Very Short Term Load Forecasting Based On Meteorological With Modeling k-NN-Feed Forward Neural Network

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This paper proposes a novel methodology for very short term load forecasting of hourly. The proposed methodology is based on meteorology data i.e. temperature, humidity, especially for optimizing the operation of power generating electricity from thermal unit generation. This modelling methodology is a combination of k-nearest neighbor (k-NN) method and feed forward-Neural Network (Feed-Forward-NN) method. The k-NN-Feed-Forward NN model is designed to prediction load for 1 hour ahead based on meteorology data for the target Thermal Unit Generation which position adjacent by twelve hydro thermal unit generation. The novelty of this model is taking into account the meteorology data. A set of load measurement samples was available from the hydro thermal unit generation in Indonesia Region 4 which is used as test data. The first model implements k-NN as a input data preprocessing technique prior to feed forward NN model. The error statistical indicators of k-NN-Feed-Forward-NN method The mean absolute deviation error statistical indicators of k-NN model is 103.48 MW and MAPE is 18.8%. On the other hand, the error statistical indicator for proposed model (Euclidean k-NN-feed forward-NN model) MAD is 19.37 MW and MAPE is 2.21%. Note that the highest mean absolute deviation (MAD) was 75,11 MW and mean absolute percentage error (MAPE) was 10.38% during the twelve period. The models forecasts are then compared to measured data and simulation results indicate that the k-NN-Feed Forward NN-based method presented in this research can calculate hourly load with satisfactory accuracy.

Keywords: Load; Forecasting; Hydro thermal generation; k-NN-Feed Forward-NN; very short term, meteorology, modelling

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1. Introduction

This research presents a section of a research in progress seeking or 1 hours ahead load. This section focuses on how to very short-term load forecast hourly for the target thermal generation using the availability of a local database hydro thermal generation and based on meteorology data. In this research, a novel methodology that combines k-nearest neighbor (k-NN) modelling and Feed Forward neural network (ANN) modelling has been developed for load forecasting. k-NN-Feed Forward NN modelling is used to load forecasting at the target thermal generation by means of calculating distance (value k) based on Euclidean and then do the testing and training data using ANN modelling. It also functions to optimize power delivery and unit commitment and by extension, it helps minimize the operating costs of power systems [1]. The performance of thermal generation systems is heavily influenced by meteorological conditions such us load, fuel, temperature, and humidity [2]. With a load forecast, it is expected that lant operation control systems can be improved, so as to balance power generation and load. Moreover, transmission and distribution load, electric energy storage, reliability and stabillity, planning operation system and energy supply will be maximized and more reliable. The relation is clear: electrical energy generated by the thermal depends on the amount of the load received by the steam and gas (combined cycle) generation. The result production steam and gas

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generation system depending on metheorology, time, load customers and geographic location. Previous research have presented a variety of mathematical method for load forecasting in relation to meteorological variables. Dunnan, et al. [3] presented A distributed short term load centralized forecasting method is difficult to accurately follow load variation and local weather information diversity throughout the region in a bulk power system that covers a large geographical area. Yi Wang, et al. [4] have presented the prevalence of smart meters, fine grained sub profiles reveal more about the aggregated load and further help improve the forecasting accuracy, an optimal weighted ensemble approach is employed to combine these forecast and provide the final forecasting result. Adopt for prediction a semi-parametric approach based on additive models. The automatic procedure for explanatory variable selection in an additive model and show how to correct middle term forecasting errors for short term forecasting, has been described in [5]. Vincent T, et al. [5] worked on electricity forecasting using multi stage estimator of nonlinear additive models. A fuzzy polynomial regression method with data selection based on Mahalanobis distance incorporating a dominant weather feature for holiday load forecasting, has been described in [6]. Young-Min Wi, et al. [6] presented holiday load forecasting using Fuzzy based on weather features and loads from season to season. Mingxi Liu, et al. [7] presented load forecasting and operation strategy electrical power system using forecasted loads, where for operation strategy designed to collect users' load information is one of variable to determine the energy input to the system and power flow inside the system. The classical forecasting approach to long term load prediction is often limited to the use of load and weather information ocurring with monthly or annual frequency, where the two variables are the main input variables as described in reference [8]. Tao Hong et al. [8] worked on the long term probabilistic load forecasting and normalization with hourly information. The load forecasting is not only used in stochastic modelling, but in other studies [9,10] attemped forecasting was analyzed using Artificial Neural Network method and probabilistic load forecasting using regression model. Kitipong et al. [9] studied the short term load forecasting based on weather forecast using multistage Artificial Neural Network. And Bidong Liu at al. [10], have presented probabilistic load forecasting combination using regression averaging. Combining a forecasting model with load is important to get a more better result, and load forecasting by the deviation analysis, Semi-Parametric Additive Model, and wavelet decomposition Neural Network model, has been described in [11-13].
Short Term load forecasting with secondary forecasting based on deviation analysis by Yang Wang et al. [11]. Shu Fan and Rob J. Hyndman [12] have presented the short term load forecasting based on a Semi parametric Additive Model. Bowen Li et al. [13], have presented the short term load forecasting method based on wavelet decomposition with second order gray artificial neural network model which combine with ADF test. Load prediction is an important problem for reliable power system operation, and also significantly affects markets and their participants, where the data in the form of time series can also be analyzed using wavelet neural networks as described in reference [14]. Ying chen et al. [14] worked on the prediction of short term load forecasting: similar day based wavelet artificial neural networks using despite of its "noisy" nature, high frequency load is well forecasting by including precipitation and high frequency component of similar day load as inputs variabel. The load forecasting is an very important role in modern smart grids, and prediction load based on resident behaviour learning and modified general regression neural network, in other studies [15,16]. Kenji Nose et al. [15] worked on short term multinodal load prediction deals with the loads of several interest nodes in an electrical network system and the load forecasting, a modified general regression artificial neural network and a procedure to automatically reduce the number of inputs of the neural network. Weicong Kong et al. [16] have presented load forecasting for short term residential based on resident behaviour learning.

Load prediction is an main problem in reliability electrical power system, where the data load in the form of the time series can also be analyzed using temperature scenario generation as described in reference [17]. Jingrui X and Tao Hong [17] have presented about the various approaches to generating probabilistic load forecasts, feeding simulated weather scenarios to a point load prediction model is being commonly accepted by the industry for its simplicity and interpretability. The efforts involved in improving the system level intraday load prediction by applying clustering to identify goups of customers with similar load consumption patterns from smart meters prior to performing load forecasting as described in reference [18]. Franklin L. Q et al. [18] worked on the efforts involved in utilizing the AMI data to improve the load prediction accuracy at the system level. Short term load forecasting is not oly using classical method, where the fisher information based meteorological factors are the main input variables as described in reference [19]. Shuping Cai et al. [19] have presented about the weather information is an main important factor in short term load forecasting, and this paper is to develop a novel methodology based on fisher information for meteorological factors and variables introduction and variable selection in short term load forecasting. The remainder of the paper is organized as follows: The modelling and data from hydro thermal generation systems describes in the section 2, section 3 presents the methodology used, i.e. k-nearest neighbor (k-NN) model and artificial neural network model, while for section 4 describes study cases of the modelling method in very short-term load forecasting and measured error. And finally, section 5 describes some concluding remarks.

2. Notation

The notation used throughout the paper is stated below.

Indexes:

K	The Kernel function
k	The length of data sets
i	The number of element
w	weighted k-nearest neighbor
Lg_{norm}	the normalized load generation
Lg_o	is minimum load generation
Lg	is the load generation

Constans:

$d(x, y)$	The forecasting (outcome) of the distance using distance
x_i, y_i	The i-th matrix corresponding scenarios composed
$W(x_i, y_i)$	Set of weight
$ds_j^k(x_i, y_i)$	is the load generation between the query point x ad the i-th case yi of the example simple
y_{ij}^k	the position hydro thermal generation
x_i^k	the d-dimensional feature vectors

3. Problem formulation

3.1. Data Collection

The load measurements were performed continuously every 1 hours in twelve hours. The dataset contains twelve hours of data (from 07:00 a.m. to 18.00 p.m) on 23 February 2018 at twelve locations of hydro-thermal generation system: Hydro Generation H1 (272°, 135km), Hydro Generation H2 (146°, 266 km), Hydro Generation H3 (186°, 260 km), Hydro Generation H4 (178°, 262 km), Hydro Generation H5 (194°, 248 km), Hydro Generation H6 (138°, 256 km), Hydro Generation H7 (124°, 251 km), Hydro Generation H8 (119°, 249 km), Hydro Generation H9 (195°, 236km), Thermal Generation T1 (171°, 307 km), Thermal Generation T2 (100°, 147 km), Thermal Generation T3 (0°, 0 km), located generation in Java, Indonesia. For this research, the very short-term forecasting for hydro thermal generation was only provided by thermal generation in generation T2 which position adjacent with another hydro thermal generation. The nearest neighbouring locations surrounding generation T2 were generation H1 , generation H2, generation H3, generation H4, generation H5, generation H6, generation H7, generation H8, generation H9, generation T1, and generation T3, can see in figure 1. These monitored data have been used to validate the methodology modelling using Euclidean k-NN-Feed Forward Neural Network as the proposed method for load generation forecasting.

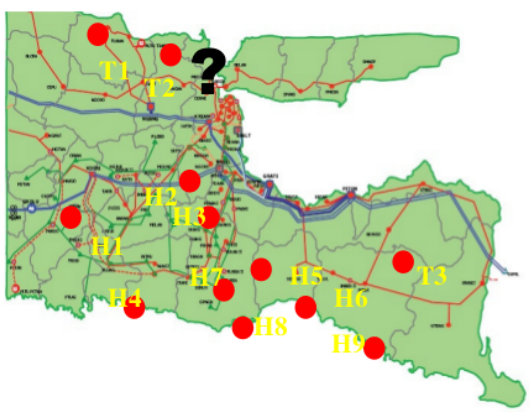


Figure 1. Modelling generation T2 which is nearest neighbor by eleven other hydro thermal generation

3.2. The Methodology

To understand the basic idea have been explain this section. The developed methodology for very short term load forecasting, namely k-NN-Feed Forward Neural Network model. In this research, the subject is the thermal generation T2, of which it is nearest neighbor by several other hydro thermal generation. The first purpose in this research is the improvement of forecasting results using k-nearest neighbor (k-NN) method which hybrid with a model of Artificial Intellegence, namely Feed Forward Artificial Neural Network (ANN) method, and the process is then used to very short term forecast load output of a thermal generation one hour or sixty minute ahead based on meteorology data. For the load forecasting, namely k-NN- Feed Forward NN model employes past meteorological data (load, temperature, and humidity). The predict horizon is eleven hours in 1-hour increments. The training of the artificial neural network can be programmed in eleven hours after the recording of the initial measurements and redone periodically during the installation's life-time as explained in the continue section.

3.2.1. k-Nearest Neighbor (k-NN) Method

The k-nearest neighbors algorithm is a non-parametric method used for classification and regression. The k-NN forecast is computed using the features assembled in the matrices in a two-steps process. In the first step, we compute calculating the pre-defined distance between the variables for the new dataset (the optimization or the testing and training sets model) and the features in the historical dataset. For a given set of features $S=\{p^1, p^2, \ldots, p^n\}$ in the new dataset with lengths $N_1, N_2, N_3, \ldots N_n$, the distances to the historical data are computed. In the second step, choosing k- nearest neighbors who owes k smallest distances from training test [20]. Let D be a collection of n class-known data tuples $\{d_1, d_2, \ldots, d_N\}$. $d_i \in D$ could be a document represented in a form of space vector $d_i = \{w_1, w_2, w_3, \ldots, w_i\}$, where w_i could be the normalization weighting representation. To find the K-Nearest Neighbors based on the Euclidean Distance, this equation is used:

$$d(x,y) = \frac{1}{K}\sum_{i=1}^{k} w_i^2 (x_i - y_i)^2 \qquad i=1, 2, 3, \ldots \qquad (1)$$

Where x_i, y_i is the i-th matrix contains the corresponding scenarios composed of N feature i for the historical dataset, such that for x, y is $x = \{x_1, x_2, x_3, \ldots, x_i\}$, and $y = \{y_1, y_2, y_3, \ldots, y_i\}$ and $d(x,y)$ is the forecasting (outcome) of the distance between two scenarios using some distance. And the weighted k-nearest neighbor is w. The distance is sorted in ascending order, and the first i elements $Ds(D_{s1} \leq D_{s2} \leq D_{s3}, \ldots, D_{si})$ and their associated i time stamps $\{\tau_1, \tau_2, \tau_3, \ldots, \tau_i\}$

3.2.2. k-Nearest Neighbor modelling

k-NN load forecasting are based on a voting scheme in which the winner is used to label the query. To explain the k-NN model forecast using the algorithm described above, several parameters need to be specified. The procedure of k-NN load forecasting for regression is as follows:

1) Choose the concrete similarity measure and create a similarity matrix from the given training dataset load hydro thermal generation
2) Set to effectively produce the prediction load generation
3) Form d-dimensional feature vectors D or y from the historical data x: $x= [x_1, x_2, x_3, \ldots, x_i]$ and $y = [y_1, y_2, y_3, \ldots, y_i]$; Their corresponding successors are denoted as x^h. They are given two pieces point x and y in space vector of n-dimensional x $(x_1, x_2, x_3, \ldots, x_n)$. This can be achived by introducing a set of weights W, one for each nearest neighbor, defined by the relative closeness of each neighbor with respect to the query point. Thus:

$$W(x_i, y_i) = \frac{\exp\left(-ds_j^k(x_i, y_i)\right)}{\sum_{i=1}^{k}\exp\left(-ds_j^k(x_i, y_i)\right)} = \frac{1/d_i^2}{sumd} x W(x_n, y_n) \qquad \ldots\ldots\ldots\ldots(2)$$

$$ds_j^k(x_i, y_i) = \sqrt{\sum_{p=1}^{n}\left(x_i^k - y_{ij}^k\right)} \quad p = 1, 2, 3, \ldots, n \qquad \ldots\ldots\ldots(3)$$

Where $ds_j^k(x_i, y_i)$ is the load generation between the query point x and the i-th case yi of the example simple, y_{ij}^k is the position hydro thermal generation and x_i^k is the d-dimensional feature vectors

4) Sort $ds_j^k(x_i, y_i)$ in ascending order and select the first K entries as the target nearest neighbors

5) Form a Kernel function: $k_i = {}^{1}\!/\!{}_{dis(i)}$ i = 1, 2, 3, ...(4)

as weighted averaging factor for k-NN aggregation.
k_i is the numbers of the nearest neighbor

3.3. Feed Forward Neural Network Method

Artificial Neural Network (ANN) is a combination of the training data data set consists of N training patterns recognition $\{(x_n, y_n)\}$, where n is the pattern value and ANN is consists of an interconnected group of neurons, and it processes information using a connectionist approach to computation. The input vector x_n and desired output vector y_n have dimensions *K* and *N*, respectively; o_n is the network output vector for the *n*th pattern. The neurons have five basic components, i.e. input, weight-bias, threshold, summing junction and output, can see figure 2. Illustrated architecture feed forward NN.

The proposed model in the research is used to forecast the load generation value for the next hours or sixty minutes ahead, prediction based on meteorology data and the load generation value data from other hydro thermal generation.

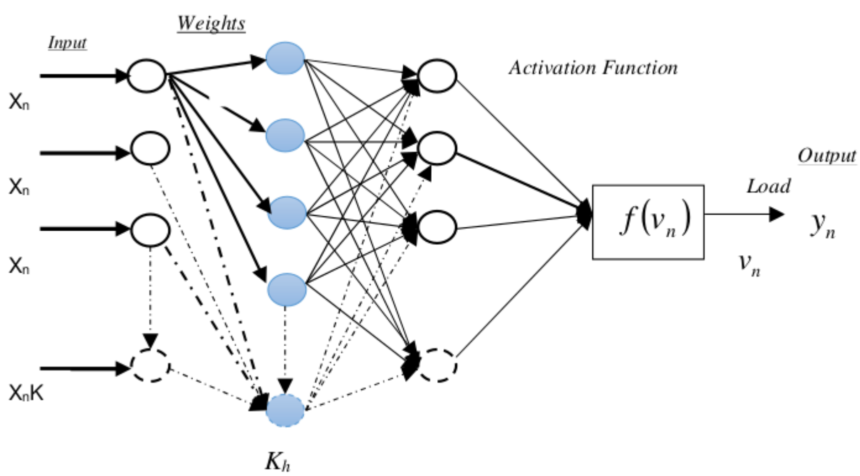


Figure 2. Basic structure architecture feed-forward neural network

For used the feed-forward artificial neural network modelling can be divided into three stages: (1) the design model and input data pattern stage which includes the choice of the ANN type, the number of its layers, the number of neurons in each layer; (2) The choice of training data and testing data in which samples based on meteorology data are presented to the feed-forward neural network and the weights are adjusted accordingly till a predetermined condition is satisfied; (3) the validation result test passed stage, in which the obtained feed-forward neural network forecasting model is tested using measurement data at hydro thermal generation. For prediction, the load generation data are normalized to the range of [0,1], to avoid neuron saturation during learning process. The neurons number of the first hidden layer 16 and we have to consider feed-forward neural network with 264 inputs load generation data for forecasting.

In the first case, ANN will learn about the load generation of the pivot location. The k-NN-feed forward NN model will be able to give the result of load forecast at the target thermal generation with fuel oil (HSD) based on meteorology data. When compared to actual data, feed-forward NN also presents the whole load values for eleven-hour window, and giving feed-forward neural network the possibility to learn the existing relationship in between them and to construct an idea about load evolution during the time window. In the second case, the entire load generation data are used for very short term forecasting using k-NN-feed-forward neural network model based on meteorological data at the target thermal generation, which position is neighbouring by eleven other hydro thermal generation stations. The research with proposed k-NN-feed forward neural Network model has to predict load generation values for the next hour or one hours ahead by taking into account the forecasting data based on meteorology data.

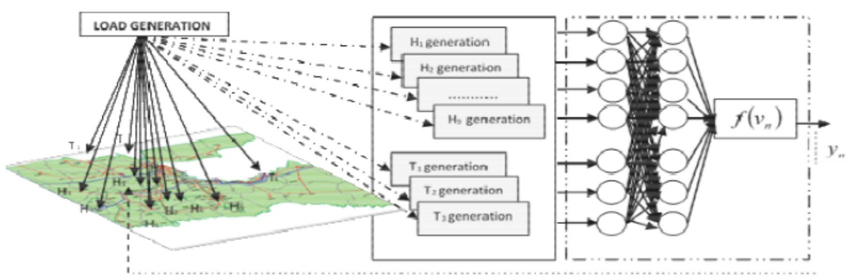


Figure 3. The proposed load generation forecasting model using k-NN-feed forward Neural Network

The special feature of this model is that measured data and hourly weather meteorology data (load generation, humidity, temperature, and fuel generation) forecasts for the adjacent eleven surrounding hydro thermal generation are used as input infoormation, as can see by Figure 3. To hybrid model the existing relationship between k-NN, feed-forward model forecasting and the real values of load generation at the target location, an feed-forward NN based model is used. The training of the feed-forward NN can be programmed in one hours ahead after the recording of initial measurements.

3.4. Hybrid Model Implementation

The well-known k-NN feed-forward NN is used for developing a suitable very short-term load generation forecasting based on meteorology model of one hour ahead. The used k-NN feed-forward NN consist of one input layer and one output layer. The input layer accepts as parameters the mean hourly load generation, the mean hourly temperature, the mean hourly humidity, and the mean fuel hydro thermal generation, while the output layer gives as parameter 60 minutes of load generation at the next hours. For the procedure of k-NN-feed forward NN hybrid model for load generation forecasting based on meteorology data, as can see Fig. 4. It has been verified that input data normalization with certain criteria, prior to a training process, is crucial in obtaining, good results as well as to fasten significantly the feedforward NN calculations. In this study for analysis, it needs normalization data for training and testing process the load generation forecasting 1 hours minutes ahead, as defined [20], which can be calculated by Equation 5.

$$Lg_{norm} = {Lg}/{Lg_0} \qquad \text{.................................(5)}$$

where Lg is the load generation, Lg_{norm} is the normalized load generation and Lg_o is minimum load generation. Normalizing the hourly twelve values of the load thermal generation , according to equation (5), can thermal generate some problems which occur generally for the twelve values.

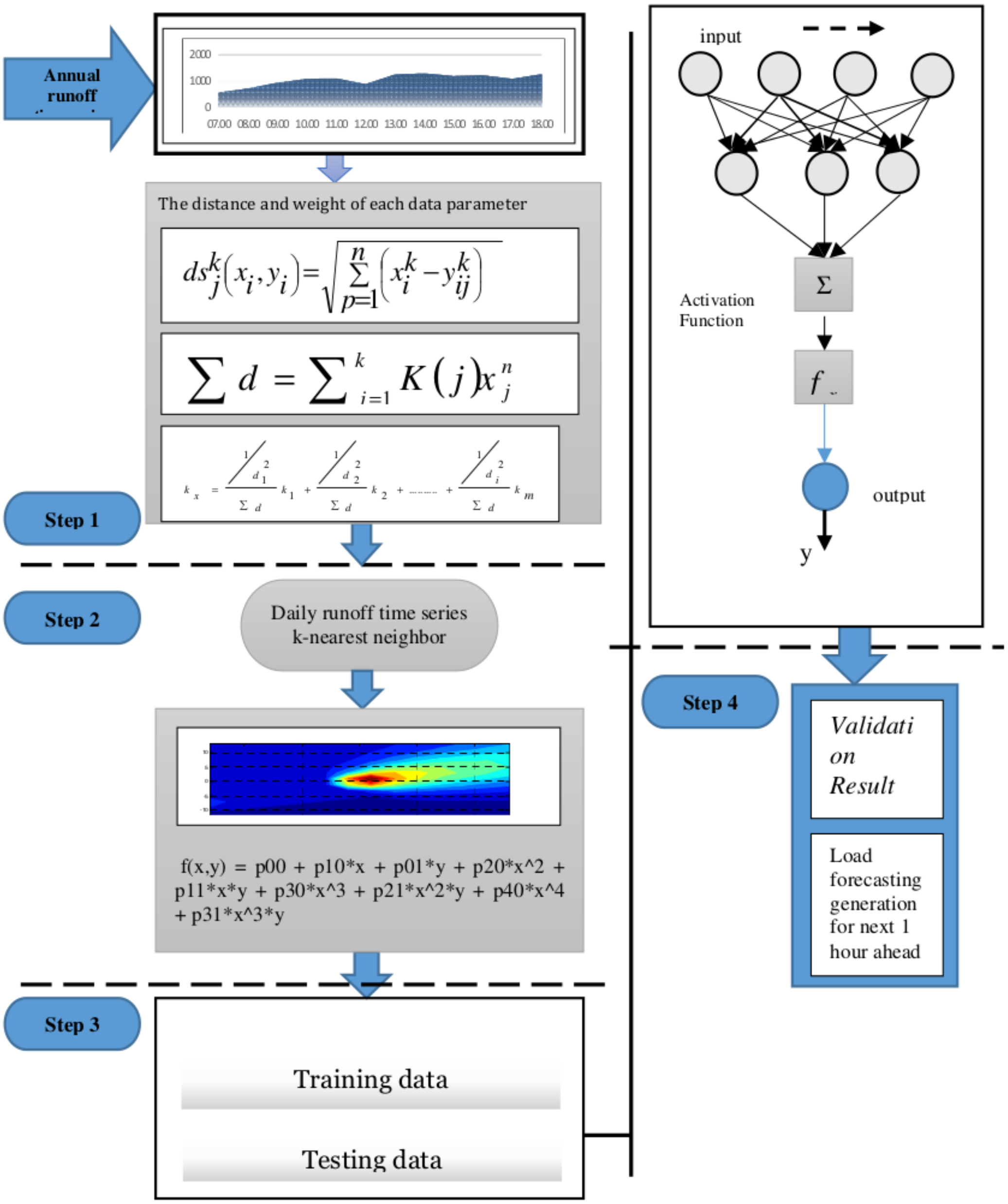


Figure 4. K-NN-Forward NN model for load generation forecasting

3.5. Results and Analysis

This section discusses the result of k-NN-feedforward NN model used to predict future load generation by using one hour ahead procedure. The k-NN-Feedforward NN modelling can be divided into three stages: (1) the topology design stage which includes the choice of the k-NN model (2) the Feed-Forward NN type, the number of its layers, the number of neurons in each layer, its inputs and outputs data from k-NN process (3) the training and testing stage during which samples are presented to the feed-forward NN and the weights are adjusted accordingly till a predetermined condition is satisfied; (4) the validation stage using k-NN- feed forward NN model. The procedure is described in Fig. 5. We test our model using previously described databases for load generation forecasting based on meteorology data, during the process forecast of 1 hours ahead.

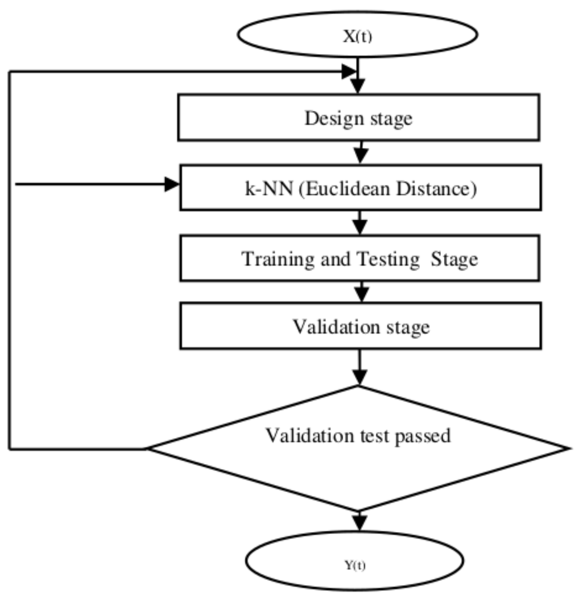


Figure 5. The flowchart of the k-NN-feedforward hybrid modelling process

3.4.1 Input Data

Using k-NN-Feedforward NN model, it is expected that a valid result of load generation forecast will be produced. The design model forecast is divided into two stages:

(a) Step 1: Calculating d-dimensional feature and n-dimensional distance based on the Euclidean distance for k-NN model every hours for all of hydro thermal generation. Data shown in Table 1 are the order parameters of each hydro thermal generation.

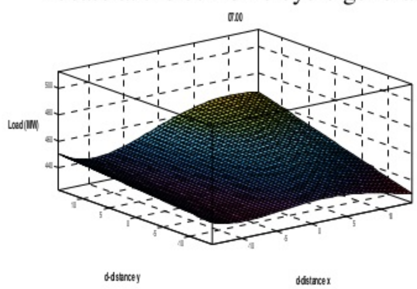
Table 1: Data Distance and Position Coordinates of Hydro Thermal Generation

No	Generation	Coordinate (x_i,y_i)	Distance	Angle
1	H1	(4.71,-134.92)	135	272
2	H2	(-10.18,-145.64)	146	266
3	H3	(-32.3,-183.17)	186	260
4	H4	(-24.77,-176.23)	178	262
5	H5	(-72.67,-179.87)	194	248

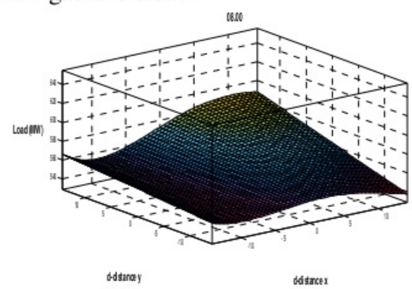
6	H6	(-33.39,-133.9)	138	256
7	H7	(-40.37,-117.23)	124	251
8	H8	(-42.64,-111.1)	119	249
9	H9	(-109.04,-161.66)	195	236
10	T1	(-84.34,53.73)	100	147.5
11	T2	(0,0)	0	0
12	T3	(102.92,-136.57)	171	307

*H=hydro generation T=Thermal generation

(b) Step 2: Using Feed Forward Neural Network based on the assumption that the existing data input testing and training is a combination the results obtained from polynomial equation k-NN method. The k-NN-Feed Forward NN model proposed in this reserach seeks to estimate and predict a PV station production 1 hours ahead, which position is locate at the combine cycle generation which gas and steam



(a)



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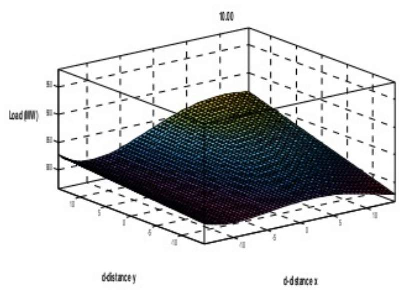

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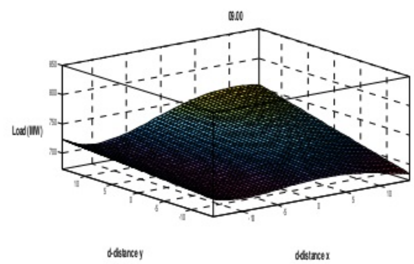

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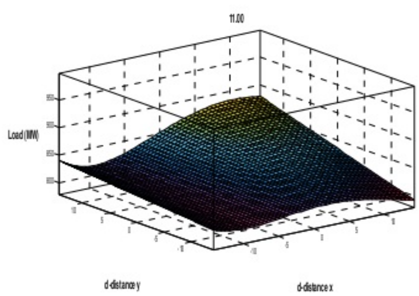

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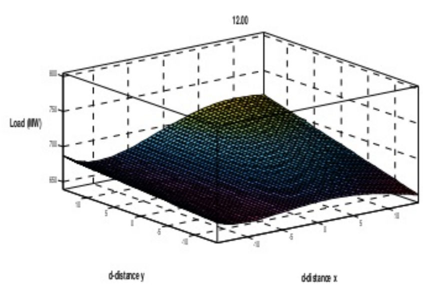


(f)

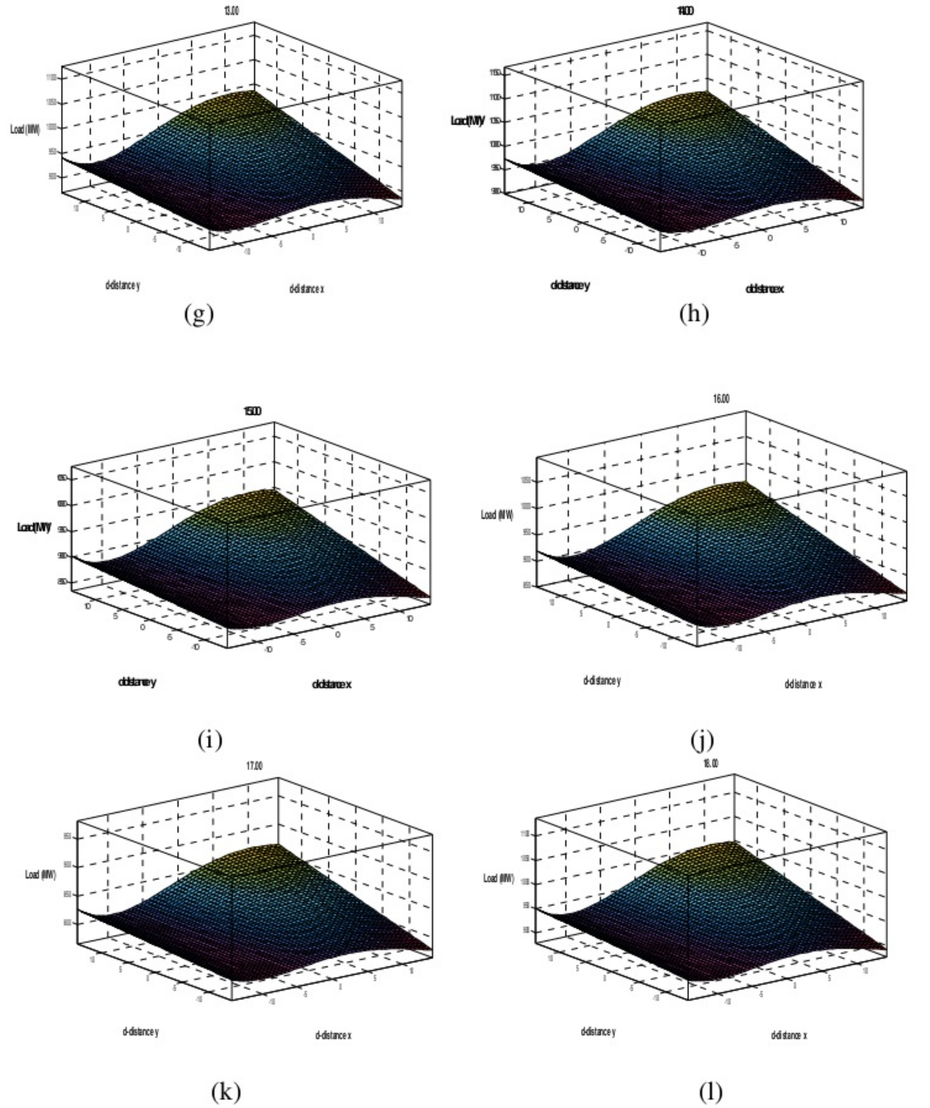


Figure 6. D-distance Hydro Thermal generation based on the Euclidean Nearest Neighbor method (from 07:00 a.m. to 18:00 a.m.)

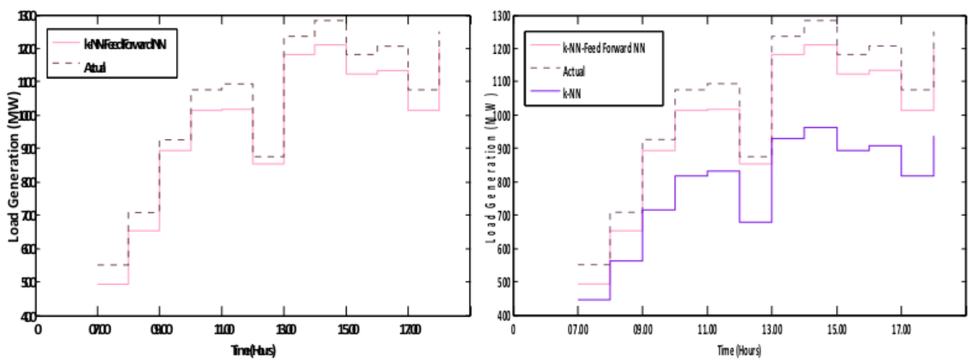
The N-dimensional feature and D-dimensional distances based on the Euclidean Nearest Neighbor model every hours for all of hydro thermal generation are shown in figure 6. From the simulation results using k-Nearest Neighbor method based on meteorological data consist of load, cost fuel, temperature, and humidity, respectively. All of them as data pre-processing testing and training on ANN model, which can be calculated by polynomial equation 5:

$$f(x, y) = p_0 + p_1 x + p_{01} y + p_2 x^2 + p_{11} xy + p_3 x^3 + p_{21} x^2 y + p_4 x^4 + p_{31} x^3 y \quad ....(6)$$

Where $f(x, y)$ is the load value of the k-nearest neighbor model and variable x, y is the coordinate value's position of the thermal generation.
Example figure 6(a). Based on the figure 6(a) can be produced by Polynomial equation :

$$f(x, y) = 447.8 + 1.141x + 0.5247y + (-0.04393)x^2 + 0.0601xy + (-0.005142)x^3 + 0.001416x^2y + 0.000187x^4 + (-0.0001473)x^3y \quad \text{........(7)}$$

In which the polynomial equation above is the result of the simulation on 07.00 AM hours using Euclidean Nearest Neighbor model to the generation T2. To validate the proposed method, load generation data of 1 hours ahead of a hydro thermal generation has been calculated using the process described in section 3. The results are then compared with the actual data of the load generation at target thermal generation as described in Section 4.
The k-NN-Feed Forward NN modelling approach is special since the neural method is initially constructed using Euclidean model, based on meteorology data. Result from Euclidean Nearest Neighbor method are then divided it into two sets of data: the training and testing data samples set and the validation samples set. After the validation data test, Feed Forward Neural Network method based on Euclidean k-NN result will be ready to use in 1 hours ahead load generation forecasting. As explained previously, the optimization parameters for load generation forecasting were obtained from a dataset based on meteorology data. The calculated values of load generation were then compared with measured values of each hydro thermal generation: hydro generation H1, hydro generation H2, hydro generation H3, hydro generation H4, hydro generation H5, hydro generation H6, hydro generation H7, hydro generation H8, hydro generation H9, thermal generation T1, thermal generation T2, and thermal generation T3.



(a) (b)

Figure 7. (a) Comparison of the two models for the load generation data for very short term load forecasting using Euclidean k-NN-Feed Forward NN hybrid model versus actual data in station. (b) Very short term load generation forecasting in 12-hours window based hybrid model, actual data, and Euclidean k-Nearest Neighbor model

Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) was used as error statistical indicator. The predict from k-NN-Feed Forward NN model was then compared with Euclidean k-NN model and mean average of meteorological data forecasts.
For the comparison, Euclidean k-NN-Feed Forward NN model performed only 1000 iterations for each learning period. For the Feed Forward Neural Network model is initially constructed based on the Euclidean k-NN model data, and after that, its training input data

is periodically performed as the database expands over time. And as seen in Fig. 7 shows comparison of the two methods for the load generation data between actual data and Euclidean k-NN-Feed Forward NN model: (a) there is a better fit between actual and forecast data for very short term load forecasting in thermal generation target T2, and (b) The normalized load generation curve using k-NN-Feed Forward NN hybrid model.

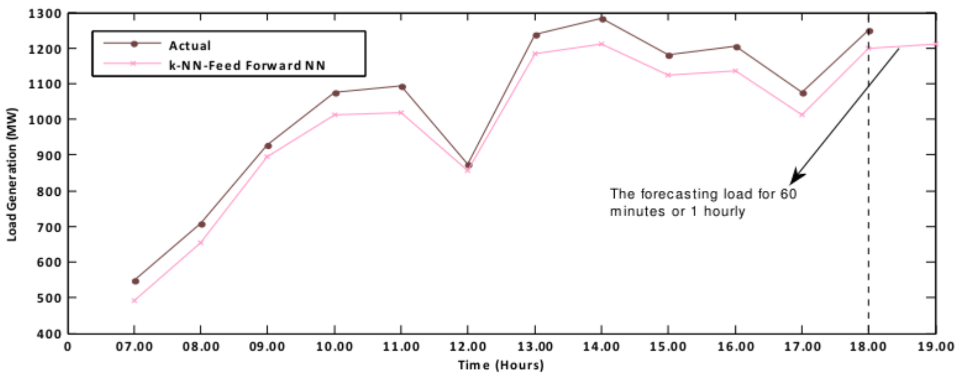


Figure 8. Very short term for 1 hours ahead load generation forecast using k-NN-Feed Forward NN versus actual data

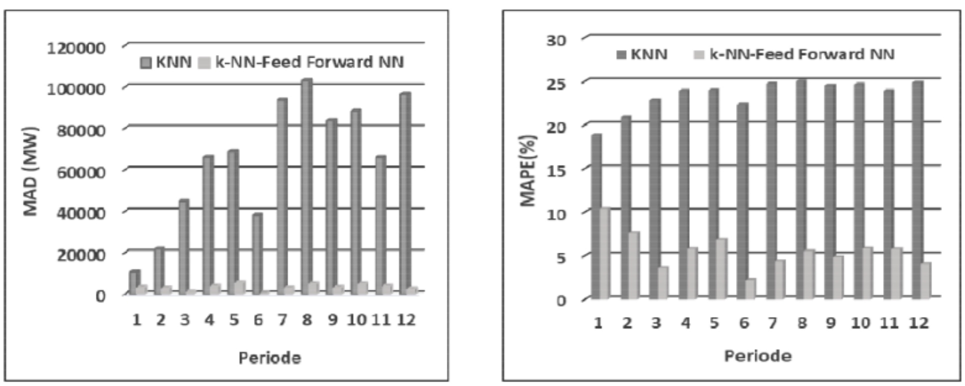


Figure 9. MAD and MAPE coefficient between actual data and load forecast based Euclidean k-NN-Feed Forward NN model

Figure 7 (a). describes the comparison of load generation forecasting in twelve-hours (07:00 to 17:00) on February 16, 2018, based on Euclidean k-NN Feed Forward NN model, actual data, and k-NN model. The value result shows that very short term load generation forecasting simulation using k-NN-Feed Forward NN method during twelve hours window gives more better result compared to k-NN model. Fig. 7 (b) illustrates very short term 1 hours ahead, where load generation forecasting using Euclidean k-NN- Feed Forward NN and its comparison with actual data. The hybrid k-NN-Feed Forward model is in a good agreement with measured data in the object position thermal generation. To analysis and evaluate the performance of the models, a statistical error measurement was used in the experiment, namely the mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE). To analysis the accuracy of each model to predict the load generation value, MAD, and MAPE coefficient between value results of Euclidean k-NN-Feed Forward NN and actual ground measurements was calculated. The result very short term for 1 hours ahead load generation forecasting we can see figure 8.

In figure 9 illustration about MAD and MAPE coefficient between actual data and very short term for 1 hours ahead forecasting performance using k-NN and k-NN-Feed Forward NN hybrid model. For more clearly, the lowest error statistical indicators of Euclidean k-NN method MAD with a value 103.48 MW and MAPE with a value 18.8% during the twelve period while the highest mead absolute deviation error with a value 321,14 MW and mean absolute percentage error with a value 25%. On the other hand, the error statistical indicator for proposed model (Euclidean k-NN-feed forward-NN model) MAD is 19.37 MW and MAPE is 2.21%. Note that the highest mean absolute deviation (MAD) was 75,11 MW and mean absolute percentage error (MAPE) was 10.38% during the twelve period. It is evident that Euclidean k-NN-Feed Forward NN hybrid model displays more better forecast than k-NN model.

5. Conclusion

A novel methodology for very short term load forecasting specifically for 1 hours a head of a target thermal generation has been introduced. In this research we proposed a new hybrid model for load generation forecasting using a combination of Euclidean k-NN modelling and Feed Forward Neural Network. The following conclusions can be drawn from this study:

- The proposed model is a combination formula for very short term load generation forecasting using Euclidean k-NN-Feed Forward NN modelling based on meteorology data. The input variable meteorology data (temperature and humidity) is of very importance.
- The novel hybrid model proposed in this research is a combination of minig data method euclidean k-nearest neighbor and Feed Forward-NN model. This study specifically and concerns on how forecast load generation data at a target thermal generation, which position is nearest by eleven other hydro thermal generation. The research also considers the realibity and availibity of a local measured database. The load generation forecasting using Euclidean k-nearest neighbor-Feed Forward NN model different for the every hours based on meteorology data, where variable the meteorology data consist of load, fuel, temperatures and humidity.

The new of this article is to forecast load generation on a thermal generation which position is at the nearest by twelve other adjacent thermal generation. In this research, the proposed Euclidean k-NN-Feed Forward NN model has more better approximation compared to k-NN model. The evaluation for very short term forecast the load generation using Euclidean k-NN-Feed Forward NN model are performed for only twelve hours and the result shown that, the Euclidean k-NN-Feed Forward NN model more better than k-NN method. The mean absolute deviation error statistical indicators of k-NN model is 103.48 MW and MAPE is 18.8%. On the other hand, the error statistical indicator for proposed model (Euclidean k-NN-feed forward-NN model) MAD is 19.37 MW and MAPE is 2.21%. Note that the highest mean absolute deviation (MAD) was 75.11 MW and mean absolute percentage error (MAPE) was 10.38% during the twelve period. The performance of the proposed Euclidean k-NN-Feed Forward NN model is more better compared with k-NN model. And the proposed Euclidean-k-NN-Feed Forward NN hybrid model in this research can be used effectively to forecast very short term the load generation with give the result output closer and match with actual measured data.

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