Short term forecasting of electrical consumption using a neural network: joint approximate diagonal eigenvalue

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ABSTRACT

This article aims to estimate the load profiling of electricity that provides information on the electrical load demand. In achieving this research implemented the neural network algorithm of joint approximate diagonalisation of eigen-matrices (JADE) to describe the load profile pattern for each point. Nowadays, utility providers claim that natural sources are used to generate power by rising consumer demands for energy. However, occasionally utility workers need to know the demand at certain location, corresponding to maintenance issues or for any shutdown area involved. A distribution pattern based on the data can be predicted based on the incoming data profile without having detailed information of certain load bus, the concept of derivatives was relevant to forecast the types of distribution data. The model was constructed with load profile information based on three different locations, and the concept of derivative was recognized, including the type of incoming data. Historical data were captured from a selected location in Malaysia that was proposed to train the JADE algorithm from three different empirical distributions of consumers, recording every 15 minutes per day. The results were analyzed based on the error measurement and compared with the real specific load distribution feeder information of needed profiles.

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1. INTRODUCTION

Many countries are facing increasing electrical demands, given the ever-increasing consumption of consumers due to population growth. The consumption of energy may involve appliances such as air conditioning, refrigerators, freezers, and other electric appliances. According to [1], the author mentioned that the most affected area in the consumption of energy is via cold appliances such as fridge and freezers. In line with advancements in technology, consumers can access their hourly load usage in measuring the consumption of energy. Traditional meters record energy consumption regulated by interval periods that provide financial settlement between the consumer and utility provider and establishing load profiles. A typical load profile serves as a reference for distributors and suppliers supported by appropriate operating systems which provide detailed information about energy consumption at any location. Various typical load shapes used for commercial, industrial, and residential purposes and consumers can be obtained via segmentation analysis such as through clustering algorithms, which are predefined for each sector and associated billing information [2]. As discussed in [3], load consumption for different types of consumers was synthesised based on the weight of the load profiles.

Generally, several strategies, such as the restoration of coordination between the generation, transmission, and distribution of power, need to be considered to produce a better performance of the power system [4]. However, limited knowledge of power system restoration during operations is often affected by its underpinning procedures or strategies. The physical process surrounding the operation of the power system is capable of computing and communicating in real-time. However, this process requires high costs and needs to be adaptive to analyse the behaviour of the system. The easiest way to investigate consumer usage is based on load forecast information, as stated in [5] without any effect on seasonal and weather conditions. Statistical tools are often used to work with a database system representing one sample customer population to understand the behaviour surrounding energy consumption. The nature of a customer's energy profile depends on the building structure, area of the room, number of rooms, and the number of occupied floors.

Previous research has demonstrated the possible contribution from the application of using an artificial neural network (ANN) for electrical load forecasting. The input value of ANN of the anomalous behaviour as described in [6], explains the analysis and trend of entropy homologous period. Though, unexpected load fluctuation may occur during special holidays or in recording data. In addressing this issue, Chicco [7]-[8] have suggested the best approach is to minimise the correlate load forecast diversion. The paper proposed the historical data lines with Kohonen Self Organisation to prevent unsupervised classification data from forecasting demand data. The application of an ANN in electrical load forecasting presents a nontrivial task that requires correction analysis to be employed once the neural network has been trained. Traditional regressive analysis obtains the non-linear and non-stationary of load data variables. The artificial intelligence (AI) technique originated from traditional econometric approaches as argued in paper [9].

Accordingly, this paper investigates how Joint Approximate Diagonalisation of Eigen-Matrices (JADE) is used in load forecasting by analysing the incoming load profile without certain load bus information. The result from this research was tested based on a consultative approach and fitting the empirical distribution data using quantile statistical plots which estimated the relationship between the result and original distribution data. The method tests the distribution data based on the statistical value from the perspective that it will fit the reference line. If two distribution data are plotted approximately against and through the regression line, the similarity of both data will match each other. In this analysis, the aim was to estimate the relationship between two variables, namely the result and original distribution data. The remainder of this paper is structured as follows. Section 2 presents the application of the ANN in load data forecasting, followed by section 3 that describes the proposed approach using JADE models used in function approximation and quantile plotting analysis after the neural network was trained. The findings from the proposed methods are then discussed in section 4, with section 5 presenting a summary of concluding remarks.

2. RESEARCH METHOD

Electric load profiling provides consumers with information on the consumption of energy extracted from the energy market and provides many types of load shapes depending on the daily consumption that needs consequent segmentation for each group of classes. Methods to generalise segmentation, such as providing a load profile, are based on consumer billing information and the identified types of sectors such as residential and commercial. Aside from that, clustering algorithms can ensure that the homogeneous of group classes are different from each sector.

Electrical load forecasting can be categorised as short-term, medium-term and long-term load forecasts consisting of different active power loads based on specific hours, monthly, and yearly [10]. The uniqueness of this research is that the historical data of each load profile was unnecessary, and the novelty is implementation of JADE algorithm to electrical area. Function of the model was required to extract non-linear and multivariate data in the model to forecast an unknown profile which is further explained in the next section. Forecasting the load profile involves large data features which may require a learning process and the need to remove irrelevant data features. The embedded technique, wrapper technique and filtering technique, are among some of the methods used to pre-process the result, correct input variables, and remove or incorporate data in the training process [11].

Therefore, to support this critical area, cyber-physical intelligence systems are installed in special areas called intelligent supervisory control and data acquisition (SCADA), where it is flexible and decentralised within the power system [12]. If technologies, such as SCADA can support the power system such as via ambient intelligence, a variety of AI devices can be implemented by replacing the operator. This also helps to control power restoration and analysis. However, if the size of the system network increases, like installing a source of renewable energy in the power system [13], it will create a problem from a technical perspective.

By using an approximation domain, the function of neural network processing referred to as ANN can be employed as a multivariate model to integrate multiple inputs directly. ANN has the potential to read linear and non-linear actions based on historical data. Choosing the perfect historical data is important during the iteration process since it will minimise errors measures. In [14], author evaluate the performance of neuro fuzzy and non-linear auto-regressive by using mean absolute percentage error (MAPE) and root mean square deviation (RMSE) achieving the short term load forecast. Though, on the other hand, the power system has its own unique challenge in electricity areas. For example, the increase in electricity demand often makes the power system network difficult to control. Whereas the ANN will facilitate the power system network to enter a new stage through the introduction of new generation plants. By combining intelligent systems, such as advanced metering infrastructure (AMI) and cyber physical system (CPS), it will create a new generation tool [15] and help the SCADA system to function in an intelligent environment. The application of ANN in load forecasting requires historical data and represents an important mechanism to train the profile distribution data by minimising the deviation data, by whitening, and centralising. This process can be undertaken by regulating the network parameter and optimising the objective function of training methods. In [16], they elaborated more on the method to minimise load forecast deviations for a certain period. Figure 1 illustrates the ANN circulated from various nodes related to this research, with several hidden neurons to relate three-element output. Referring to the nine independent elements from the input layer (number 1 to 9) that are absorbed into the function of weighted and output neuron (alphabet A to C) depends on the type of load forecast. Here, [17] and [18] stated that the deviation error from the real and estimated value could be minimised by adjusting the historical data (1-9) of the network parameter. Additionally, the training method, such as Levenberg can be used to converge the method. With mysterious of hidden information, the output can be predicted.

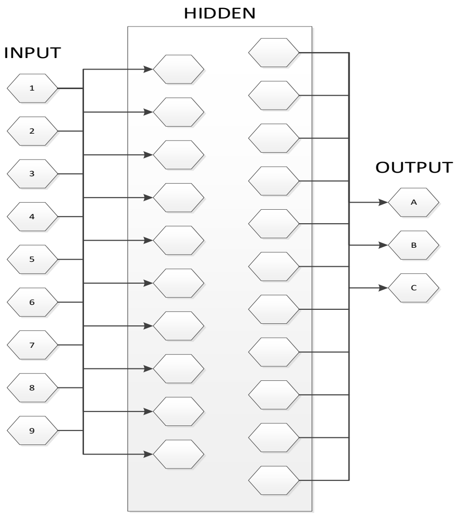

Figure 1. Circular nodes represented in an artificial neural network (ANN)

3. METHOD

3.1. Consideration of electrical load composition of this research

Load profiles serve as a reference for distributors and suppliers and refer to the details concerning the consumption of energy at any location. The load profiles gained from traditional meters record the total energy consumption through different interval periods. This section explains the electricity area involved in this research. In terms of residential consumption, it represents a relatively low voltage of consumer electricity usage used in forecasting issues [5]. In this paper, the effect of load profile knowledge was investigated, which is simple information in the investigation of load forecasts.

Consumption data were used in this study collected from low voltage consumers with an interval period of 15 minutes. Nine consumer locations were selected as the original preferred data leading to an accumulated load diagram, shown in Figure 2. The data logger located in three feeders marked as dotted red and this historical data represented as mixed-signal data represented in Figure 3. This data was considered as an input to JADE algorithm. The patterns in Figure 3 composited at the incoming feeder appears like a commercial pattern only, even though it is not. The main objective of this research is to forecast end consumer profile data with limited information by using the JADE algorithm.

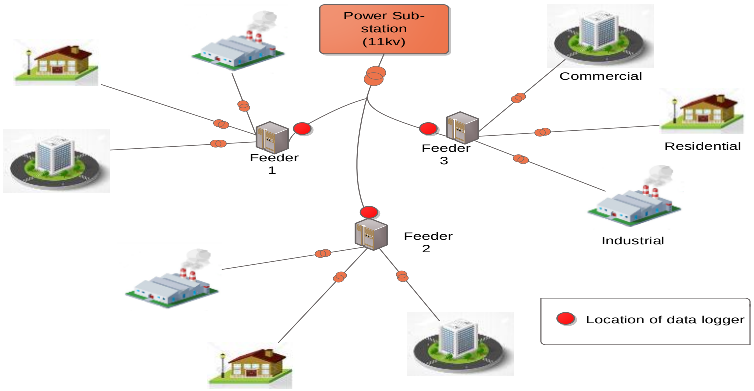

Figure 2. Layout of the three incoming feeders

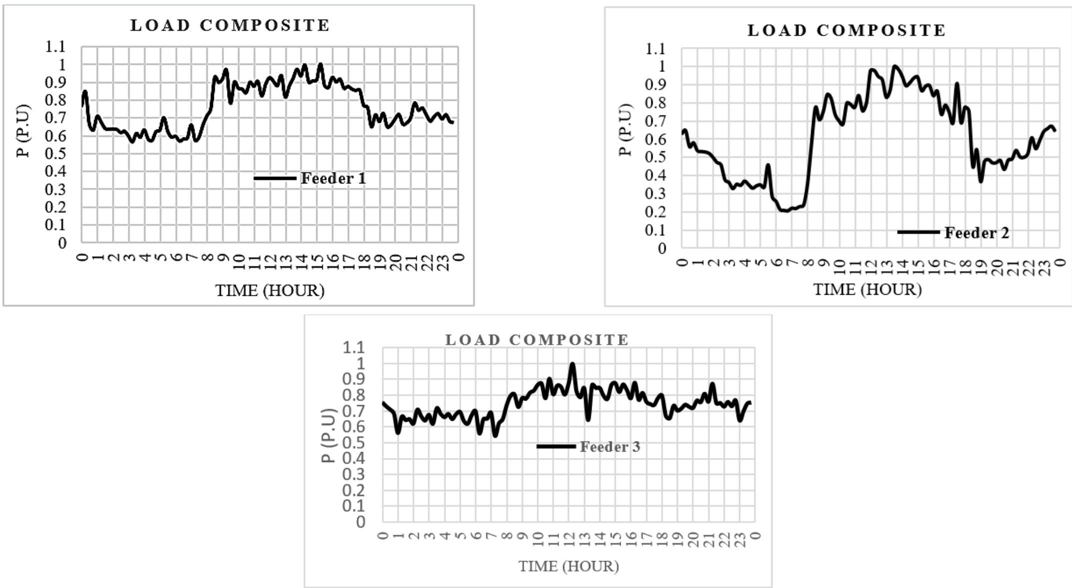

Figure 3. Input consumption of Feeders 1, 2 and 3 in the distribution network

3.2. Joint approximate diagonal eigenvalue (JADE)

The ANN is typically 59iagonaliz and found in the human brain, handwriting recognition, medical diagnosis, and human fashion. The ANN was initially inspired by a computation model incorporating an algorithm having the ability to improvise from complex data in determining the required pattern of the data from critical measured data. The ANN can also analyse and work with valuable data and classify them into an expected output having limited knowledge of the data. JADE is one of the neural networks that consequently makes sense of the required objective of this research. Mostly previous research implementing JADE algorithm to estimate source of speech signals in noise of environment. In this research, it was used to identify types of electricity consumption of each load.

JADE implements the fourth-order cumulant matrices to observe an expected value from the mixtures [19] representing the estimated raw matrix, where S can be estimated from the mixing matrix A, and where it is implemented in the time-series load flow situation. This estimated raw data needs to be whitened, based on the columns of orthogonal with variance. Moreover, this whitening makes the diagonal matrix remain at the required matrix following the second stage, which is transformed on the proposed algorithm. The whitening process recovered the source signal in this study by making the second-order decorrelation and rotating matrix data [20]. This step was enhanced from the performance of Blind Source Separation (BSS) algorithms provided in this research.

Next, to explain how the JADE algorithm functions in separating the mixed data profiles, reference is made to Figure 4. Here, the mixing matrix A, is the inverse proportion to a demixing matrix, W. As explained in [19], the mixing matrix, A is Xrc × S^{-1} is used to estimate the value of raw matrix S. A matrix of W then needs to be calculated. The formula for estimating the original raw data S, is shown in (1).

$$S = X \times W^T \quad (1)$$

Next, the data needs to be whitened using P_W, the column of orthogonal with variance, as stated in [19]. In this paper, the mixing data $X_{rc,}$ was transformed through Principle Component Analysis, (PCA) by rotating the P_W explained in previous research [21]. The vectors were 60iagonalized when studying $P_{W,}$ in which and it became statistically independent. The P_W was then rotated using cumulants computation and PCA loadings so that the column vectors could be independent, called higher-order statistics. In this study, the higher-order statistics known as fourth-order cumulants (kurtosis) of equal variances in P_W was calculated [19]. The equation of kurtosis is shown in (2):

$$k = EX^4 - 3 \times E^{(2)}X^2 = M_i \quad (2)$$

where k is the kurtosis of real random variable for X value and E is number of order comulants.

The fourth-order cumulants is then transferred into n (n + 1) / 2 orthogonal eigenmatrices, M_i. In order to 60iagonal fourth-order cumulants, the M_i* is transformed from M_i which is called orthogonal diagonal eigenmatrices. A diagonal constraint was provided to avoid an imbalance in the solution, as stated in [22]. After pre-processing, the whitened matrix will 60iagonalized fourth-order cumulants rotated the process to decomposed and reshaping eigenmatrix until independent vector were produce unmixing matrix of W, given by $W_{(r\times n)} = B^T V^T$, where B is whitened matrix. Finally, the estimated profile data, S is observed based on (1). This JADE algorithm is simulated using MATLAB software and the details presented in Figure 4. The uniqueness of this research is by implementing the cumulants of the JADE algorithm into the electrical engineering sector predicting some of load profiles shape by using mixed data from incoming feeder.

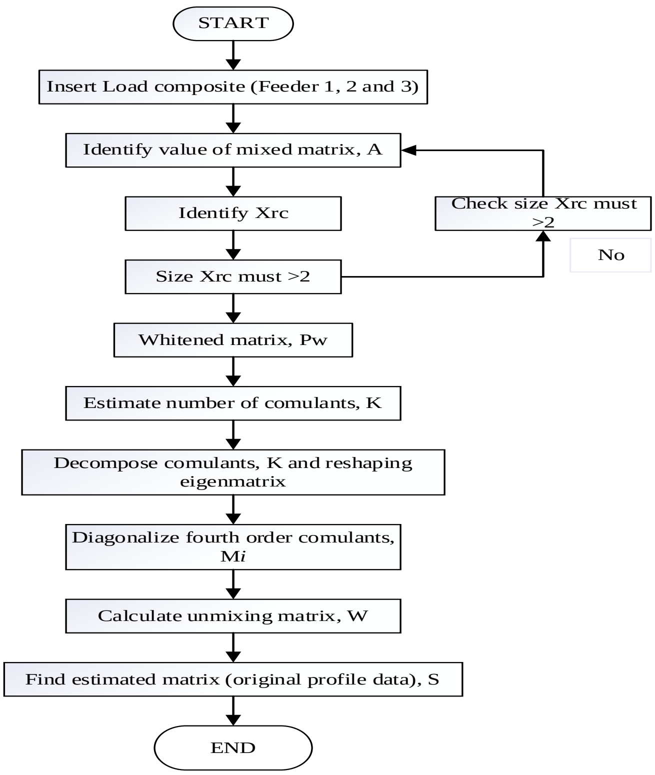

Figure 4. Process of separating mixed profile data

3.3. Linear regression diagnostic measure

Bestfit, Arena Input Analyser, and Expertfit are test software products which are available, with the ability to perform fit distribution function data sets [23]. However, there are several advantages and disadvantages to using such software. The popular diagnostic tool, quantile statistic plots, can be used to estimate the ordinary regression error from linear deviance models. The quantile statistic plot is a graphical technique that requires at least two probability distributions by plotting their quantiles against each other. The technique is used to plot the quantiles of the first data against the quantiles of the second distributed data. Quantile statistic plots tend to be convenient than probability plots for graphical estimation [24]. Nevertheless, probability plots are more convenient for probabilities estimation. Quantile statistic plots were implemented in this study to identify the results from the same distribution family. In [25] develop the linear regression model from previous data mining to predict the electrical price by using Support Vector Machine (SVM). It is observed efficient method and benefit to energy management center.

The following image is an example of a graphical technique of the steps incorporated using the quantile statistic method of two samples. The straight line represents the reference line (also called a regression line) of the quantile plot. If the data fell near the straight line, it is reasonable to assume that the samples came from the same distribution family. As a result, data analysis would become much easier if applying a graphical method compared to a numerical summary. As an example, the data coming from a similar group distribution were tested. In Figure 5, X and Y quantiles are plotted in the vertical and horizontal axis for data set 1, represented as original data, Z_1 and estimated data, Z'_1 respectively. From this quantile statistic, graphically, there is evidence of estimated signals from a similar distribution group of original signals since the collection points in Figure 5 lie roughly on the straight line.

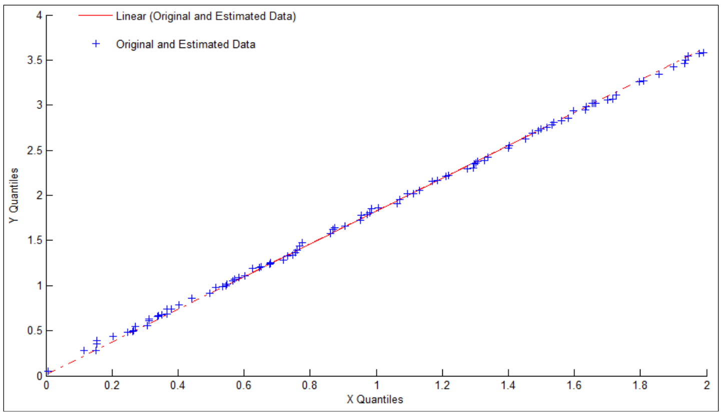

Figure 5. Quantile plot for sample data Z_1

3.4. Performance indices: error measures

This research measures maximum error, maximum absolute error (MAE), mean absolute percentage error (MAPE), coefficient of determination (R^2) R^2) and correlation coefficient (R) to analyze the result of determination. The basic equation for percentage error is shown in (3).

$$Percentage\_Error = \frac{|Measure - Actual\_Value|}{Actua\_Value} \times 100\% \qquad (3)$$

Meanwhile, the performance of the estimations follows MAE and MAPE criteria below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - E_i| \qquad (4)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - E_i}{O_i}\right| \qquad (5)$$

Coefficient of determination is measuring the percentage of total variation between two variables. The equation to calculate coefficient of determination is defined in equation (6). If coefficient of determination is large, indicates that it can be explained by linear relationship between two variables when the variables is separated by JADE. The range for coefficient of determination is $0 \leq R^2 \leq 1$. The coefficient of determinant and correlation coefficient formula are [21],

$$R^2 = \frac{SS_{reg}}{SStot} = \frac{\in(\tilde{y}_1 - \bar{y})^2}{\in(y_i - \bar{y})^2} \quad (6)$$

$$R = \sqrt{\frac{\in(\tilde{y}_1 - \bar{y})^2}{\in(y_i - \bar{y})^2}} \quad (7)$$

where:
O_i = Original data
E_i = Estimated data
n = Number of iterations, n = 1, …, i
SS_{reg} = Regression sum of square
SS_{tot} = Total sum of square
$\widetilde{y_i}$ = Estimated JADE result
y_i = Original data profile
$\bar{y}$ = Average for original data profile

The correlation coefficient can truly measure the strength and linear relationship between two variables. If the value of correlation coefficient is close to value 1, it is implying that the two variables belong to the same source. Range for value R is $-1 \leq R \leq +1$. Negative sign represents negative linear correlations and positive sign represent as positive linear correlations. If the value of R is zero illustrate that there is no linear correlation or weak linear correlation. Meanwhile, if all the data points are lie on the straight line, the product of determination has perfect correlation coefficient. The relationship between two variables is strong if the correlation coefficient is greater than 0.8. However, it is become weak if correlation is less then 0.5.

4. RESULT AND DISCUSSION

This section presents the result of the load profiles separating the incoming profiles using the JADE algorithm and analysis based on error measures, regression fitting data, and quantile analysis. The methodology was successfully constructed and was analysed concerning the regression line and R-square. An incoming load profile distributed to three feeders was employed in this method. Figure 6 represents the chronological load curves estimation of three load profiles once filtered using the JADE algorithm. The result is then compared to the original profile data. The statistical analysis in Figure 7 aims to check the result of the validity regarding the pattern based on the graphical method. It demonstrates the comparison between the estimated result using the JADE algorithm and the original load profiles for three types of load shapes, namely commercial, industrial, and residential profile data, respectively.

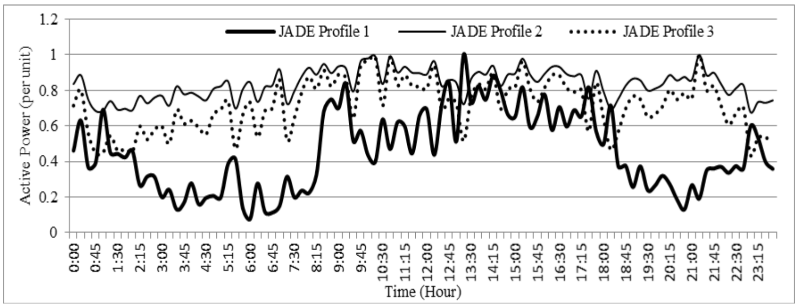

Figure 6. Output data of load profile estimation using Joint Approximate Diagonal Eigenvector (JADE)

Table 1 shows the error measures between the original and estimated load profiles, and elaborates on the JADE algorithm, which heightened the accuracy of the maximum absolute error, MAE, and maximum absolute percentage error, MAPE in favour of load commercial num. 3, industrial num. 1 and residential num. 3 which are 68.448, 7.186 and 40.381, respectively. The statistical data analysis calculated in Table 2 shows that the correlation coefficient, R of the linear regression for the commercial load profile is reached close to 1, indicating that the estimated and original load profile match them having high accuracy. Table 2 represents value of correlation coefficient of commercial 3, industrial 1 and residential 3 were 0.8872, 0.8180 and 0.4923, respectively. This can be concluded that the better correlation coefficient approach 0.8 is commercial load num. 3 and industrial load num. 1. Based on these error measures and linear diagnostic measures, the best JADE result is near perfect to the profiles of commercial num. 3 and industrial num. 1 according to the regression lines and chi-square of quantile analysis since the points on the quantile plots fall approximately on the regression line. Figure 7 also represents linear regression diagnostic measures of the best load profiles.

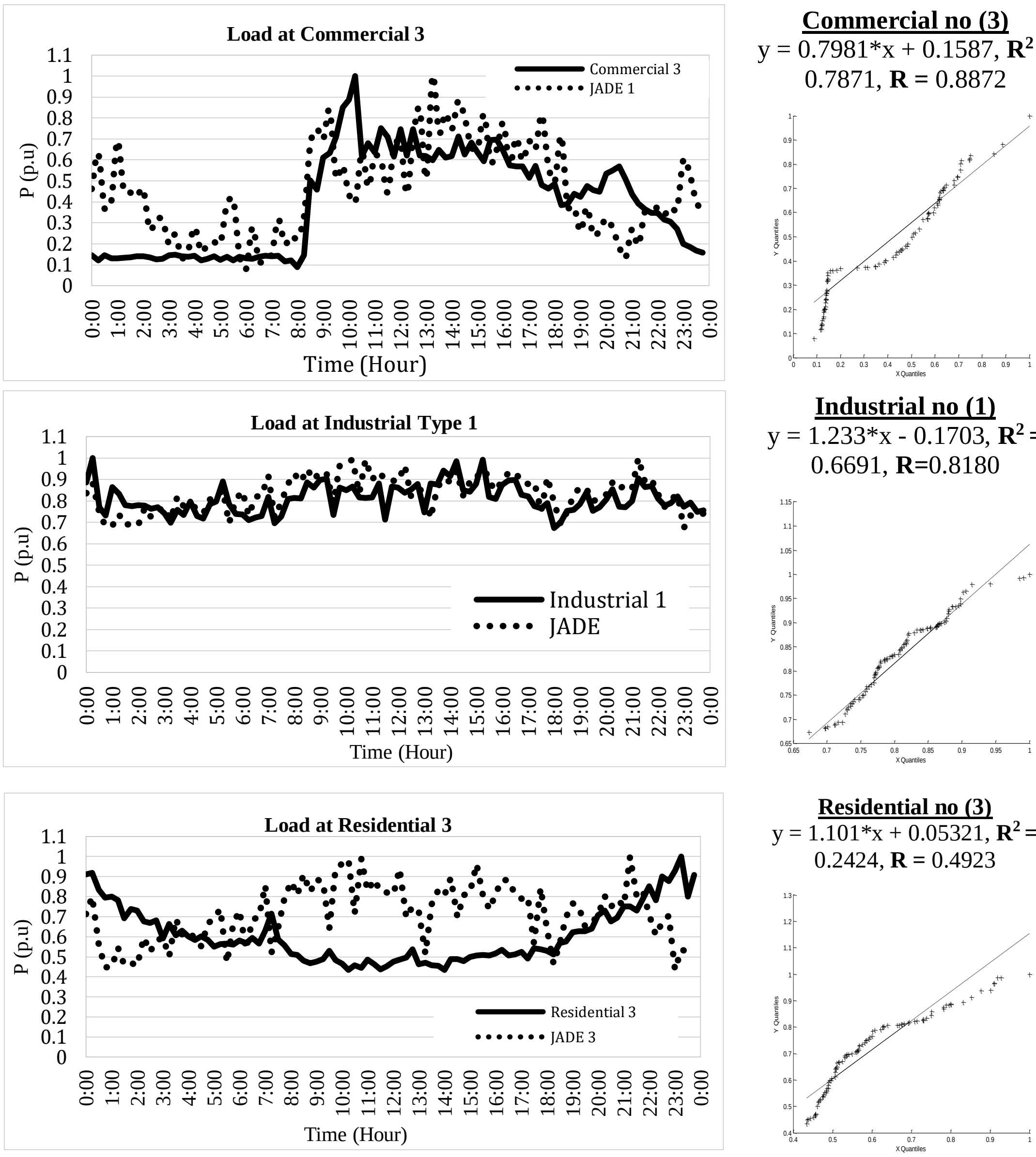

Figure 7. Comparison of the result of the JADE algorithm profile num. 1 and the original profiles of commercial 1, 2 and 3

Table 1. Error calculation between the estimation and actual profiles in the DC power flow dow distribution system using JADE

Load classifications	Collection point	Maximum Error	MAE	MAPE
Commercial	(1)	0.5653	0.1837	76.610
	(2)	0.5825	0.1825	86.086
	(3)	0.5998	0.1661	68.448
Industrial	(1)	0.1869	0.0577	7.186
	(2)	0.7365	0.2688	70.151
	(3)	0.2188	0.0990	13.808
Residential	(1)	0.7144	0.2805	68.026
	(2)	0.5877	0.2328	42.543
	(3)	0.5514	0.2230	40.381

Table 2. Error calculations between the estimation and actual profiles in the DC power flow distribution system using JADE

Load classifications	Collection point	Reg Line
Commercial	(1)	y = 0.5035*x + 0.2122 **R^2 =** 0.6491 **R =** 0.8057
	(2)	y = 0.52*x + 0.216 **R^2 =** 0.6478 **R =** 0.8049
	(3)	y = 0.7981*x + 0.1587 **R^2 =** 0.7871 **<u>R = 0.8872</u>**
Industrial	(1)	y = 1.233*x - 0.1703 **R^2 =** 0.6691 **<u>R = 0.8180</u>**
	(2)	y = 0.3742*x + 0.5779 **R^2 =** 0.0207 **R =** 0.1439
	(3)	y = 1.194*x - 0.052 **R^2 =** 0.5676 **R =** 0.7534
Residential	(1)	y = 0.7839*x + 0.3068 **R^2 =** 0.2025 **R =** 0.4500
	(2)	y = 1.069*x + 0.0771 **R^2 =** 0.2181 **R =** 0.4670
	(3)	y = 1.101*x + 0.05321 **R^2 =** 0.2424 **<u>R = 0.4923</u>**

5. CONCLUSION

The findings reported that JADE algorithm has the potential to be utilised as a neural network and tool that can be implemented into electrical engineering in determining load profile information for forecasting and in guiding future electricity demands. The results of this study revealed that the MAPE of load commercial 3, industrial 1, and residential 3 were better MAPE compared to original approaches. Besides, the linear diagnostic measures are illustrated similar results. From this perspective, it demonstrated that the neural network could be optimised by utilising the method of predicting the network profiles in the short term. The relative JADE gradient algorithm was shown to be suitable for forecasting the load data matrix based on limited information regarding the profiles. On the other hand, the JADE algorithm was able to forecast the end profile consumer using limited knowledge of the mixed electrical profile data. This will help planning department identify types of end user profile data. The regression fitting of the quantile plot demonstrates the better performance of approximate joint diagonalisation compared to the original data profile data taken from the selected location. With limited knowledge of the network, the joint approximate algorithm was adopted in forecasting the pattern types of the distribution data from the needed location since regression fitting, chi-square, and quantile plots achieved their required grade tested, where the points mostly fell on the line. As such, the relative method has confirmed in determining the end load profile since the method was efficient even in robust data conditions. In conclusion, the proposed model can be considered with regards to forecasting electric demand tools. However, the algorithm needs to be improved since the error on the residential data is high. Future development, this method will help electrical utility companies reduce the labour and equipment costs such as data allocate the loggers to certain location to identify the end profile data composition.

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