Short term load forecasting of anomalous load using hybrid soft computing methods

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Abstract. Load forecast accuracy will have an impact on the generation cost is more economical. The use of electrical energy by consumers on holiday, show the tendency of the load patterns are not identical, it is different from the pattern of the load on a normal day. It is then defined as a anomalous load. In this paper, the method of hybrid ANN-Particle Swarm proposed to improve the accuracy of anomalous load forecasting that often occur on holidays. The proposed methodology has been used to forecast the half-hourly electricity demand for power systems in the Indonesia National Electricity Market in West Java region. Experiments were conducted by testing various of learning rate and learning data input. Performance of this methodology will be validated with real data from the national of electricity company. The result of observations show that the proposed formula is very effective to short-term load forecasting in the case of anomalous load. Hybrid ANN-Swarm Particle relatively simple and easy as a analysis tool by engineers.

1. Introduction
Short Term Load Forecasting is a type of electrical load forecasting conducted through the analysis of electrical load patterns (weekday electrical load, weekend electrical load or anomalous electrical load) within a short time series [1][2][3]. The results of short term load forecasting have a very important role in improving the performance of problem solving--the problems on power systems such as economic dispatch, unit commitment, power flow analysis, maintenance scheduling, etc [4].

The main objective of short term load forecasting is to obtain accurate prediction results. Therefore, to gain highly accurate results, various methods were developed that support the forecasting process. At the beginning of its development, the methods frequently used by the forecasters were conventional methods, such as automatic regressive moving average, exponential smoothing models, stochastic processes, linear regression models, etc [5].

Conventional methods have limitations in processing inaccurate or incomplete input data, resulting in predictions that were not adequately good. Nowadays, the methods used by the forecaster are no longer conventional since the forecasters tend to shift to artificial intelligence-based soft computing, such as fuzzy logic, expert systems, artificial neural networks and so forth [6][7].

Nowadays one of the methods often used in short term load forecasting is artificial neural network with Back Propagation algorithm. The strength of this algorithm lies on its learning process where any error obtained at each iteration will be tracked back as feedback which is then studied, so there is improvement in result accuracy (through weights and biases improvement) in the next iteration. To
improve the pattern recognition accuracy resulted by Back Propagation, another algorithm which has the strength of optimization was added, that was Particle Swarm Optimization. The hybrid of these two algorithms becomes an optimal combination for the forecasting process. Based on this background, the authors raised this issue into a research entitled "Short Term Load Forecasting of Anomalous load using Hybrid Soft Computing Methods."

2. Methods
The data of electrical load output during national holidays and collective leaves was based on the data in the Indonesia National Electricity Market in West Java region. This data was plotted to determine the characteristic patterns of electrical load during those days. Analysis of characteristic patterns produced the results about the days which showed normal load pattern and the days which showed anomalous load pattern. The algorithm used was a hybrid of back propagation - swarm particle. The steps of short term anomalous load forecasting using this algorithm can be seen on the following flowchart:

![Flowchart](image)

**Figure 1. Flowchart of Back Propagation – Swarm Particle Hybrid Algorithm**

The above flowchart is explained more clearly [8][9][10] The normalization of electrical load data during national holidays, determination of the type of Back Propagation, the number of neurons on hidden layer and initialization of initial weights and biases randomly between 0 and 1 and then, Initialization of initial position and velocity of particles, number of particles, upper limit and lower limit of search space and number of iterations that would be used. After that, initialing position and velocity of particles were determined randomly with a range between 0 and 1 obtained through Back Propagation. The position was its weight and bias, while the velocity was the value which affected the position.
change at each iteration. So, the amount of particles that would be deployed was determined (N). In addition, the upper limit and lower limit range, the position and velocity of particles and number of iterations used on Swarm Particle were specified.

Forward phase of Back Propagation was conducted:

The data was spread on input layer towards the hidden layer by multiplying each data on input layer neuron unit with the weights that connected neurons, then the multiplication results were added and the biases were also added. Each signal was activated using sigmoid activation function.

\[
z_{in_j} = v_{oj} + \sum_{i=1}^{n} x_i \cdot w_{ij}
\]

\[
z_j = f(z_{in_j}) = \frac{1}{1 + \exp\left(-z_{in_j}\right)}
\]

The signal that had been activated was sent to the output layer by multiplying the signal on hidden layer with the weights connecting neurons to the output layer, then the biases were added up to the multiplication results. Then, Neurons on the output layer were activated in order to get the output.

\[
y_{in_k} = w_{0j} + \sum_{j=1}^{p} z_{j} \cdot w_{jw}
\]

\[
y_k = f(y_{in_k})
\]

The output was compared with the target data to obtain fitness. Fitness value was obtained from MAPE (Mean Absolute Percentage Error), and then Particle Swarm Optimization on back propagation was performed by evaluating the fitness value of each particle by determining Pbest (Pbest is the function best value/smallest value for each particle along iteration) and Gbest (Gbest is the function best value/smallest value for the overall particles along the iteration). The position and velocity of particles were updated using particle velocity equation, and this update was affected by inertia coefficient.

\[
v(t+1) = w(t) \cdot v(t) + c_1 \cdot rand_1(t) \cdot (Pbest(t) - x(t)) + c_2 \cdot rand_2(t) \cdot (Gbest(t) - x(t))
\]

To find the best particles based on Pbest and Gbest after the position and velocity were updated, the fitness value of each iteration was calculated. So, the results of Pbest and best Gbest were saved as weights and continuous optimization was performed until Gbest experienced convergence and until the maximum iteration, then the algorithm was shifted into backward phase of Back Propagation. Then the algorithm diverted to backward phase of the Back Propagation. The input parameters of Back Propagation algorithm were set using the weights and biases obtained from Swarm Particle. The parameters of learning rate (\(\alpha\)) and the maximum value of the epoch were defined and to discover the average MAPE, the objective function at each iteration was calculated. Last Step, weights and biases were fixed, steps 22 to 23 were repeated until the maximum value of iterations was reached, the output was denormalized, and then MAPE of the denormalized output was calculated.
3. Results and Discussion

Results on figure 2 shows that the prediction result using BP-SP Hybrid algorithm without any optimization can still produce a fairly good accuracy, with the average accuracy value obtained in the initial prediction reached the value of 98%. Although the highest error at one point reached 7%, error value of initial prediction could be minimized by finding the factors/parameters that can be optimized, the optimization factors can be obtained by conducting trials testing on the value of the initial parameter setting so that the best prediction results with the highest accuracy is obtained.

![Figure 2. Curve of prediction result compared with the target](image)

90 experiments were conducted with a fixed value setting, which was obtained from the optimization parameter testing in previous discussion. Error range obtained during the experiments were 0.77 to 2.875, thus 1 trial that showed the smallest error from these 90 experiments was sampled, that is the trial with the error value of 0.77 with the curve shown in figure 3.

![Figure 3. Prediction results (optimization) curve compared with target curve](image)
4. Conclusions
Based on the discussions and findings obtained in this research, there are several things that can be concluded regarding predetermined problem scope. The first conclusion, regarding the pattern characteristics, it was discovered that electrical load conditions during national holidays can be defined as anomalous load condition if the load condition is compared with the load patterns showed during weekdays. Second, regarding short term load forecast process using back propagation - swarm particle hybrid algorithm, it can be concluded that this algorithm is an algorithm that has a very good accuracy, and this conclusion is based on the percentage of prediction accuracy. Compared with targets, this algorithm demonstrated the value of 98.126%. Third, the results of the prediction results of back propagation - swarm particle hybrid algorithm can be optimized by finding the correct input parameter values suitable to produce low error prediction, and in this study it can concluded that the parameters of the optimization were achieved by setting 10 data as the number of input data. In addition, the number of hidden layer should also be set on 1 layer and the learning rate should be set on the value of 0.6. These values of the optimization settings can improve the prediction accuracy of 1.104%.

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