8	22	91.7	24	100
13th	18	75	20	83.3	23	95.8
14th	19	79.2	22	91.7	24	100
15th	20	83.3	23	95.8	24	100

Table 4.2
Day load forecasting precision analysis of BP -NN [90].

Model	Error < 2%		Error < 3%		Error < 4%	
	Number	%	Number	%	Number	%
9th	13	54.2	19	79.2	21	87.5
10th	14	58.3	21	87.5	23	95.8
11th	15	62.5	20	83.3	24	100
12th	15	62.5	19	79.2	21	87.5
13th	14	58.3	21	87.5	24	100
14th	15	62.5	19	79.2	22	91.7
15th	16	66.7	19	79.2	22	91.7

will help the AI to balance the stability of forecasting when facing large data set. In addition, this SI also will discover the best optimal point through the search space in getting the best performance of forecasting.

Table 4.3
The performance comparison between the different evolved Artificial Neural Network [91].

Model	The average relative error rate (%)	The average time using (second)
The GA-ANN	4.74	65.3
The PSO-ANN	2.58	38.7
The CPSO - ANN	1.13	27.1

4.2. Hybrid artificial neural network

Researchers have recently stepped forward to conduct researches by using the hybrid approach. Although using a single method may have some weaknesses, as reviewed by [50], by using the hybrid method, it can be guaranteed to improve the performance of the method. In this study, ANN was used with swarm intelligence (SI) as hybrid method [88,89] and is described first.

In 2006, Sun, Zhang [90] conducted a hybrid of ANN with optimization with the first families of SI, which is the particle swarm optimization (PSO) for the short-term load forecasting. In this research, two hybrid methods had been compared; BP-ANN and PSO –ANN, to show the speed of calculation of the methods. The results showed that the PSO –ANN was faster than the BP – ANN, as shown in Table 4.1 and Table 4.2.

ShangDong and Xiang [91] developed a new algorithm of ANN incorporated with Chaotic PSO (CPSO) in 2006. The main objective of this combination is to improve the performance of load forecasting. The algorithm comparison had also been conducted in this research with PSO-ANN and GA-ANN. Table 4.3 shows the performance comparison between the different evolutions of Artificial Neural

Table 4.4
Summary of ANN with swarm intelligence.

Number	Techniques	Objective	Type of inputs	References
1	ANN with PSO	To improve the forecasting precision and speed	Historical Load, Weather, Temperature and type of date	[90]
2	ANN with Chaos PSO with adaptive inertia weight	To enhanced the searching quality of forecasting	Historical Load, Meteorological data	[91]
3	BP neural network with PSO	To improve the learning speed of network and forecasting precision	Historical Load, Weather data	[92]
4	RBF neural network with PSO	To improve the precision of electric power system short term load forecasting	Historical Load, Weather condition	[93]
5	RBF neural network with ARIMA and ACO	To improve the accuracy of load forecasting	Historical Load	[94]
6	Fuzzy neural Network with PSO	To improve the accuracy of load forecasting	Historical Load	[95]
7	BP neural network with PSO	To improve the weight and threshold values	Historical Load	[96]
8	Feed Forward neural network with PSO	To forecast electrical energy consumption of equipment maintenance	Historical Load, Weather data	[18]

Table 4.5
Forecasted results for different models.

	Type of Model	MAPE
[97]	**BPNN**	2.77
	FI	2.58
	PSO-SVM	**2.35**
[98]	**BPNN**	2.77
	PSO – SVM	2.58
	SAPSO – SVM	**2.19**

Table 4.6
Summary of the results of the forecasting models [100].

Model	Training accuracy evaluation MAPE	Forecasting accuracy evaluation MAPE
MLR	0.025	0.027
OTS – SVR	0.029	0.025
ANN - APSO	0.035	0.032
MLR – OTS – SVR	0.014	0.014
OTS – SVR - ARIMA	0.021	0.019

Network.

In 2007, Sun and Zou [92] proposed a 24-h prediction based on the neural network trained by PSO. They had chosen the back propagation (BP) neural network to be optimized with the PSO. This research had also been conducted using two methods, which were conventional BP algorithm and PSO-BP algorithm. The data set had been divided into three; training data, validation data and testing data. Both methods had been compared to get the best result in load forecasting. The results showed that the average error of the proposed model was 1.24% while the error of conventional BP was 3.53%.

In 2009, Lu and Zhou [93] utilized the PSO algorithm and radial basis function (RBF) neural network to improve the prediction of load forecasting. The comparison was done with the conventional RBF algorithm to prove that the proposed method could perform better in terms of accuracy. The performance analysis of the algorithm had been conducted for one day (24 h) and it was shown that the difference in the average percentage error between both algorithms was 0.93%, which represented the difference in value of 1.34% for PSO–RBF algorithm and 2.27% for the RBF algorithm.

The ant colony optimization (ACO) has also been used with the neural network as a hybrid method. In 2010, Niu, Wang [94] had applied this method for power load forecasting. In the study, the RBF neural network was selected to be combined with the ACO and was compared with three other methods; GM (1, 1), GM (1, 1, 0) and ARIMA. Absolute average error had been used in the study to differentiate the performance of the methods. The ANN–ACO had the best performance by having the lowest value for the absolute average error of 1.139% compared to others, GM(1,1) (2.339%), GM (1,1,0) (1.257%) and ARIMA (2.048%).

The daily load forecasting had been conducted by Rong-Jong, et al. in 2012 using fuzzy neural network (FNN) and PSO algorithm [95]. In the study, they had forecasted the load for the next day by using the historical load data. The historical data was designed to simplify the forecasting structure and to reduce the cost of the equipment for data collection. The testing data had been prepared for four months (March, September, October and November). They had also compared this method with the other methods by using MAPE as a weightage to determine the accuracy. It was found that the PSO structure had a value of MAPE less than 4% while the others had higher MAPE values such as FNN-PSO (4%), FNN-BP-V (4.5%), FNN-BP (4.97%) and NN-BP (5.12%).

A combination of back propagation neural network and self-adapting particle swarm optimization (BPNN – PSO) was utilized by He and Xu [96] for power load forecasting in a city in China. The objective of the study was to improve the parameter of BPNN which employs the PSO algorithm. In addition, comparison was also made between traditional back propagation (BP) and their proposed method.

Table 4.7
Summary of SVM with swarm intelligence.

Number	Techniques	Objective	Type of inputs	References
1	SVM with PSO	To investigate the feasibility of using SVM to forecast electricity load	Historical Load, Temperature, Meteorological data	[97]
2	SVM with Stimulated Annealing PSO	To enhanced the accuracy and the convergence ability and reduced operation time	Historical Load, Temperature	[98]
3	SVM with PSO	To improve the efficiency of load forecasting	Historical Load	[99]
4	SVM with ACO	To improve the accuracy of load forecasting	Historical Load	[3]
5	SVM based on optimal training subset with adaptive PSO	To consider the electric load series for seasonal cycle and the forecasting accuracy	Historical Load	[100]

The result showed that the mean absolute error difference between both methods was 1.14% while the maximum relative error was 2.389%. Therefore, the proposed method (BPNN –PSO) had an improved performance over the traditional BP in forecasting precision.

In 2013, Jiang, Ling [18] developed a new adaptive PSO algorithm to be incorporated with the ANN (ANN – APSO) algorithm for forecasting electrical energy consumption of equipment maintenance. They used historical dataset from 1999 to 2011 of the number of equipment repaired and the total electrical energy consumption as the input. By using four approaches for the testing of MAPE percentage, the ANN-APSO showed a significant performance difference between the other three methods.

This section has presented a review on the hybrid method between ANN and SI families in forecasting electrical energy consumption of building, as summarized in Table 4.4. For the analysis of nonlinear problems, this hybrid method has shown improvement in the performance of accuracy of building load forecasting. Indeed, ANN has been widely utilized in different applications, but its hybridization with other methods has been proven to improve the accuracy of forecasting electrical load of building.

4.3. Hybrid support vector machine

Using a similar approach as the ANN hybrid algorithm, the Support Vector Machine has also been matched with PSO due to its ability to solve the nonlinear problem by using small quantity of data. In 2006, Changyin and Dengcai [97] studied the combination of the support vector machine and particle swarm optimization algorithm for short-term load forecasting. By using the mean absolute percentage error (MAPE), they found that the combination of SVM–PSO resulted in a lower MAPE than the fuzzy inference (FI) and BPNN, as illustrated in Table 4.5.

In 2007, Wang, Zhou [98] forecasted electricity load using the support vector machine method with the simulated annealing particle swarm optimization (SAPSO-SVM). To complete this study, they used the weather condition and historical data as the main data inputs. The study had been conducted to collect the data for one month by using different models, as listed in Table 4.5. The proposed method showed the best average mean absolute percentage error compared with the other two methods of BPNN and PSO – SVM.

In 2009, Lu, Zhou [99] hybridized the support vector machine and particle swarm optimization for load forecasting. They used historical data from one of the cities in China from December 11, 1999 to January 5, 2000, as the input data to forecast the load for the next day which was January 6, 2000. In the study, two methods were compared, which were PSO–SVM and SVM algorithm. The mean absolute percentage error parameter had been calculated, which showed that the PSO–SVM model performed better than the single SVM method with a difference of 0.79%.

In 2010, Niu, Wang [3] presented a new hybrid method for the swarm intelligence by using the combination of support vector machine and ant colony optimization (SVM–ACO) for load forecasting. The performance of the SVM–ACO in the analysis was measured by using root means square relative error (RMSE). The RMSE result was evaluated using different methods of ANN, SVM and SVM-ACO and had taken about 24 h. Among these methods, the SVM–ACO had the lowest average RMSE value compared to the other two methods.

In 2014, Che [100] conducted a short-term load forecasting by using a support vector regression model based on an optimal training subset and adaptive particle swarm optimization (SVR-OTS-APSO). A novel hybrid model had been chosen to be compared with the SVR-OTS-APSO to achieve the interpretability of the seasonal cycles and the forecasting accuracy. The proposed method was found to perform better than the other methods according to the MAPE parameter, as listed in Table 4.6.

The hybrid methods between SVM and SI families have been reviewed in this section. Although individual SVM and ANN methods can solve the nonlinear problems, the hybrid of SVM and SI families can perform better than ANN alone. Since the SI family is relatively new in the load forecasting application, there is room for studying the method in this field. However, the use of LSSVM in forecasting electrical energy consumption of building cannot be neglected since it can produce good forecasting results. Moreover, the combination of LSSVM and SI families can improve the time series forecasting accuracy. Further research needs to be conducted to discover the possibility of combining the LSSVM and SI families in building load forecasting. The summary of SVM techniques with swarm intelligence is as illustrated in Table 4.7.

4.4. Discussion on hybrid methods

Through the above discussion, it appears that hybrid methods are potential to enhance the performance of forecasting electrical load of building. The combination of AI and SI can result in superior performance for forecasting. This is because hybrid methods utilize the advantages of both methods for more accurate forecasting.

The type of input is also one of the factors that influence the forecasting performance. As can be seen from Table 4.4 and Table 4.7, most researchers consider only the historical electrical energy consumption data and not other influencing factors. The electric power load is a complex nonlinear system, thus there are many factors that may influence the level of load consumption such as weather conditions and indoor data [90]. The weather condition and history of electrical energy consumption are also important factors for short-term load forecasting [93]. This shows that other influencing factors need to be considered in order to get better performance for electrical energy consumption forecasting.

5. Conclusion

This paper has reviewed previous research works on forecasting electrical energy consumption of building using conventional and artificial intelligence methods. Each method has its own advantages and disadvantages for different types of applications. Among these methods, AI has gained the most attention of numerous researchers, due to of its forecasting performance accuracy. Conventional methods are easy to be developed and applied in real buildings. As non-linear factors such as weather and indoor conditions of a building have a significant impact on the performance accuracy of electrical energy consumption forecasting, conventional methods may not be able to provide the required accuracy in this forecasting. AI is the most suitable method to manage non-linear factors as it is able to provide better forecasting performance. Furthermore, this forecasting method does not only fixed for certain performance analysis but it may also be vary on the situation in conducting the research. Combining two or more methods such by hybridization method can further improve the forecasting accuracy. In this study, the hybrid between AI and SI methods has shown significant potential in improving the accuracy performance of load forecasting. The capability of the SI method in balancing exploration and exploitation helps to avoid the issues faced by the AI method. The hybrid of SVM and SI families has also shown able to perform better than the hybrid of ANN and SI.

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