Hybrid PSO-ANN Application for Improved Accuracy of Short Term Load Forecasting

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Abstract: - Short Term Load Forecasting (STLF) is a power system operating procedures that have an important role in terms of realizing the economic electric production. This research focuses on the application of hybrid PSO-ANN algorithm in STLF. Load data grouped by the type of weekdays and holidays. Consumption of electricity load in West Java Indonesia, used as input to the learning algorithm PSO-ANN. Data are grouped according to three clusters, namely the weekdays that starts on Monday to Friday. Weekends are Saturdays and Sundays and national holidays. The forecasting results from the PSO-ANN algorithm compared against the load planning system (LPS) from Indonesia Power Company. The results from the load forecasting PSO-ANN algorithm has a better accuracy than the forecasting of the LPS. Load forecasting accuracy will reduce the level of energy losses and cost of generation.

Key-Words: - Particle Swarm Optimization, Artificial Neural Network, Short Term Load Forecasting.

1 Introduction

Modern power operation systems will be associated with a variety of planning procedures. Planning includes the methodology and operation of the decision-making process. Electric power system is designed to primarily the load in the network. Criteria of technical performance and economic performance has been established in the planning. The planning process begins with a projection operation of electrical load distribution, by performing load forecasting. Load forecasting is divided into three types: short term load forecasting (STLF), medium term load forecasting (MTLF), and long term load forecasting (LTLF). Forecasting methods vary depending on the specific purpose.

STLF is problem-based forecasting of the time series analyzes of short-term load pattern. Result of STLF is the main input in the unit commitment, economic dispatch, fuel scheduling, load flow analysis and maintenance scheduling. Load forecasting which has a highly accuracy is required, and the main problem implementation for the electric company. The problems caused the characteristics of the load has complex patterns [1]. Load pattern is non linear and random, such as weather factors, social and economic [2].

Accurate load forecasting requires consideration of time factor, weather data, and local activities [3]. Time factors, including the type of day in the week and type of hours in a day. Electrical energy use by consumers is certainly different to regular weekdays, on weekends and during holidays. Likewise, in the days of electricity usage will be very unusual when the base load and peak load. The characteristic of consumers of electricity in Indonesia is unique and different from the behavior of electricity consumers in other countries. Weather factors do not affect the behavior of the use of electricity, while local activities such as broadcast television that captivated greatly affect. Based on these problems required electrical load forecasting model in Indonesia.

The conventional method consists of STLF: exponential smoothing techniques, regression methods, and statistical analysis [4]. Regression method developed involves factors of weather, day type, and class consumers [5]. The uses of ARIMA methods are popular in 1987. This model was developed based on the assumption that the data used has an internal structure of auto correlation, trends and variations of state [6].

Currently load forecasting method has been using soft computing applications. This method has excellent performance to solve the problems that are non-linear, which has been difficult to resolve with time series method. Its method does not use complex mathematical formulations and use only a qualitative correlation between input and output.

Some derivatives are used in soft computing load predictions include: artificial neural network with the algorithm of multi-layer perceptron, radial basis function, Kohonen, counter propagation, recurrent and others [7] - [9], fuzzy systems [10] - [12] and the use of expert system method [13].

2 Problem Formulation

2.1. Particle Swarm Optimization

Particle swarm optimization (PSO) is an evolutionary computational technique to find the best solution to simulate the movement of the social behavior of a group of birds. Introduced by James Kennedy and Russell Eberhart in 1995 [14] [15] [16]. The algorithm works begin by initializing a random group of birds that are heading somewhere. Each bird is called the particle. These particles are moving at a certain speed in an attempt to find the best position after a few iterations. So that the particle is not out of the search space should be limited search space. Its search speed is limited so that each particle does not move too fast spread [17]. At each iteration of each particle considered himself as the best position (Pbest). Global optimal value (Gbest) could be identified after a search of the Pbest. Velocity and position update equation of the particle that has been optimized by adding inertial (ω) It is as follows [17] [18]:

$$v(t+1)=\omega(t)*v(t)+c_1*rand_1(t)*\left(Pbest(t)-x(t)\right)+c_2*rand_2(t)*(Gbest(t)-x(t)) \quad (1)$$

$$x(t+1)=x(t)+v(t+1) \quad (2)$$

Variable to control the speed of the particle is called inertia (ω) parameters. These parameters can be said to have a good performance, if it has a range of 0.4 up to 0.9 [18] [19]. Variable parameters c_1 and c_2 are the cognitive and social, which can be calculated by the equation [17][20]:

$$c_1(t)=\left(c_{1max}-c_{1min}\right)\left(\frac{Iter_{max}-Iter(t)}{Iter_{max}}\right)+c_{1min} \quad (3)$$

$$c_2(t)=\left(c_{2max}-c_{2min}\right)\left(\frac{Iter_{max}-Iter(t)}{Iter_{max}}\right)+c_{2max} \quad (4)$$

2.2. Backpropagation Algorithm

Artificial neural network (ANN) was introduced by the Mc Culloch and Pitts in 1943. They concluded that the combination of multiple simple neurons into a neural system will improve the computing capability. Before the introduction of the backpropagation (BP) algorithm, previous researchers only use a single-layer network architecture. BP algorithm was introduced in 1974 by Werbos [21]. In 1986, Rumelhart continued the BP algorithm for the hidden layer. This algorithm has a parameter called the learning rate for the control convergence algorithm for optimal local solution [22].

BP training algorithm includes three phases. The first phase is the phase advance (feedforward). Advanced input pattern is calculated starting from the input layer become to the output layer, using the predetermined activation function. The second phase is a phase of moves back (backpropagation). The difference between the network output with the desired target is the error that occurred. This error propagated backwards, starting from the line that relates directly to the units in the output layer. The third phase is a modified weighting (weight) that can reduce errors that occur. Figure 1 show the architecture in advanced phase and back propagation used during this study.

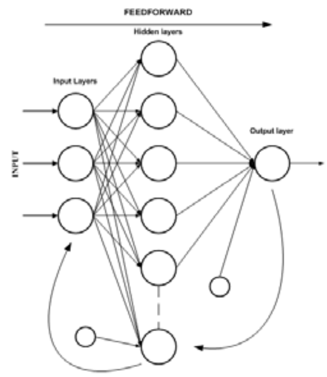

Fig. 1. Backpropagation architecture

2.3. Load Forecasting Methods

Input data using the daily electricity load in 2011 until 2012 from the Indonesian Power Company [23]. Data are grouped according to three clusters, namely the weekdays (Monday to Friday), weekend (Saturday and Sunday) and national holiday, shown in Table 1. The data is used as input to the training and testing of the PSO-ANN algorithm. ANN algorithm used is the feedforward backpropagation algorithm (BP).

Table. 1.Input Training and Target

Input	Weekday	Weekend	National holiday
t-10	9/04/12	18/03/12	01/02/11
t-9	10/04/12	24/03/12	22/04/11
t-8	11/04/12	25/03/12	16/05/11
t-7	12/04/12	31/03/12	02/06/11
t-6	13/04/12	01/04/12	03/06/11
t-5	16/04/12	07/04/12	17/08/11
t-4	17/04/12	08/04/12	25/12/11
t-3	18/04/12	14/04/12	01/01/12
t-2	19/04/12	15/04/12	23/01/12
t-1	20/04/12	21/04/12	23/03/12
t-0	23/04/12	22/04/12	06/04/12

Figure 2 shows the flow-chart of STLF using PSO-ANN algorithm. The calculation begins with the steps: normalizing the data, determine the number of hidden layer neurons, randomly determine the weights and biases and disseminate data on the input layer to the hidden layer. Each signal is activated with a sigmoid function. Signal has been activated transported from the output layer to the hidden layer.

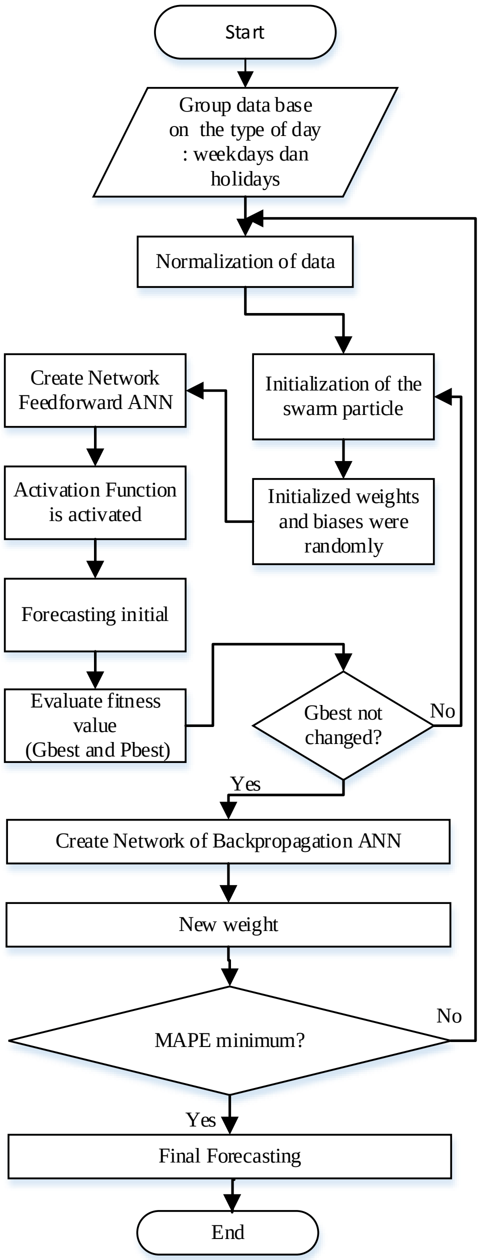

Fig. 2. Flow-chart of STLF using PSO-ANN

PSO algorithm is used to optimize the weights and biases. First step: determine the initial position and velocity of particles, number of particles, the upper limit and lower limit of the search space and the number of iterations. The position is the weight and bias, and the speed is affecting the value of the position change with each iteration. Weights and biases of PSO are used as the optimal weights and biases in BP. Learning rate parameter used 0.6. The maximum value of the epoch is 10000.

The average value of the error will be obtained after the calculation of the value of objective function at each epoch. Once the maximum value of iterations is obtained, the next step did convert the output. The final step is to calculate the MAPE.

MAPE forecasting accuracy using the formula:

$$\text{MAPE}=\frac{1}{N}\sum_{1}^{N}\left|\frac{\text{Actual}_i-\text{Forecasting}_i}{\text{Actual}_i}\right|\text{x100} \tag{5}$$

N is the total number of hours. Mean squared error is used as a function generator on the PSO algorithm and ANN.

3 Problem Solution

Figure 3 shows the load pattern on weekdays, weekends and public holidays. Load pattern in all three categories had a considerable margin. Load average weekday, weekend holidays and public holidays respectively of 3518.10 MW, 3130.83 MW and 2885 MW. Electricity consumption patterns in holiday weekend and national holiday decreased by 11% to 17.99% compared with weekdays. Load pattern on a holiday weekend has decreased but not so pointed when compared to the national holiday. The pattern of electricity consumption has decreased on the weekend but not so penetrating when compared to the national holiday. This is expected to industrial consumers simultaneously not break its activities.

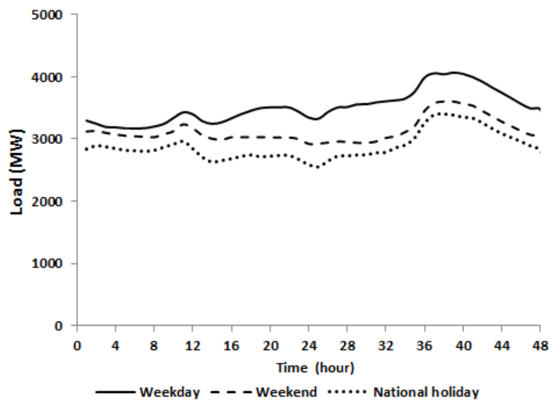

Fig. 3. Comparison of the daily load pattern on weekdays, weekends and national holidays

Input training on BP-ANN algorithm using 10 data load, the weight optimization using PSO algorithm. A characteristic of the electrical load pattern in Indonesia is not influenced the weather, then these aspects are refused.

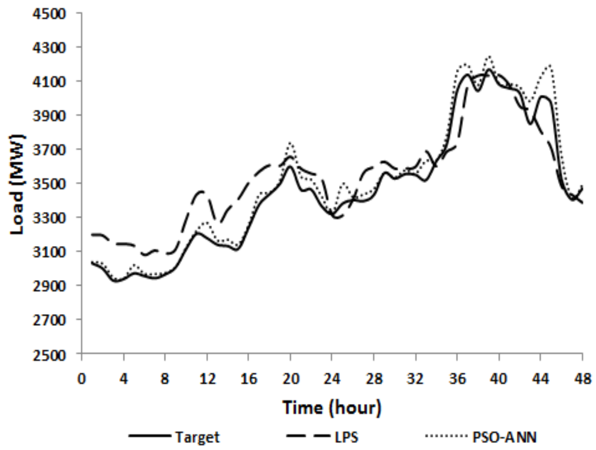

Fig. 4. Load forecasting on weekday

Figure 4 shows the simulation results of load forecasting on weekdays. Input learning using electricity load for Monday to Friday, while the ANN architecture using layers of 10-5-1 and learning rate 0.2. Load forecasting results show that the PSO-ANN weekday's algorithm gives better accuracy than the forecasting results LPS. The absolute value of MAPE Obtained PSO-ANN is 1.26 and LPS was 3.81. Figure 5 shows a comparison of the forecasting error PSO-JST and LPS at every hour.

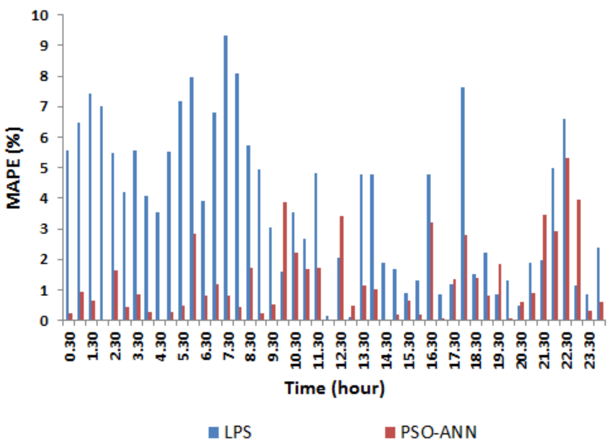

Figure 5. Comparison of MAPE between PSO-ANN algorithm with LPS forecasting for weekdays.

Figure 6 and Figure 7 respectively shows the simulation results of load forecasting on weekends and MAPE comparison between PSO-ANN and LPS. Experiments performed using neural network architecture 10-5-1, and the learning rate was tested over the range of 0.1 to 0.9.

MAPE optimal PSO-ANN was 1.295, compared with the more exact forecasting results LPS. LPS load forecasting results at the weekend give a fairly accurate prediction, because the resulting MAPE does not exceed 2%, although when compared against the results of the PSO-ANN, the results are a still more precise algorithm PSO-ANN, but the difference is not significant.

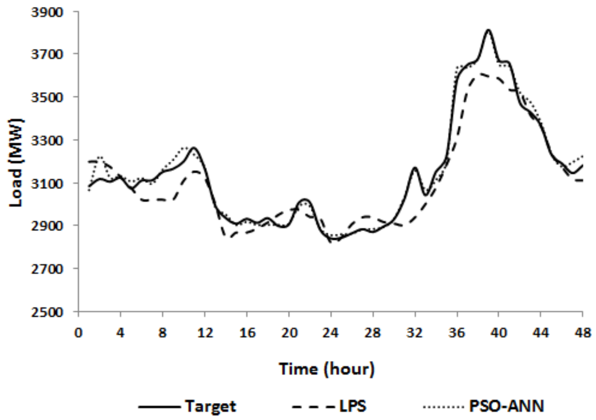

Fig. 6. Load forecasting on the weekend.

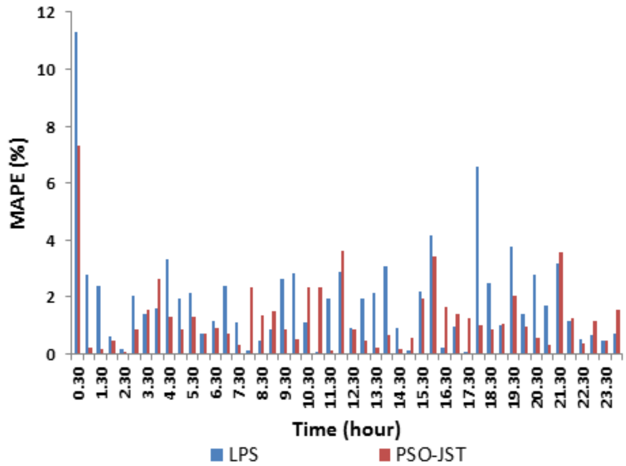

Figure 7. Comparison of MAPE between PSO-ANN algorithm with LPS forecasting for weekend.

The results are very interesting observed from the effects of load forecasting national holiday. LPS forecasting results provide a very large error is 6.71%, meaning that there is a loss of operational generating significant losses, especially the loss of energy and electrical production costs. It should not have occurred if using the load forecasting model better. PSO-ANN algorithm provides a level of accuracy that is steady, with the average absolute value of MAPE 1.25%. Simulation results are shown respectively in Figure 8 and Figure 9.

The increased accuracy of STLF using a PSO-ANN algorithm impact on the reduction of production costs of generation every day. Power generation in Indonesia is generally a thermal unit that uses fuel oil and coal. Accurate forecasting results certainly impact the environment, mainly expected to reduced pollution.

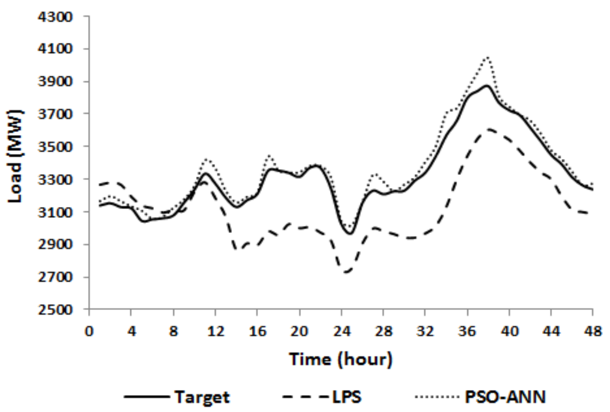

Fig. 8. Load forecasting on national holiday

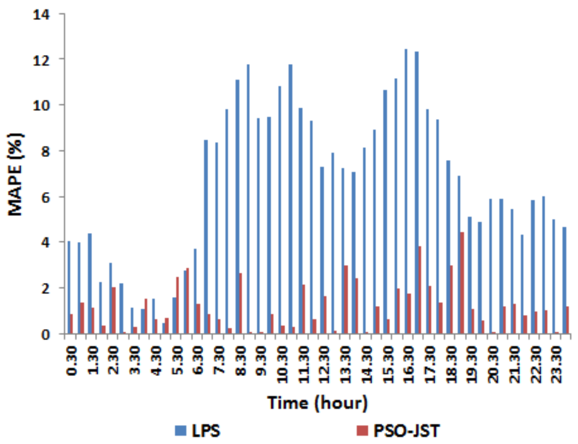

Fig. 9. Comparison of MAPE between PSO-ANN algorithm with LPS forecasting for national holiday.

4 Conclusion

STLF accuracy is better to consider the type of day of the week and the type of holiday. The experiments carried out showed that the manufacture of the cluster can improve forecasting accuracy. This will result in efficiency to the Power Company, reduce operating costs and generation will indirectly affect the low cost of electricity production. Results accurate prediction of electricity load will affect the economic operation of power systems, especially related to decision making in electricity production and transmission load planning, unit commitment, scheduling generating units, and hydro-thermal coordination. Understanding the behavior of the load through the STLF is essential for determining the base price and the restructuring of the electric power industry.

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