International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:4, No:12, 2010

Neural Network Optimal Power Flow (NN-OPF) based on IPSO with Developed Load Cluster Method

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***Abstract*—**An Optimal Power Flow based on Improved Particle Swarm Optimization (OPF-IPSO) with Generator Capability Curve Constraint is used by NN-OPF as a reference to get pattern of generator scheduling. There are three stages in Designing NN-OPF. The first stage is design of OPF-IPSO with generator capability curve constraint. The second stage is clustering load to specific range and calculating its index. The third stage is training NN-OPF using constructive back propagation method. In training process total load and load index used as input, and pattern of generator scheduling used as output. Data used in this paper is power system of Java-Bali. Software used in this simulation is MATLAB.

***Keywords*—**Optimal Power Flow, Generator Capability Curve, Improved Particle Swarm Optimization, Neural Network

I. Introduction

THE recent development of optimal power flow method has adopted the artificial intelligence (AI) algorithm in gaining optimal solution of generator scheduling. The most popular intelligence optimization technique already applied were genetic algorithm, fuzzy, simulated annealing, expert system, neural network, PSO and the hybrid of them [1-12]. Among of these, PSO is the one received greatest attention caused by its capability in avoiding local optimal solutions. Most PSO papers stress are on developing new techniques in effort to achieve optimal solution considering non linear power system characteristic [5-7]. Only view papers give attention in developing proper or more realistic constraint to the optimal power flow problem. As an example, more tight constraints such as Sudhakaran et,al, Pablo et.al and Gaing et.al [1-3] were used in solving economic dispatch problem. 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 P_{min}/P_{max} and Q_{min}/Q_{max} to limit the generator output inside the secure operating condition. Matlab in its Power System Simulation Package used more realistic generator security constraint that is the generator capability curve which is approximated with five straight lines [4]. Although it is already better than P_{min}/P_{max} and Q_{min}/Q_{max} but the generator still can't operate in the marginal area in order to get lower operation cost.

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We had developed neural network based generator capability curve and the security check algorithm that be used as enhanced constraint of optimal power flow. The algorithm is very simple and flexible especially for representing non linear generation operation limit near steady state stability limit and under excitation operation area.

The online assasement needs a quick response of the system. OPF-IPSO with capability curve constraint is able to get a combination of generation cheaper, but the process is quite old [13].

This research is aimed to develope NN-OPF to replace OPF-IPSO with generator capability curve constraint to get response system more quickly, so that it can be applied to the system on line. In order be able to replace OPF -IPSO with generator capability curve constraint, NN-OPF need the input and output data as a reference in establishing the network and testing the performance of OPF-NN. Input is the load on each bus, and the output is a combination of the cheapest generation. The training process OPF-NN is done in the load range 25% to 100%. To speed up the training process the methods used Constructive Backpropagation (CBP) which has advantage in determining the number of neuron in the hidden layer automatically.

OPF-NN is expected to perform the generation optimization faster so that it can be applied to the system online. OPF-NN results are expected to be the same with the result of OPF based on PSO with capability curve constraint. The simulation is conducted at 500 kV Java-Bali Power System [13].

II. Methodology

In order that NN-OPF has fast response and has accuracy same as OPF-IPSO, so that Design of NN-OPF consist of three stages. The first stage is OPF-IPSO design, the second stage is load clustering and load index calculating, and the third stage is NN-OPF training to get NN model which replaced OPF-IPSO. The process sequence shown in the flowchart in fig.1.

A. *Design OPF-IPSO using Generator Capability Curve Constraint*

The detailed design of OPF-PSO has been discussed in reference [13]. In spite of PSO, IPSO will be used in this paper as optimization method. The optimization process of OPF-IPSO is time consuming so it is not effective in some applications, such as applications that require fast processing time (online). On the other hand, generator capability curve used as a constraint by OPF-IPSO can make a superior capability in determining cheaper generation scheduling pattern but still safe [13]. All of the result of OPF-IPSO algorithm will be used as a reference by NN-OPF to produce performance like OPF-IPSO that can operate at various online load conditions.

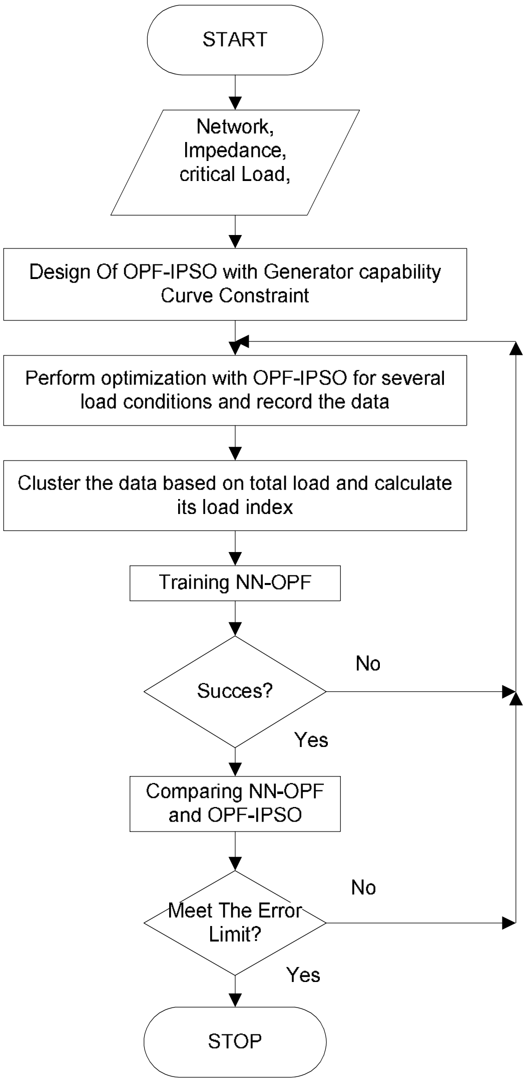

Fig. 1 Flowchart Design of NN-OPF

Design of OPF-IPSO started with developing NN models to recognize image of generator capability curve by sampling picture along the curve. The NN models of generator capability already being developed in [13] and will be adopted here. NN models of generator capability were used as a constraint replacing Pmin-Pmax and Qmin-Qmax constraint. The use of generator capability curve as constraint in OPF was objected to operate generator more realistic while IPSO method was chosen because it has good ability in avoiding local optimum problem. All of OPF-IPSO design can be seen in the flow chart in Figure 2.

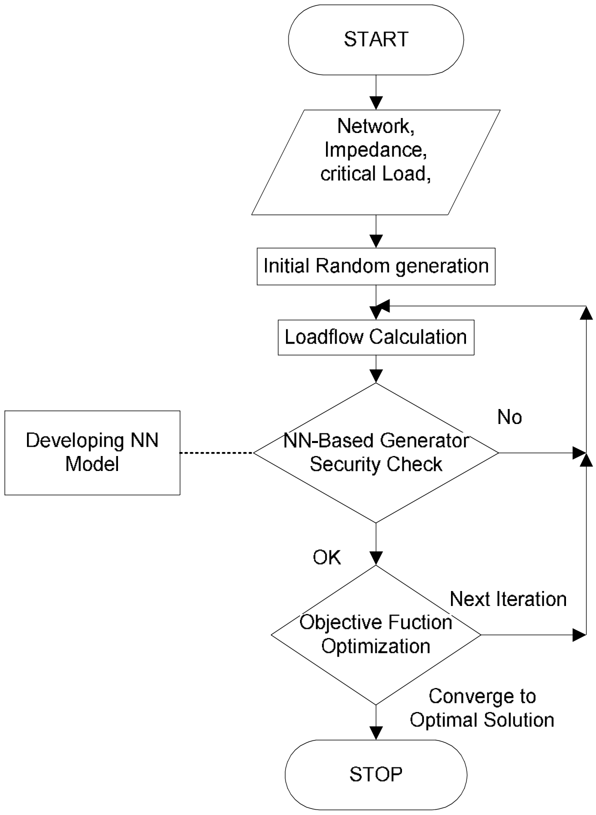

Fig. 2 IPSO based OPF Flowchart

IPSO used in this paper was developed by Jong Bae Park et al [14]. Unlike the standard PSO developed by Kennedy and Eberhart [15], IPSO has additional algorithms called chaotic sequences, as techniques that guarantee a global solution search process becomes faster with the possibility of trapped into local solutions are smaller. One of the chaotic sequences that can be used to accelerate the search of global solutions - as an example of factor – can be written in the form:

$$f_k = \mu . f_{k-1} .(1 - f_{k-1})$$

This factor is derived from iterator phenomenon called logistic map. Factors will be the multiplier of the weight factors of position and velocity transition equation:

$$\omega_{new} = \omega . f$$

Movement of this position is accelerated to get condition of global optimum solution.

B. Load Clustering and Calculation of Load Index

Irregular load changes on each bus make NN difficult to get model that can work like OPF-IPSO. That problem can be minimized by clustering load into several clusters and each cluster related to one NN model. Step by step load clustering are as follows:

Step 1.

From data in Table III, calculate the total load (active power and reactive power) from all bus.

Step 2.

Load clustering is based on the total load, every 5% of the total load will be assumed as one cluster. Minimum load used in the simulation is 25% of total load (TL) so there will be 15 clusters formed with the load range ($1 \leq TL < 0.95$; $0.95 \leq TL < 0.90$;.......... ... . $0.3 \leq TL < 0{:}25$). For each cluster of load there will be one related NN model.

Step 3.

Each load index is calculated using the following equation.

$$Load\ Indeks = \frac{\sum \frac{(|Xref_i - X_i|)}{Xref_i}}{n}$$

$Xref_i$= maximum loading capacity in the i^{th} bus
X_i= Load in the i^{th} bus
n = Number of buses

Total load and load index will be used as input in NN-OPF trainning.

C. *Training NN-OPF*

Design Algorithm of NN-OPF model is described as follows:

Step 1.

Prepare pairs of input and output datas for NN training which taken from results of running OPF-IPSO in some load conditions (minimum load - peak load).

Step 2.

Number of inputs used in NN training is two, the total load and load index. Number of output equal to the number of generators, while the number of hidden layers will be determined automatically by using the constructive-backpropagation.

Step 3.

Before training, NN-OPF should determine load cluster based on total load. Every cluster will relate with one NN model.

Step 4

After training process is success, NN-OPF model resulted will be tested with the data that have not been taught in the training process, and compare the results with OPF-IPSO. If the results of NN-OPF model similar to the results of OPF-IPSO (according to the degree of error) then the design is complete. If the results is not similar the design should be repeated starting from step one.

Design of NN-OPF used can be seen in Fig. 3. Weight determination on Training NN-OPF follow the rules of Constructive-Backpropagation, in detail can be seen in reference [16].

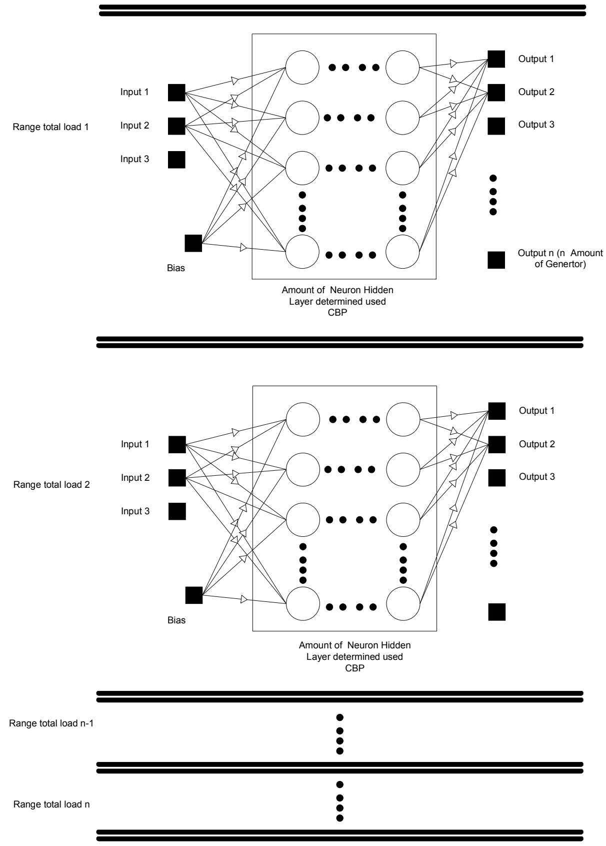

Fig. 3 Model NN-OPF

III. Simulation and Analysis

A. *Plant Data*

The Plant used for simulation is the 500 kV Java-Bali Power System as shown in Figure 4. The data of generator characteristics and cost, line impedances and an operating condition are shown at Table I-III.

TABLE I
GENERATOR DATA

Unit	Caracter function of Generation	Production Cost (Rp/KWh)
1(Suralaya)	$65.94P_1^2 + 395668.05P_1 + 31630.21$	0.1380
8(Muara Tawar)	$690.98P_8^2 + 2478064.47P_8 + 107892572.17$	1.4500
10(Cirata)	$0 + 6000.00P_{10} + 0$	1.0000
11(Saguling)	$0 + 5502.00P_{11} + 0$	0.9170
15(Tanjung Jati)	$21.88P_{15}^2 + 197191.76P_{15} + 1636484.18$	0.0770
17(Gresik)	$132.15P_{17}^2 + 777148.77P_{17} + 13608770.96$	0.3780
22(Paiton)	$52.19P_{22}^2 + 37370.67P_{22} + 8220765.38$	0.0300
23(Grati)	$533.92P_{23}^2 + 2004960.63P_{23} + 86557397.40$	1.0670

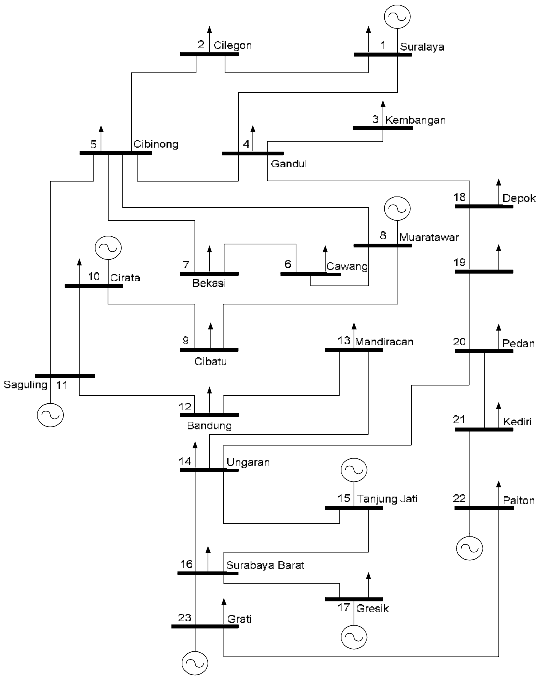

Fig. 4 500 kv Java Bali power system

TABLE II
NETWORK DATA

No.	Line	Z (ohm/km/phasa)	C (mF/km)	B(pu)
1	2	0,000626496	0,007008768	0
1	4	0,006513273	0,062576324	0,0119796400
2	5	0,013133324	0,146925792	0,0070611410
3	4	0,001513179	0,016928309	0
4	5	0,001246422	0,011975010	0
4	18	0,000694176	0,006669298	0
5	7	0,004441880	0,042675400	0
5	8	0,006211600	0,059678000	0
5	11	0,004111380	0,045995040	0,0088419460
6	7	0,001973648	0,018961840	0
6	8	0,005625600	0,054048000	0
8	9	0,002822059	0,027112954	0
9	10	0,002739960	0,026324191	0
10	11	0,001474728	0,014168458	0
11	12	0,001957800	0,021902400	0
12	13	0,006990980	0,067165900	0,0128582700
13	14	0,013478000	0,129490000	0,0247896240
14	15	0,013533920	0,151407360	0,0072765220
14	16	0,015798560	0,151784800	0,0072644380
14	20	0,009036120	0,086814600	0
15	16	0,037539629	0,360662304	0,0172613390
16	17	0,001394680	0,013399400	0
16	23	0,003986382	0,044596656	0
18	19	0,014056000	0,157248000	0,0302288740
19	20	0,015311000	0,171288000	0,0329278810
20	21	0,010291000	0,115128000	0,0221318550
21	22	0,010291000	0,115128000	0,0221318550
22	23	0,004435823	0,049624661	0,0095396930

TABLE III
OPERATING CONDITION

No	Bus	Total Power	
		P Load (MW)	Q Load (MVar)
1	Suralaya	146	43
2	Cilegon	672	217
3	Kembangan	727	249
4	Gandul	521	174
5	Cibinong	667	206
6	Cawang	727	174
7	Bekasi	618	163
8	Muaratawar	0	0
9	Cibatu	787	304
10	Cirata	651	234
11	Saguling	0	0
12	Bandung Selatan	564	336
13	Mandiracan	380	130
14	Ungaran	314	347
15	Tanjungjati	0	0
16	Surabaya Barat	824	304
17	Gresik	201	87
18	Depok	0	0
19	Tasikmalaya	265	16
20	Pedan	501	233
21	Kediri	343	197
22	Paiton	803	260
23	Grati	125	184

B. *Result and Analysis*

NN-OPF model is obtained from the training process with stages that have been described in the item II.C. The load cluster used in the simulation is in the range (0.95 – 1). There are two kinds of training patterns, the first is the total load made fix and the load index made varies, the second is the total load made varies and the load index made fix, so that resulted NN-OPF model that capable works such as OPF-IPSO.

TABLE IV
COST OF GENERATIONS

NN-OPF			OPF-IPSO		
P(MW)	Q(MVar)	COST	P(MW)	Q(MVar)	COST
2975.31	2843.10	0.2430+e009	2859.69	1067.85	0.2306e+009
1040.00	582.34	4.9770+e009	1040.00	1240.77	4.9770e+009
786.67	189.58	0.0047+e009	536.11	352.56	0.0032e+009
710.29	180.98	0.0036+e009	408.59	153.20	0.0021e+009
600.00	285.17	0.0098+e009	600.00	240.02	0.0098e+009
491.22	107.05	0.1615+e009	489.65	239.79	0.1610e+009
3749.29	2008.81	0.0265+e009	4396.09	2628.87	0.0354e+009
150.00	454.70	0.4261+e009	150.00	421.00	0.4261e+009
Total Cost		5.8522e+009	Total Cost		5.8452e+009

To compare performance of NN-OPF and OPF-IPSO used data shown in Figure III. Error in Operation cost has resulted by NN-OPF and OPF-IPSO is 0.12%. That data is shown in Table IV.

Not any differences in determination of active power but there are differences in determination of reactive power, because it used to maintain the voltage at 0.95 <V (pu) <1:05, so that at the same operation cost can happen difference reactive power, as shown in Fig. 5, Fig.6. and Fig.7.

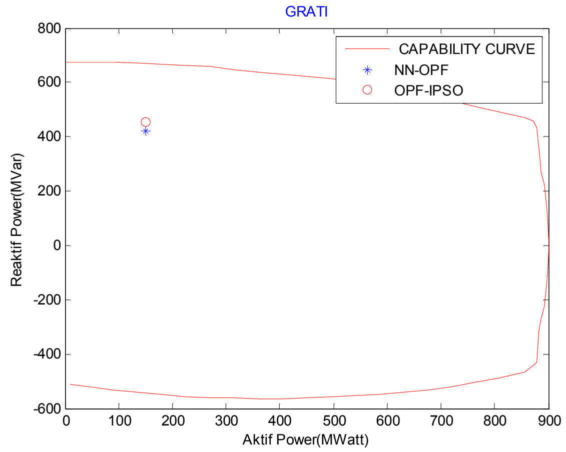

Fig. 5 NN-OPF and OP-IPSO at Grati Generator

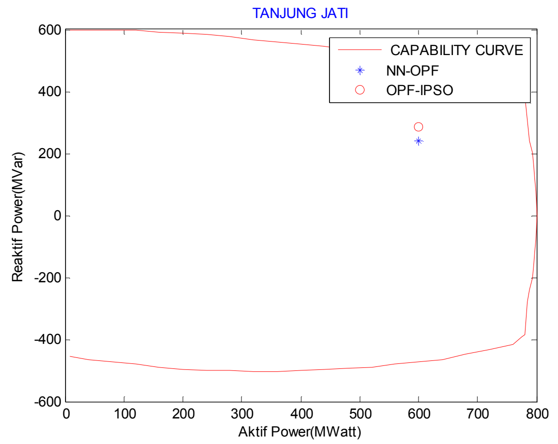

Fig. 6 NN-OPF and OP-IPSO at Tanjung Jati Generator

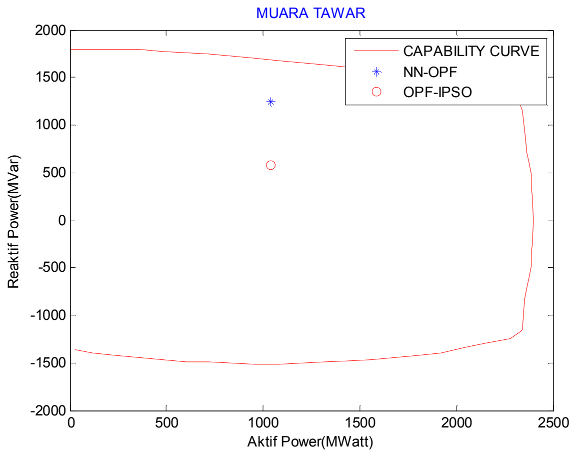

Fig. 7 NN-OPF and OP-IPSO at Muara tawar Generator

IV. Conclusion

Optimal Power Flow based on NN (NN-OPF) with clustering, able to determine operation cost same as OPF-IPSO, with the response more quickly. Few differences occurred in the process optimization reactive power because optimization reactive power aims to maintain the voltage at 0.95 <V (pu) <1:05, so the differences nominal reactive power is allowed during voltage level is at the allowable limit.

Acknowledgment

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

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