Mat Syai'in
Adi Soeprijanto

J. Electrical Systems 8-2 (2012): 198-208

Regular paper

Combination of Generator Capability Curve Constraint and Statistic-Fuzzy Load Clustering Algorithm to improve NN-OPF performance

The inclusion of statistic-fuzzy Load clustering method in algorithm of NN-OPF is intended to make the NN-OPF robust in load changing at a certain load range. Whereas, The inclusion of Generator Capability Curve (GCC) as a constraint in NN-OPF is to ensure cheap and safe operation of generators. NN-OPF is built with reference to a Particle Swarm Optimization Optimal Power Flow (PSO-OPF). There are three stages in Designing NN-OPF. The first stage is design of PSO-OPF with generator capability curve constraint. The second stage is load clustering using statistic-fuzzy method. The third stage is training NN-OPF using constructive back propagation method. In training process of Neural Network (NN), the nearness index of load curve (FW_{ik}) resulting from statistic-fuzzy method, and total load (active power, reactive power), are used as input. The pattern of generator scheduling resulting from PSO-OPF is used as outputs. In this paper, the Java-Bali power system is used as sample system to verify the validity of this method. The simulation results using MATLAB software have shown that the proposed method has good performance. The proposed method is possible to apply in on-line system in normal condition, especially in representing non linear generation operation limit near steady state stability limit and under excitation operation area.

Keywords: Generator Capability Curve, Particle Swarm Optimization, Neural Network, Optimal Power Flow, Statistic-Fuzzy.

1. INTRODUCTION

The optimal power flow has been growing since a few decades ago, many methods have been developed such as the merit order, linear programming [1] Lagrange and combination of them [2]. In other hand artificial intelligence (AI) has been widely adopted to improve the performance of optimal power flow. The most popular intelligence optimization technique already applied were genetic algorithm, fuzzy, simulated annealing, expert system, neural network, PSO and the hybrid of them [3-13]. Among of these, PSO and its Improving is the one received greatest attention caused by its capability in avoiding local optimal solutions [8]. Only view papers give attention in developing proper or more realistic constraint to the optimal power flow problem. As an example, Onate Yumbla et.al used security constraint in optimal power flow [14], and Zwe-Lee et.al considered generator constraint in solving economic dispatch problem[15]. As a consequence, such tight constraint will result a pessimistic solution. Actually the optimum value of the objective function –in this case system operation cost– can still be reduced if we can alleviate the constraint especially generator security constraint. So far researchers used rectangular constraint (P_{min}/P_{max} and Q_{min}/$Q_{max)}$ to limit the generator output inside the secure operating condition [4, 11, 16].

We had developed realistic generator capability curve based on neural network and the security check algorithm that be used as enhanced constraint optimal power flow based on PSO. The algorithm is very simple and flexible especially for representing non linear

Corresponding author : Matt.Syaiin@gmail.com
Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember (ITS) and Surabaya Shipbuilding State Polytechnic (PPNS), Surabaya, Indonesia, 60111.

generation operation limit near steady state stability limit and under excitation operation area, that method is able to get a combination of generation cheaper and safe, but the process is quite old [17]. We also had developed optimal power flow based on NN (NN-OPF) which is built based on OPF-IPSO with developed load clustering. On that paper the load clustering is expressed based on load index [20]. Load index is calculated from simple equation. So when there are many loads curve pattern the load index sometimes cannot represent the load clustering accurately. For example: Load index curve A is near load index curve B, load index curve B is near load index curve C and load index curve C is near load index curve D, it is cannot guarantee that curve A is stay in one cluster with curve D, because of that sometimes the error exceed of limit, but the speed of optimization process is fast [20].

This research is aimed to developed optimal power flow based on NN (NN-OPF). In order to NN-OPF can be robust in changing of load on a certain range, we use statistic-fuzzy methods to clustering load based on load curve pattern. The load must be declared in per unit [18]. In NN-OPF case the load curve pattern is used to represent losses in the system. The same total load with the different load curve pattern will result the different pattern of generation, because the value of losses is different.

To speed up the training process of NN the methods used is constructive back propagation (CBP) which has advantage in determining the number of neuron in the hidden layer automatically [19]. The numbers of inputs used in training process are 2, while numbers of outputs are 8 (number of generator). The reference used in training process is the OPF-PSO with a constraint generator capability curve [17]. The target at the end of the training process is NN-OPF capable to work as OPF-PSO with a faster response. NN-OPF is expected to perform the generation optimization faster so that it can be applied to the system online in normal operation especially in representing non linear generation operation limit near steady state stability limit and under excitation operation area. The simulation is conducted at 500 kV Java-Bali Power System.

2. METHODOLOGY

Design of NN-OPF consists of three stages. The first stage is design of OPF-PSO with realistic generator capability curve constraint, the second stage is load clustering using statistic-fuzzy methods, and the third stage is NN-OPF training to get NN model using constructive back propagation.

2.1 Design OPF-PSO using Generator Capability Curve Constraint

To design OPF-PSO, there are three stages to be done. The first step is developing NN model for generator capability curve, the second step is developing security check algorithm and the third step is to perform optimization with PSO. These stages have been described in detail in the reference [17], starting from the NN model used, the stages in making a realistic generator capability curve based on NN, and an algorithm to use the NN model as a constraint OPF. The difference is only in the data used in the simulation. In the previous discussion we use 7(seven generator) but in this discussion we used 8 (eight) generator. PSO model used in this paper is same as model used in reference [17].

2.2 Load Clustering using statistic-fuzzy methods

The load clustering is based on the surface of the load curve that is the pattern of the nominal load values at all buses. Fig. 1 describes the meaning of load curve surface.

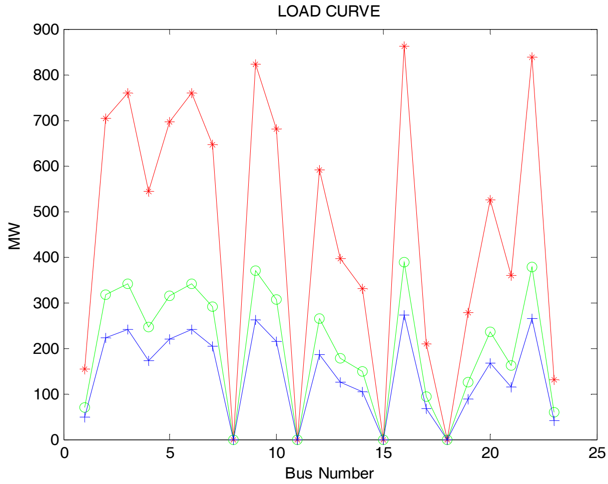

Figure 1: Example of Three Load Curve Surfaces in MW.

From fig.1 it can be seen that there are three load curves expressing the value of bus power variable in MW. To get the accurate results in load clustering, before load clustering done, power variable must be normalized based on the highest value. So it is possible there are two curves having different nominal loads values (MW) grouped into the same cluster. For example if the value in figure 1 is converted from MW to pu(%) based on the highest value at each load curve, the three load curves in Figure 1 after normalized will be coincide as at figure 2.

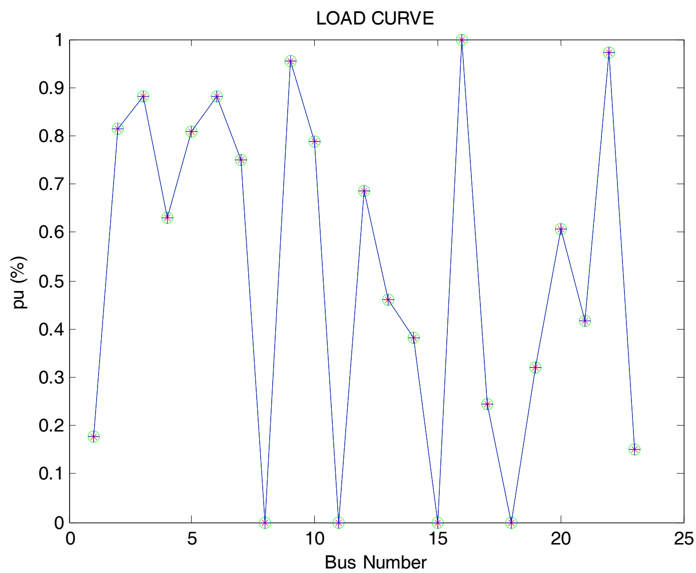

Figure 2: Same Load Curve Surface in pu(%) of Three Different Load Curve in MW

Step by step process of load clustering has been described in the reference [18] and will be adopted here with slight modifications. Equations used are as follows:

$$W_{ik} = \frac{\sum_{l=1}^{n} X_{il} X_{kl}}{\sqrt{\left(\sum_{l=1}^{n} X_{il}^2\right) \cdot \left(\sum_{l=1}^{n} X_{kl}^2\right)}} \tag{1}$$

W_{ik} = The nearness coefficient between the two load curve vectors (load curve i and load curve k)

X_{il} = normalized load value at bus l in surface (state) i

X_{kl} = normalized load value at bus l in surface (state) k

Results of load clustering process will be used as input data in the training process NN-OPF. The stages should be done in order that load clustering results can be used as inputs in the training process of NN-OPF are as follows:

Step 1

The nearness coefficient between the two load curve vectors (W_{ik}) of all patterns of the load curve is calculated using equation (4) and expressed in the matrix. The diagonal matrix value is always 1, because load curve compare to itself, while the rows and columns in the off diagonal matrix show nearness coefficient between two load curves.

The W_{ik} cannot be used to cluster load curves directly. For example, curve A near curve B, curve B near curve C, curve C near curve D, and curve D near curve E, it cannot guarantee curve A near curve E.

Step 2

In order to W_{ik} can used to cluster load curve, it needs to process in fuzzy system. The process of fuzzification usually uses triangle, trapezoids, or normal curve distribution. In this paper we used statistic equation (4) to process fuzzification. The fuzzy rule base used in this paper is min-max system and combined with equation (5).

$$FW_{ik} = \sum_{l=1}^{n} W_{il} W_{kl} \tag{2}$$

FW_{ik} = The nearness index between the two load curve vectors (load curve i and load curve k)

W_{il} = The nearness coefficient between the two load curve vectors (load curve i and load curve l)

W_{kl} = The nearness coefficient between the two load curve vectors (load curve k and load curve l)

W_{il} and W_{kl} are processed in step 1, FW_{ik} calculated using equation (5) but the product of two elements is replaced by taking the minimum one and the addition of two products by taking the maximum one.

Step 3

The threshold which is used to cluster patterns is 95%. Inside each cluster, the average value of FW_{ik} all patterns will be used as reference pattern of each cluster in the next training process of NN-OPF.

2.3 Training Process NN-OPF

There are two data inputs used in the training process: Total Active Power / Reactive Power load and nearness coefficient (FW_{ik}) obtained from the statistic-fuzzy load clustering that calculating in the item 2.2. The output is the pattern of generation resulted by OPF-PSO at each load curve pattern. The complete steps to do training NN-OPF is as follows:

Step 1

Preparing the input and output data. For the active power optimization, the inputs used are:

(1) Total active power load

(2) Nearness coefficient of load clustering (FW_{ik})

and the outputs are:

(1) Pattern of active power generation that is resulted by OPF-PSO

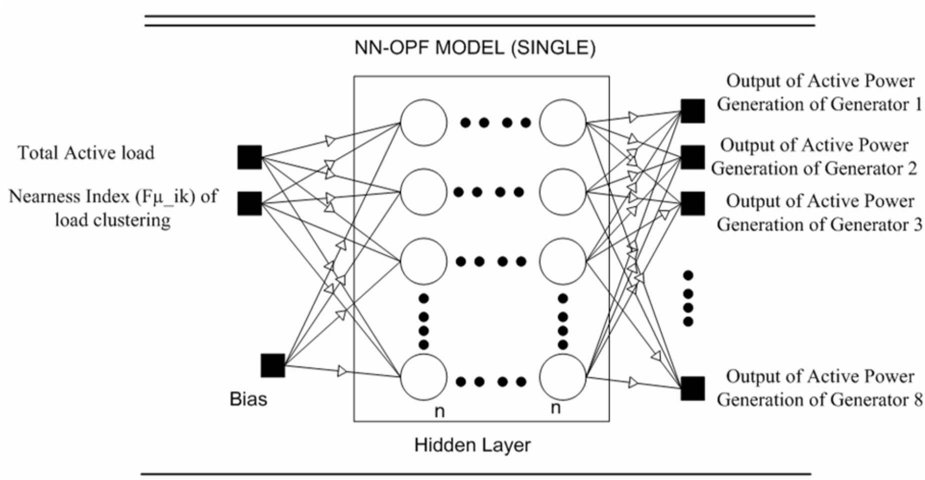

Figure 3: NN-OPF Model (single) for the active power optimization.

For reactive power optimization, the inputs used are:

(1) Total reactive power load

(2) Nearness coefficient of load clustering (FW_{ik})

and the outputs are:

(1) Pattern of reactive power generation that is resulted by OPF-PSO

Step 2

All input data must be normalized, so that its value is in the range 0 to 1 for active power and -1 to 1 for reactive power, and then determining threshold function for training NN. In this case tansig and logsig were used as activation function and constructive back propagation as training method. The logsig is used for active power optimization because the value of logsig is between 0 and 1. The tansig is used for reactive power optimization because the value of tansig is between -1 and 1. The Constructive back propagation method is used as methods in this paper because it can determine the number of neuron in hidden layer automatically, so the process of training is relatively fast. Step by step Constructive back propagation method has been explain detailed in reference[19]

Step 3

After training process completed, NN is tested with other data to determine the performance of NN-OPF. If the error between the NN-OPF and OPF-PSO meet then the process is complete but if the error limit is not meet then back to step 1.

Actually, the load change at any time so if we only use one NN for all changes the load, NN will be difficult to follow the performance of OPF-PSO. For that reason in this proposed method we use some NN that working together based on the range of total load as shown at Figure 5.

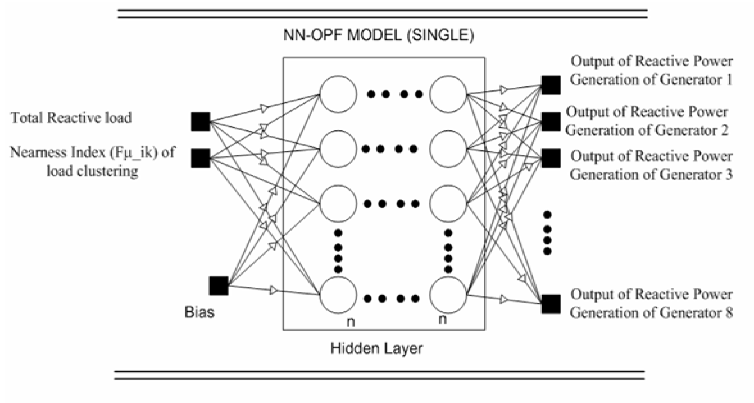

Figure 4: NN-OPF Model (single) for the active power optimization.

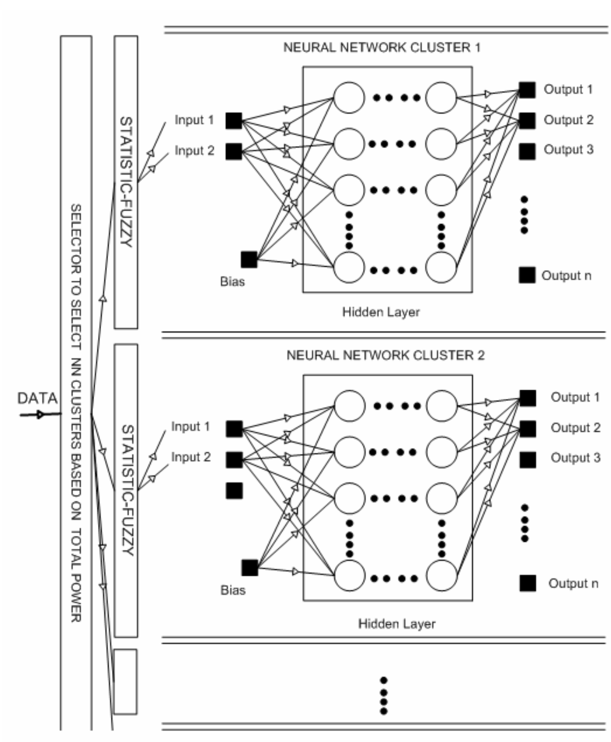

Figure 5: NN-OPF Model for Large Load Variation

In this paper, for every 5% of the total load will be created one NN correspond to one group. Minimum load used in the simulation is 25% of total load (TL), so there will be 15 single NN-OPF corresponds with 15 groups.

2.4 Mechanisms of Using NN-OPF

When the NN-OPF is ready to use, the mechanism of using NN-OPF can be seen at Figure 6, below. Diagrams in Figure 6 can be explained step by step as follows.

Step 1

Input data must be grouped based on total load to determine the NN that will work.

Step 2

Input data must be normalized according to the normalization at the training process.

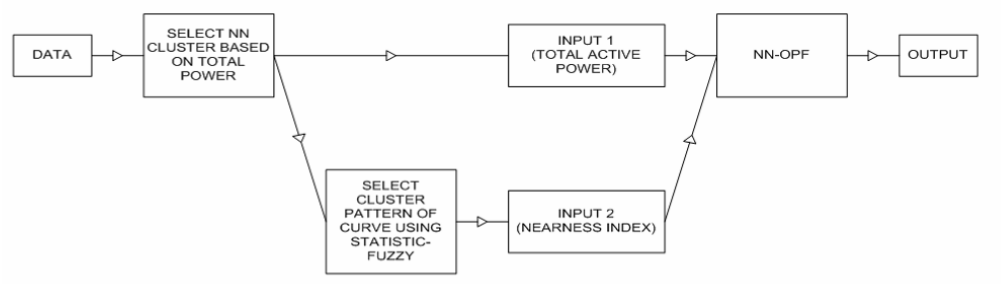

Figure 6: Mechanisms of Using NN-OPF

Step 3

Calculating Nearness index (FW_{ik}) input data (i) and reference data (k) using statistic-fuzzy method to determine the cluster of load clustering.

3. SIMULATION AND ANALYSIS

3.1 Result and Analysis

The Plant used for simulation is the 500 kV Java-Bali Power System. The data of generator characteristics and cost will be shown in table 1. While the other data shown in appendix.

Table I: Generator Data

Unit	Character function of Generation	Production Cost (Rp/KWh)
Suralaya (bus 1)	$65.94P_1^2 + 395668.05P_1 + 31630.21$	0.138
Muara Tawar (bus 8)	$690.98P_2^2 + 2478064.47P_2 + 107892572.17$	1.450
Cirata (bus 10)	$0 + 6000.00P_3 + 0$	1.000
Saguling (bus 11)	$0 + 5502.00P_4 + 0$	0.917
Tanjung Jati (bus 15)	$21.88P_5^2 + 197191.76P_5 + 1636484.18$	0.077
Gresik (bus 17)	$132.15P_6^2 + 777148.77P_6 + 13608770.9$	0.378
Paiton (bus 22)	$52.19P_7^2 + 37370.67P_8 + 8220765.38$	0.030
Grati (bus 23)	$533.92P_8^2 + 2004960.63P_8 + 31630.21$	1.067

NN-OPF model is obtained from the training process with stages that have been described in the item 2.3. The size of NN-model resulted from the training process has 3 layers in the hidden layer with number of neuron on layer1 is 11 neurons, in layer2 is 25 neurons, and in layer3 is 25 neurons. The activation functions used are logsig for optimizing active power and tansig for optimizing reactive power. For each total load of 0.5 pu one group is made, so there are 15 groups between 1pu and 0.25pu. Test presented in this paper only on the range 1pu - 0.95 pu, while similar characteristics assumed for the other groups.

Training process uses only 2 input as representative of the input characteristics. The first input is the total power P or total power Q, depend on the optimization which performed. To optimize power P, the first input used is the total power P, while for the optimization of power Q the first input used is the total power Q.

The second input is nearness index load curve that resulted by statistic-fuzzy methods. Different load curves but same total load might resulted different total generation, because load curve pattern is related to losses in network.

Performance comparison between the NN-OPF and OPF-PSO can be seen in table II below. Table II shown the error between NN-OPF and OPF-PSO on operation cost 0.12 % and power generation (MW) 0.312% which is small enough.

Table. II: Cost of Generations

NN-OPF			OPF-PSO		
P(MW)	Q(MVar)	COST	P(MW)	Q(MVar)	COST
1500.00	1012.57	74 1 898 705.2	1519.46	1145.83	753 473 072.9
1040.00	803.08	3 432 443 589.0	1040.00	586.93	3 432 443 589.0
787.27	371.89	4 723 602.4	779.82	391.93	4 678 905.3
648.00	464.48	3 565 305.9	670.51	458.12	3 689 167.3
743.31	432.26	160 299 920.6	748.42	428.88	161 475 023.8
392.71	294.73	339 180 169.7	392.21	294.94	338 740 163.4
4728.85	1177.88	1 352 013 925.0	4721.22	1417.70	1 347 965 310.0
149.99	670.98	399 294 066.6	149.71	671.01	398 695 696.8
Total Cost : 6 433 419 284.4 Total Generation (MW) : 9990.13 Total Load (MW) : 9768 Total Loss (MW) : 222.13 Execution time : 0.096131sec.			Total Cost : 6 441 160 928.5 Total Generation (MW) : 10021.35 Total Load (MW) : 9768 Total Loss (MW) : 253.35 Execution time : 130.2518 sec.		

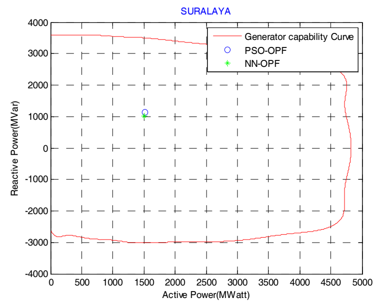

Figure 7: NN-OPF and PSO-OPF at Suralaya Generator

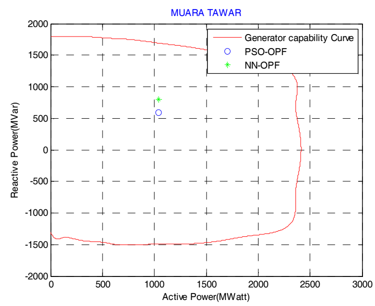

Figure 8: NN-OPF and PSO-OPF at Muara Tawar Generator

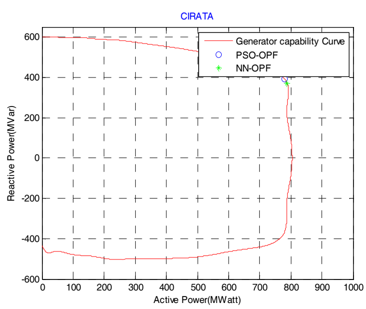

Figure 9: NN-OPF and PSO-OPF at Cirata Generator

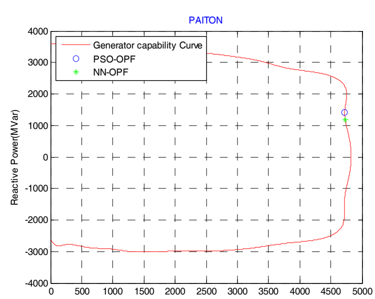

Figure 13: NN-OPF and PSO-OPF at Paiton Generator

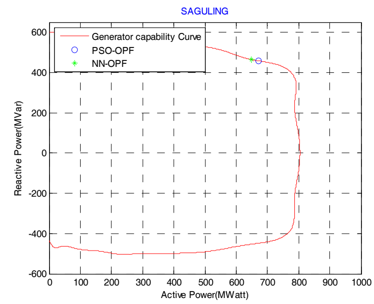

Figure 10: NN-OPF and PSO-OPF at Saguling Generator

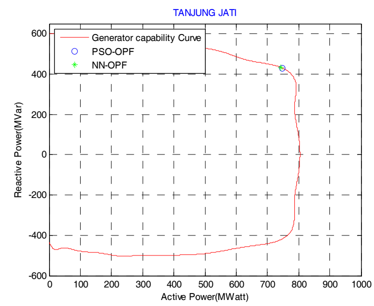

Figure 11: NN-OPF and PSO-OPF at Tanjung Jati Generator

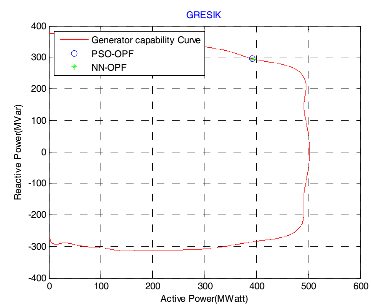

Figure 12: NN-OPF and PSO-OPF at Gresik Generator

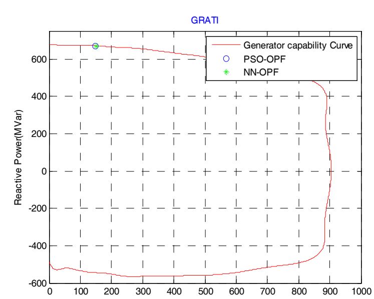

Figure 14: NN-OPF and PSO-OPF at Grati Generator

Figure 7 -14 is the visualization of optimization results of P and Q by using the NN-OPF and OPF-PSO expressed on generator capability curve. Fig.9, fig.11, fig.12 and fig.14 which is related to Generator Cirata, Generator Tanjungjati, Generator Gresik and Generator Grati respectively show that the results is almost coincide for both method. For Generator Suralaya, Generator Muaratawar and Generator Paiton (fig.7, fig.8, fig.13) there is a slightly difference result in value of Q. Generator Saguling there is a slightly difference result in value of P. These differences occur because of two reasons, firstly caused by the lack of the data used in the simulation and the second is the threshold value used during the clustering pattern of the load curve is not big enough. The error results of NN-OPF and OPF-PSO can be minimized by increasing the threshold value and adding the data pattern of clustering.

In Generator Cirata, Generator Saguling, Generator Tanjungjati, Generator Paiton and generator Grati (fig.9, fig.10, fig.11, fig.12, fig.13 and fig.14) optimization results are exactly coincide with the generator capability curve. Operation in this condition is still safe because the generator capability curve used in this simulation already considering security factors.

4. CONCLUSION

Optimal Power Flow based on NN (NN-OPF) with statistic-fuzzy clustering are able to achieve operation cost same as OPF-PSO, with faster response. Few differences occurred between two optimization method that is 0.12% in cost approximation and 0.312% in power generation. This occurs because lack of the data taught in the NN-OPF and the threshold in Statistics-fuzzy clustering was not big enough.

ACKNOWLEDGMENT

Thank You for the Indonesian Government Electrical Company for supporting all the data and the Indonesian Government for supporting financial needed in this research.

REFERENCES

[1] Sheble, G.B., *Real-Time Economic Dispatch and Reserve Allocation Using Merit Order Loading and Linear Programming Rules*. Power Engineering Review, IEEE, 1989. 9(11): p. 37-37.

[2] Vo Ngoc, D. and W. Ongsakul. *Improved Merit Order and Augmented Lagrange Hopfield Network for Ramp Rate and Transmission Constrained Unit Commitment*. in *Power Engineering Society General Meeting, 2007. IEEE*. 2007.

[3] Venkatesh, B., M.K. George, and H.B. Gooi, *Fuzzy OPF incorporating UPFC.* Generation, Transmission and Distribution, IEE Proceedings-, 2004. 151(5): p. 625-629.

[4] Mori, H. and T. Horiguchi. *A genetic algorithm based approach to economic load dispatching*. in *Neural Networks to Power Systems, 1993. ANNPS '93., Proceedings of the Second International Forum on Applications of*. 1993.

[5] Yurong, W., L. Fangxing, and W. Qiulan. *Reactive power planning based on fuzzy clustering and multivariate linear regression*. in *Power and Energy Society General Meeting, 2010 IEEE*. 2010.

[6] Abido, M.A. *Multiobjective particle swarm optimization for optimal power flow problem*. in *Power System Conference, 2008. MEPCON 2008. 12th International Middle-East*. 2008.

[7] dos Santos Coelho, L. and V.C. Mariani. *Economic dispatch optimization using hybrid chaotic particle swarm optimizer*. in *Systems, Man and Cybernetics, 2007. ISIC. IEEE International Conference on*. 2007.
[8] Jong-Bae, P., et al., *An Improved Particle Swarm Optimization for Nonconvex Economic Dispatch Problems.* Power Systems, IEEE Transactions on, 2010. 25(1): p. 156-166.
[9] Weibing, L., L. Min, and W. Xianjia. *An improved particle swarm optimization algorithm for optimal power flow*. in *Power Electronics and Motion Control Conference, 2009. IPEMC '09. IEEE 6th International*. 2009.
[10] Aquino, R.R.B., et al. *Recurrent neural networks solving a real large scale mid-term scheduling for power plants*. in *Neural Networks (IJCNN), The 2010 International Joint Conference on*. 2010.
[11] Roa-Sepulveda, C.A. and B.J. Pavez-Lazo. *A solution to the optimal power flow using simulated annealing*. in *Power Tech Proceedings, 2001 IEEE Porto*. 2001.
[12] Swarnkar, K.K., S. Wadhwani, and A.K. Wadhwani. *Optimal Power Flow of large distribution system solution for Combined Economic Emission Dispatch Problem using Partical Swarm Optimization*. in *Power Systems, 2009. ICPS '09. International Conference on*. 2009.
[13] Panta, S. and S. Premrudeepreechacharn. *Economic dispatch for power generation using artificial neural network ICPE’07 conference in Daegu, Korea*. in *Power Electronics, 2007. ICPE '07. 7th Internatonal Conference on*. 2007.
[14] Onate Yumbla, P.E., J.M. Ramirez, and C.A. Coello Coello, *Optimal Power Flow Subject to Security Constraints Solved With a Particle Swarm Optimizer*. Power Systems, IEEE Transactions on, 2008. **23**(1): p. 33-40.
[15] Zwe-Lee, G., *Particle swarm optimization to solving the economic dispatch considering the generator constraints.* Power Systems, IEEE Transactions on, 2003. **18**(3): p. 1187-1195.
[16] Yalcinoz, T., H. Altun, and U. Hasan. *Constrained economic dispatch with prohibited operating zones: a Hopfield neural network approach*. in *Electrotechnical Conference, 2000. MELECON 2000. 10th Mediterranean*. 2000.
[17] Mat Syai'in , Adi Soeprijanto,, and Takashi Hiyama,, *Generator Capability Curve Constraint for PSO Based Optimal Power Flow.* International Journal of Energy and Power Engineering, 2010. **3**(2): p. 61-66.
[18] Wenyuan, L., et al., *A Statistic-Fuzzy Technique for Clustering Load Curves.* Power Systems, IEEE Transactions on, 2007. **22**(2): p. 890-891.
[19] Gunaseeli, N. and N. Karthikeyan. *A Constructive Approach of Modified Standard Backpropagation Algorithm with Optimum Initialization for Feedforward Neural Networks*. in *Conference on Computational Intelligence and Multimedia Applications, 2007. International Conference on*. 2007
[20] Mat Syai'in , Adi Soeprijanto, *Neural Network Optimal Power Flow (NN-OPF) based on IPSO with Developed Load Cluster Method*, in WASET Vol 72 pp no.10 2010