ISBN 978-602-17688-9-1

PREDICTION OF ELECTRICITY DEMAND BY USING SMOOTHING METHOD AND ARTIFICIAL INTELLIGENCE

(case study : SulutGo system)

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Abstract

Electrical energy is a basic need and plays an important role for people's lives. Electricity needs can be divided into the household sector, business, public and industry. Electricity consumption increases with the number of consumers. Electricity consumptions demand in North Sulawesi and Gorontalo provinces in next periods requires an appropriate predictive model. This study aims to predict the amount of electricity demand in these provinces by using secondary data time series from 2012 to 2016. The method used are artificial intelligence and smoothing method. The facts revealed by the data existing from PT. PLN SulutGo. The model and its prediction result are expectd to be used as inputs for the planning of electricity systems construction.

Keywords*: Electrical energy, electricity demand, artificial intelligence, smoothing*

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INTRODUCTION

The progress of development in North Sulawesi, especially in the housing sector is a logical consequence of increased electricity needs. In addition, local government policy on investment interest to the investors to invest and also contributed to the increase in the electricity demand. Now, the electrical system in the North Sulawesi supplied from Sulutenggo system, which provides electricity for North Sulawesi, Central Sulawesi and Gorontalo.

To achieve this, the electrical system SULUT should be able to meet the electricity needs independently. A comprehensive study of the long term in the framework of the provision of electricity in SULUT become an urgent need. One factor that is crucial in making the operation plan of electric power system is forecast electrical load to be borne by the electric power system.

The ability to predict and optimize electricity consumptions demmand is very important, to re-duce time and cost. The difficulties in optimizing conditions of input is how to understand the relationship to the responses. Nevertheless, for low levels case, multiple regression analysis using second-order polynomial equation will generate poor optimization of optimal formulation. To solve this problem, BPNN was combined (Subramaniam et al., 2004).

Back propagation model, which was originally proposed by Rumelhart (1986), is able to effectively deal with prediction and optimization problems. In 1993, Khajavi and Komanduri have shown that the Back propagation Neural Network (BPNN) model is able to predict the drill wear employing multiple sensors. Liao and Chen (1994) and Fuh and Wang (1997) explored BPNN in creep feed grinding process. Ezugwu et al. (1995) predicted tool life and failure mode in machining of gray cast iron with ceramic cutting tools with this model. Dutta et al. (2000) found fuzzy controlled BPNN model for predicting the tool wear in face milling process. Ojha and Dixit (2005) employed BPNN to estimate and predict low, most likely, and higher estimates of tool life. Dutta et al. (2006) proposed a modified BPNN with delta bar delta to predict the wear of the tungsten carbide inserts. Panda et al.

ISBN 978-602-17688-9-1

(2006) proposed BPNN for predicting flank wear on HSS twist drill while drilling mild steel work piece on the other hand Garg et al. (2007) compared BPNN with RBFN for prediction of flank wear in drilling process. Furthermore, Patra et al. (2007) found that using BPNN for predict drill wear can provide better value compared to a regression model in accuracy. Especially Liao and Chen (1994) have tried to observed BPNN model to predict and optimize creep feed grinding process. They found that the result better than the regression method's result.

The motivation behind this research is to apply artificial intelligence, specially back propagation neural network, based on happenstance data. The objective is to predict the amount of electricity demand in North Sulawesi and Gorontalo provinces by using secondary data time series from 2012 to 2016.

Based on the above, the formulation of the problem in this study are as follows:

- ✓ How to estimate the demand for electricity in North Sulawesi?
- ✓ How to develop artificial intelligence models to estimate the demand for electricity?

This study wants to implement the use of artificial intelligence to the analysis of the electrical energy needs and its implementation strategy based on the condition of power that exist today. Benefits to be gained from this research are:

- ✓ the determination of the factors that influence changes in demand for electricity in SULUT
- ✓ estimated well to increase the demand for electricity in the province of North Sulawesi for some years in the future,
- ✓ comparison between the need and availability of electrical energy in SULUT in the next few years, and

The remaining parts of this paper are organized as follows. In second part, we describe the review of literature. Model and the prediction process is described in third part. Illustrative example presented in fourth part and the conclusions are in final part.

Literature Review

Estimation is basically conjecture or predictions regarding the occurrence of an event or events in the future. Predictions can be qualitative or quantitative. Qualitative predictions difficult to obtain good results because the variables are very relative. Estimation (quantitative prediction) is divided into single prediction and prediction intervals. Prediction single consists of one value, while the prediction interval consists of some value, in the form of an interval defined by the lower limit value and the upper limit. Estimates, related to a necessity, given the state: (1) what is required, (2) how many and (3) when it should be provided. Estimates of needs in the coming period is necessary to do a comparison of the condition of the actual needs of the moment.

Artificial intelligence (AI) is a part of computer science utilizing the machine (computer) that can behave intelligently, and do the job as good as it is done by humans. John McCarthy defined AI as getting a computer to do things which, when done by people, are said to involve intelligence. This special science develops software and hardware to mimic human actions, for example reasoning, vision, learning, problem solving, natural language understanding, and so on. Artificial intelligence can be viewed from various perspectives, such as:

(i) Intelligence perspective, how to make a smart machine that can do things that previously could be done by a human

(ii) Business perspective, AI is a group of efficient tools that can be used in some methodologies to solve business problems

(iii) Programming perspective, AI includes the study of symbolic programming, problem solving and searching process

(iv) Researching perspective, AI's researches began in the early1960s with focus on experiment are chess game's program, theory's proving, and general problem solving.

Artificial intelligence includes the following areas of specialization that are robotics, computer vision, natural language processing, patterns recognition, artificial neural network, voice recognition, genetic algorithms and expert system.

ISBN 978-602-17688-9-1

Artificial neural network is an information processing system that has characteristics similar to biological neural networks. Artificial neural network was first introduced by McCulloch and Pitts in 1943. They concluded that the combination of several simple neurons into a nervous system will increase the computational capability. In 1958, Rosenblatt began to develop Perceptron network model. Widrow and Hoff (1960) developed the Perceptron training rule by introducing the network, known as delta rule. Rumelhart (1986) developed a back propagation perceptron which allows the network are processed through multiple layers.

Several network architectures are often used in artificial neural networks. They are single-layer networks, multi-layer networks and recurrent networks. Application of artificial neural networks that have been successfully carried out are classification, pattern recognition, forecasting and optimization.

Artificial neural network with a single layer has limitations in pattern recognition. This weakness can be eliminated by adding a hidden layer between input and output screens, is the formation of back propagation. Back propagation word refers to how to calculate the gradient of the weight changes. Use of more than one hidden layer has more benefits for some cases, but the training requires a longer time. It can have a number of inputs, one or more hidden layers consisting of a number of units (plus a bias), and a number of output units.

Some related research in the field of electrical energy requirements can be outlined below:

- Campillo et al. (2012): Discussing the model of the structure: short-term forecasting models and long-term forecasting models to predict energy consumption
- Kheirkhah et al (2013): Using the method of artificial neural network, principal component analysis, the data envelopment analysis and Anova to predict the electricity needs for the changing seasons and the monthly electricity consumption
- Ozoh et al. (2014): Using the technique of time-series and artificial neural network to predict electricity consumption

MODEL PROPOSED

In this study, neural networks used as a tool to forecast the electricity demand because this method is very powerful in non-linear optimization problems and quite easy to be learned. The overall procedure of the proposed approach is depicted in Fig. 1.

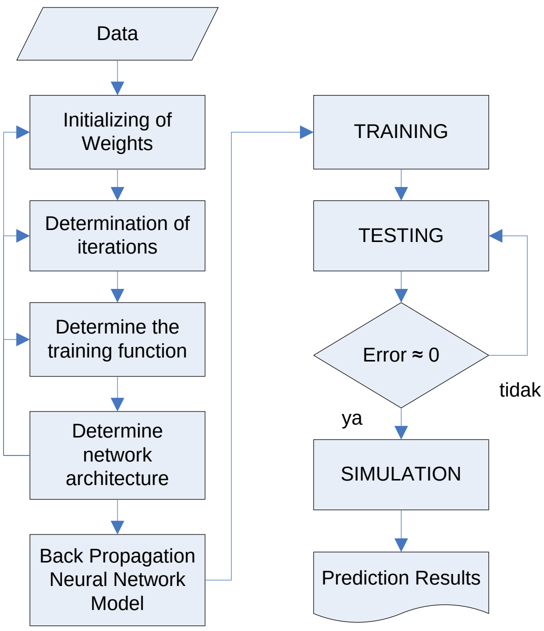

Figure 1. BPNN approach

The model of neural network for the training process (using Matlab R2014b programming) can be written as follow:

```
p=[ …; …; … ]; % input
t=[ … ; …]; % target
net=newff(minmax(p), [10,5,1], {'tansig','tansig','purelin'}, 'trainlm');
        % network building_12-10-5-1
net.trainParam.lr= …;
net.trainParam.epochs= …; % Max epochs
net.trainParam.show= …; % MSE freq.
net.trainParam.goal= …; % limit of MSE
net = train (net, p,t); % network training
[y,Pf,Af,e,perf] = sim (net,p,[],[],t)
% record the optimal weight and bias
net.IW {1,1}
net.b {1}
net.LW{2,1}
net.b {2}
net.LW{3,2}
net.b {3}
```

The model of neural network for the validation process, using Matlab R2014b programming, is written as follow:

```
p=[ …; …; … ]; % input
net=newff(minmax(p), [10,5,1], {'tansig','tansig','purelin'}, 'trainlm');
        % network building_12-10-5-1
% weight and bias_result from training
net.IW {1,1}=[ … ; … ; … ; … ; … ; … ; … ];
net.b {1}=[ … ; … ; … ; … ; … ; …; … ];
net.LW{2,1}=[… ; … ; … ; … ; …];
net.b {2}= [… ; … ; … ; … ; …];
net.LW{3,2}=[ … ; … ];
net.b {3}= [ … ; …];
net.trainParam.lr= …;
net.trainParam.epochs= …; % Max epochs
net.trainParam.show= …; % MSE freq.
net.trainParam.goal= …; % limit of MSE
net = train (net, p,t); % network training
[y,Pf,Af,e,perf] = sim (net,p,[],[],t)
```

For the simulation process, neural network model (using Matlab R2014b) programming is written as follow:

```
p=[ …; …; … ]; % input
net=newff(minmax(p), [10,5,1], {'tansig','tansig','purelin'}, 'trainlm');
        % network building_12-10-5-1
% weight and bias_result from training
net.IW {1,1}=[ … ; … ; … ; … ; … ; … ; … ];
net.b {1}=[ … ; … ; … ; … ; … ; …; … ];
net.LW{2,1}=[… ; … ; … ; … ; …];
net.b {2}= [… ; … ; … ; … ; …];
net.LW{3,2}=[ … ; … ];
net.b {3}= [ … ; …];
[y] = sim (net,p)
net.trainParam.lr= …;
net.trainParam.epochs= …; % Max epochs
```

```
net.trainParam.show= …; % MSE freq.
net.trainParam.goal= …; % limit of MSE
net = train (net, p,t); % network training
% record the optimal weight and bias
net.IW {1,1}
net.b {1}
net.LW{2,1}
net.b {2}
net.LW{3,2}
net.b {3}
[y] = sim (net,p)
```

ILUSTRATIVE EXAMPLE

The number of hidden nodes in a network is critical to network performance. Too few nodes can lead to under fitting. Too many nodes can lead the system toward memorizing the patterns in the data. Subramanian (2004). Nielsen (1987) in Subramanian et al (2004) paper said that according to Kolmogorov's theorem, it was understood that twice the number of input nodes plus one is sufficient to compute any arbitrary continuous function. The architectures of BPNN used in this study is shown in Fig. 1. They were designed using Matlab R2014b. The network consists of 12 inputs, 2 hidden layers and 1 output. First hidden layer using 10 nodes and second hidden layer using 5 nodes.

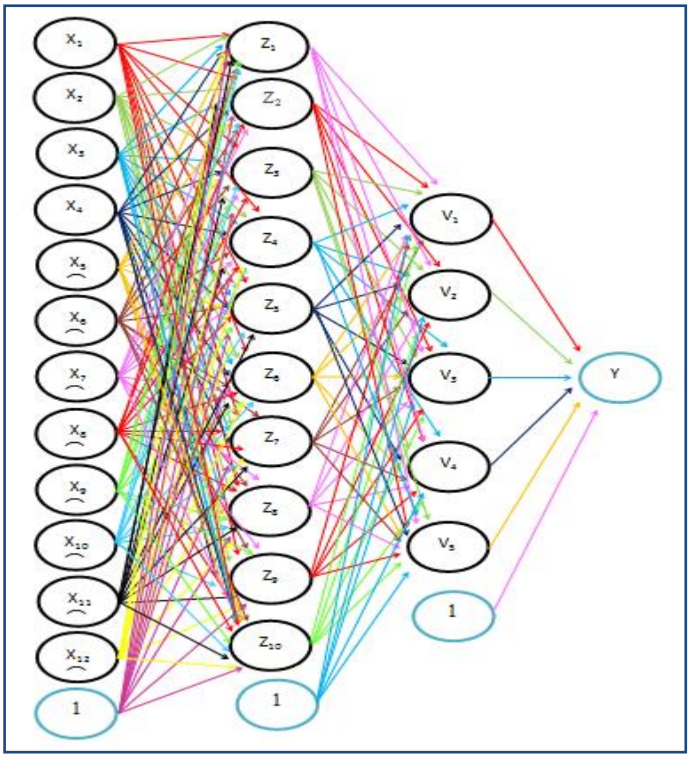

Figure 2. Network Architecture of Example

A feed-forward BPNN was used to predict electricity demand. This BPNN model employ Levenberg-Marquard's searching method as learning rule because it gives the best performance to model than another methods.

ISBN 978-602-17688-9-1

Table 1. Learning Rule Alternatives

No	*Learning rule*	*Performance (MSE)*	*Epoch*	*Time (s)*
1	traingd	1.97×10^{-4}	10000	448
2	traingdm	9.99×10^{-6} 9.79	6880	293
3	traingda	9.79×10^{-6}	334	14
4	traingdx	7.78×10^{-6}	126	5
5	trainbr	5.6×10^{-7}	6	1
6	trainc	9.6×10^{-6}	147	19
7	traincgp	9.87×10^{-6}	38	2
8	traincgb	5.82×10^{-6}	29	1
9	trainlm	1.89×10^{-6}	1	1
10	trainoss	9.25×10^{-6}	27	2
11	trainr	9.95×10^{-6}	83	29
12	trainrp	1.02×10^{-5}	98	4
13	trainscg	9.92×10^{-6}	11	2

Applying BPNN model to the data peak load and sold energy of electricity, the prediction result for next 12 months can be drawn in Fig. 4 dan Fig. 5.

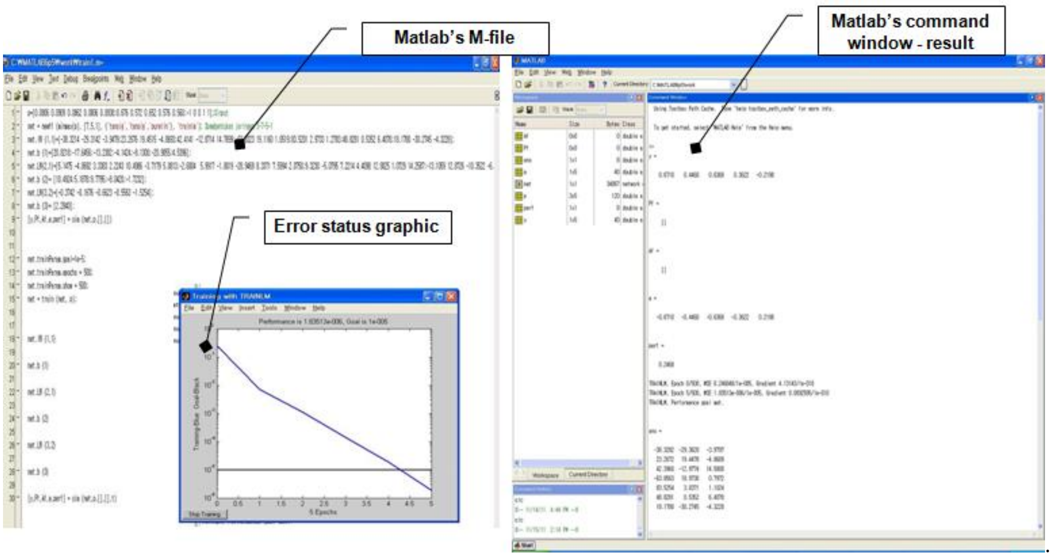

Figure 3. Screen Capture of Matlab Implementation

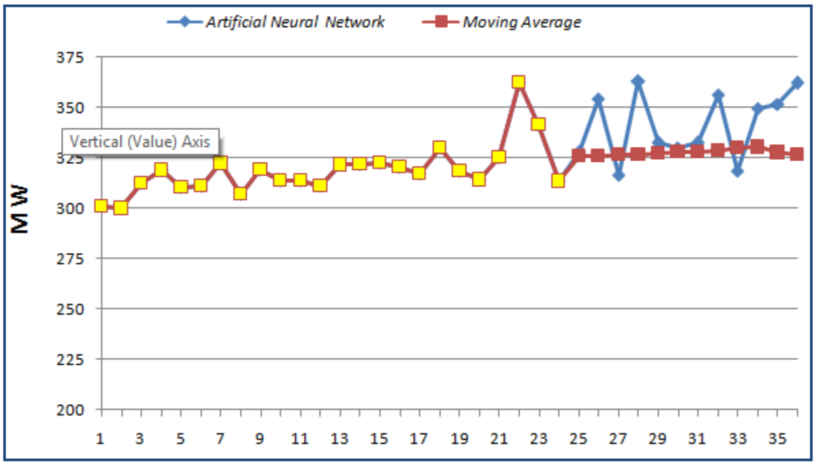

Figure 4. Comparison Result BPNN to Moving Average Prediction

From Fig. 4, the prediction using artificial neural network (BPNN) more volatile than using moving average method. This is due to the characteristics of these estimation method. BPNN can estimate by means of pattern recognition of past data, resulting in the estimated value of which tend to be similar to the pattern. On the other hand, moving average can estimate by means of averaging the historical data, resulting in estimated values are more stable.

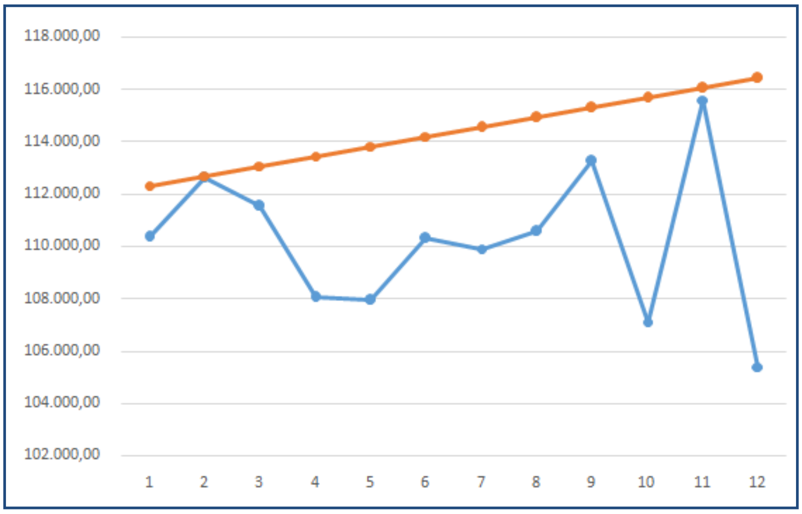

Figure 5. Comparison Result BPNN to Exponential Smoothing Prediction

Fig. 5 describe the ability for predicting from the two compared methods. It can be seen that BPNN has a better outcome for predicting electricity demand, sold electricity energy, in the future because it can procede data accurately and can read actual fluctuations data. While, exponential smoothing use only one recent data to predict the next months value.

CONCLUSION

In this article, a BPNN model used to predict the electricity demand in North Sulawesi. The proposed approach consists of three main stages. In the first stage, this model train a group of data to identify its pattern. Based on the result of training process, different set of data used to validate the model. If the error (MSE) reach to zero value, then simulation process can be done. Based on peak load and sold energy of electricity prediction results, BPNN can predict well based on happenstance (monthly past) data.

Acknowledgement

This work is supported by Riset Unggulan Universitas PNBP UNSRAT tahun 2016. The author also gratefully acknowledge the helpful of reviewer from UMJ.

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ISBN 978-602-17688-9-1

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