DEVELOPMENT OF SHORT TERM LOAD FORECASTING BASED ON FUZZY SUBTRACTIVE CLUSTERING

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ABSTRACT

A short term load forecasting model non linear based on Artificial Intelligence and Fuzzy Logic approach using algorithm Fuzzy Subtractive Clustering is developed. Computer code is generated by applying software Matlab 7.1 of Mathwork Corp. As a result, obtained short term load forecast using Fuzzy Subtractive Clustering is nearly its actual data and gives significant meaning compared to "Load coefficient" obtained by Electrical Public department's method. Statistically, accuracy average level of load coefficient obtained by Electrical Public department's method and by algorithm fuzzy subtractive clustering is 92,41% and 95.79% respectively.

Keyword : Short Term Load Forecasting, Fuzzy Subtractive Clustering

INTRODUCTION

High accuracy of the load forecasting for power systems improves the security of the power system and reduces the generation costs. The load forecasting is highly related to power system operations such as dispatch scheduling, preventive maintenance plan for the generators, and the reliability evaluation of the power systems. In addition, the accurate estimated loads are necessary for estimation the electric power price forecast on the electric power markets. However, the electric power load forecasting problem is not an easy task because of the nonlinear and the random-like behavior of system loads, as well as weather conditions and variation of economic environments. So far, many studies on the load forecasting have been developed to improve the prediction accuracy using various conventional methods such as deterministic, stochastic, knowledge based,fuzzy logic and artificial neural net (ANN) methods.

Consider international trend on electric power load forecasting techniques such as neural net and fuzzy theory. They are now actively utilized to reduce the uncertainty and the nonlinear property which are latent to the problem of electric power load forecast. Recently, researchers have concentrated on short-term load forecasting with ANN because of the following two advantages: one is capability of approximating any nonlinear function and the other is model determination through the learning process. In addition, fuzzy inference has been adopted into the load forecasting problem. It turns out that fuzzy inference method minimizes model errors and the number of the membership functions to grasp nonlinear behavior of power system short-term loads.

Load forecasting may be applied in the long, medium, short, and very short term time scale. Electricity demand is accumulated on different time scales exhibits different characteristics, e.g. daily detailed variations are lost when demand is accumulated at weekly level. Hence, forecasting models must be appropriately adapted to the time scale of interest.

Electricity usage may be predicted using data from previous history of load, temperature, humidity, luminosity, and wind speed among other factors. However, accurate models of load forecasting that use all these factors increase modeling complexity. In this paper we present a simple accurate model to forecast electricity load using Fuzzy Logic. Using data from the PT.PLN (Indonesia Public Electrical Department). The applied Algorithm is fuzzy subtractive clustering.

FUZZY SUBTRACTIVE CLUSTERING ALGORITHM

The common approach of all the clustering techniques in this paper is to find *cluster centers* that will represent each cluster. A cluster center is a way to tell where the center of each cluster is located, so that the next step it will be presented with an input vector, the system can tell which cluster of this vector belongs to by measuring a similarity metric between the input vector and al the cluster centers, and determining which cluster is the *nearest* or most similar one.

Some of the clustering techniques rely on knowing the number of clusters apriority. In that case the algorithm tries to partite the data into the given number of clusters. K-means and Fuzzy C-means clustering are of that type. In other cases it is not necessary to have the number of clusters known from the beginning; instead the algorithm starts by finding the first large cluster, and then goes to find the second, and so on. Mountain and Subtractive clustering are of that type. In both cases a problem of known cluster numbers can be applied; however if the number of clusters is not known, K-means and Fuzzy C-means clustering cannot be used.

Fuzzy Subtractive clustering solves this problem by using data points as the candidates for cluster centers, instead of grid points as in mountain clustering. This means tthe computation is now proportional to the problem size instead of the problem dimension. However, the actual cluster centers are not necessarily located at one of the data points, but in most cases it is a good approximation, especially with the reduced computation this approach introduces.

Since each data point is a candidate for cluster centers, a *density measure* at data point x_i is defined as :

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{(r_a/2)^2} \right), \tag{1}$$

where r_a is a positive constant representing a neighborhood radius. Hence, a data point will have a high density value if it has many neighboring data points.

The first cluster center x_{c1} is chosen as the point having the largest density value D_{c1} . Next, the density measure of each data point x_i is revised as follows:

$$D_i = D_i - D_{c_1} \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_{c_1}\|^2}{(r_b/2)^2} \right) \tag{2}$$

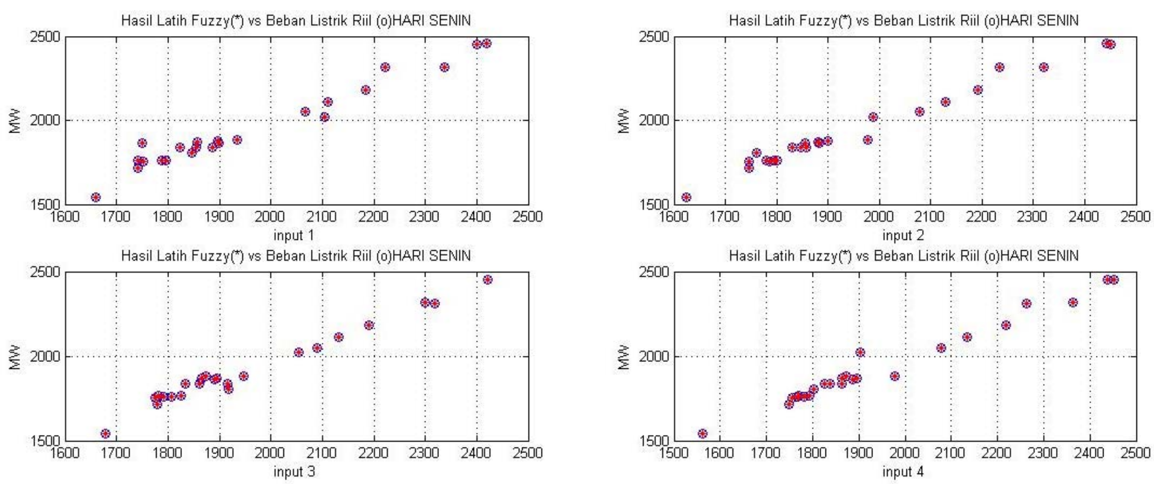
Where r_b is a positive constant which defines a neighborhood that has measurable reductions in density measure. Therefore, the data points near the first cluster center x_{c1} will have significantly reduced density measure. After revising the density function, the next cluster center is selected as the point having the greatest density value. This process continues until a sufficient number of clusters is attained.

RESULT AND DISCUSSION

Pattern of activity consumer at workday and weekend is remain unchange. Pattern of consumer activity would be recuring every week. For example Thursday load curve pattern in the current week will look like load curve pattern at Next Thursday. Load curve pattern for Monday during 10 weeks, starts from date of 6 March 2006 up to 8 May 2008 is shown in picture 1. Practical experience of dispatcher in Electrical Public department's Cigereleng Bandung West Java indicates that electrical load at one particular day influenced by electrical load at days before that.

Picture (1) .Daily Electrical Load Curve Pattern

According to Fuzzy Subtractive Clustering characteristic, General electrical load forecast system in this research consists two modes. They are learning phase mode (training) and assign phase mode. This mode given training data e.g. input couple and output of target saved in one form of scale matrix 10 x 24 in format " Name Of Hari.dat "
(example : senin.dat, selasa.dat, etc). As a Result of simulation is prediction data of electrical load from time range [01.00-24.00] starting from training data with assign data, RMSE, graphic result of clustering and the prediction errors graph.



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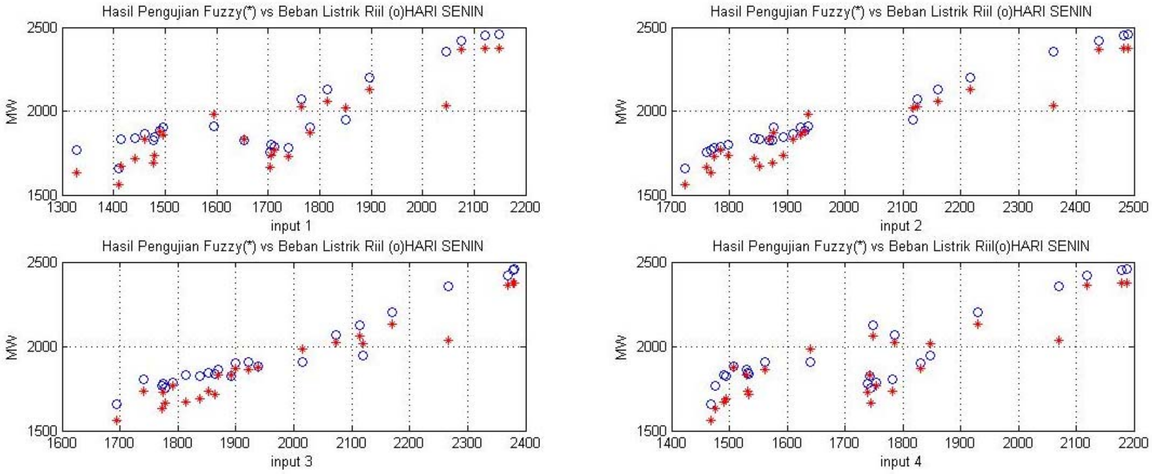
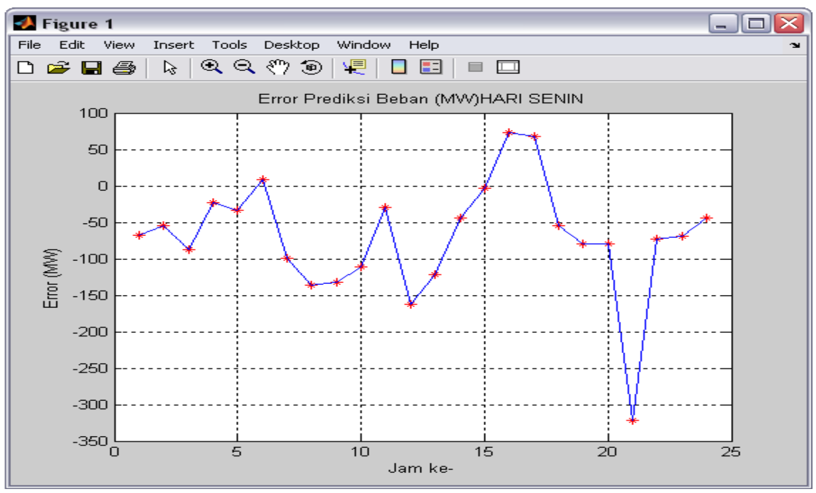
Picture(2). Graph Clustering Training Data



Picture (3). Graph Clustering Assign Data



Picture (4). Graph Prediction Error

Simulation of software fuzzy subtractive clustering is proposed to determine influence range and number of cluster(rule) to be obtained an prediction of short term load forecasting with errors a minimum and obtained in precise. Tables 1 shows end result obtained with experiment some values influence range and yields RMSE (Root Mean Square Error) immeasurable. Setting of value influence range (ra) correctly will determine accuracy result of prediction of electrical load. Result of inference shows relation between influence range, RMSE and number of cluster. If influence range smaller, hence amounts cluster yielded to be more, is meaning level of accuracy result of common sense also would increasingly good. If amounts cluster yielded too much exactly will generate existence of redundancy is causing increasingly of computing load.

Tables 1. Calculation results with Various Influence Range

SENIN									
Performance	**Influence Range ra**								
Measure	**0.06**	**0.07**	**0.08**	**0.09**	**0.1**	**0.9**	**0.92**	**0.94**	**0.95**

RMSE	104.1519	187.0798	213.0082	218.5220	221.5825	282.885	288.2312	292.3937	294.0910
Accuracy(%)	95.56	91.77	90.60	90.35	90.2	84.83	84.48	84.2	84.09
SELASA									
Performance	**Influence Range ra**								
Measured	**0.06**	**0.07**	**0.08**	**0.09**	**0.1**	**0.9**	**0.92**	**0.94**	**0.95**
RMSE	109.0116	109.2133	117.9961	119.5989	107.9621	208.3200	207.7263	207.1171	202.7223
Accuracy(%)	95.02	95.02	94.50	94.42	95.10	90.07	90.10	90.14	90.25
RABU									
Performance	**Influence Range ra**								
Measured	**0.02**	**0.03**	**0.04**	**0.05**	**0.07**	**0.08**	**0.09**	**0.1**	**0.12**
RMSE	228.1349	114.4418	114.3717	113.6423	125.9994	160.4383	215.7097	416.9488	363.3094
Accuracy(%)	93.70	94.80	94.80	94.92	94.03	92.63	90.83	89.30	85.58
KAMIS									
Performance	**Influence Range ra**								
Measured	**0.03**	**0.05**	**0,07**	**0.1**	**0.13**	**0.15**	**0.17**	**0.19**	**0.2**
RMSE	66.1613	67.1466	65.2073	71.4601	106.3173	139.8192	130.9508	377.0406	334.4535
Accuracy(%)	97.10	97,06	97.13	96.92	95.62	94.35	94.55	81.41	84.35
JUMAT									
Performance	**Influence Range ra**								
Measured	**0.03**	**0,05**	**0,07**	**0,08**	**0,09**	**0,1**	**0,11**	**0,12**	**0,13**
RMSE	145.5767	180.9148	167.1672	162.1107	161.9984	161.491	160.8815	169.6222	241.3381
Accuracy(%)	94,51	93.50	93.99	94,33	94.31	94.31	94.31	93.61	93.30
SABTU									
Performance	**Influence Range ra**								
Measured	**0.03**	**0,05**	**0.07**	**0,1**	**0,11**	**0,88**	**0.9**	**0.95**	**0.98**
RMSE	128.8645	128.9292	128.8484	129.6685	128.1449	381.3581	371.0230	366.9604	386.1696
Accuracy(%)	96,28	96,27	96,27	96,24	96,54	83,28	83,95	84,22	83,15
MINGGU									
Performance	**Influence Range ra**								
Measured	**0,03**	**0,05**	**0,07**	**0.09**	**0,1**	**0,11**	**0,12**	**0,13**	**0,15**
RMSE	66.5791	67.1354	68.8950	70.6041	83.7776	73.2725	73.9363	73.6382	133.0127
Accuracy(%)	96,80	96,74	96,65	96.53	96,05	96,43	96,44	96,47	93,48

CONCLUSION :

Obtained short term load forecast using Fuzzy Subtractive Clustering is nearly its actual data and gives siginificant meaning compared to "Load coefficient" obtained by Electrical Public department's method. Statistically, accuracy average level of load coefficient obtained by Electrical Public department's method and by algorithm fuzzy subtractive clustering is 92,41% and 95.79% respectively.

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