PARTICLE SWARM OPTIMIZATION BASED OPTIMAL POWER FLOW FOR VOLT-VAR CONTROL

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ABSTRACT

Evolutionary computation (EC) techniques such as genetic algorithms (GAs), utilize multiple searching points in the solution space like PSO. Whereas GAs can treat combinatorial optimization problems, PSO was aimed to treat nonlinear optimization problems with continuous variables originally. Moreover, PSO has been expanded to handle combinatorial optimization problems and both discrete and continuous variables as well. Efficient treatment of mixed-integer nonlinear optimization problems (MINLPs) is one of the most difficult problems in practical optimization. Moreover, unlike other EC techniques, PSO can be realized with only a small program; namely, PSO can handle MINLPs with only a small program. This feature of PSO is one of its advantages compared with other optimization techniques. In this paper, the basic PSO method is combined with Newton's method, and interior point method for the optimal power flow/volt-var optimization. The results obtained on IEEE 30-bus system showed that the hybrid method based on PSO-IPM gives the best results compared to the other methods. It has been demonstrated that the proposed method can be easily applied to large systems.

Keywords: optimal power flow, PSO, VAR control, voltage control.

1. INTRODUCTION

Natural creatures sometimes behave as a swarm. One of the main streams of artificial life research is to examine how natural creatures behave as a swarm and reconfigure the swarm models inside a computer. Reynolds developed boid as a swarm model with simple rules and generated complicated swarm behavior by computer graphic animation [1]. Boyd and Richerson examined the decision process of human beings and developed the concept of individual learning and cultural transmission [2]. According to their examination, human beings make decisions using their own experiences and other persons' experiences.

A new optimization technique using an analogy of swarm behavior of natural creatures was started in the beginning of the 1990s. Dorigo developed ant colony optimization (ACO) based mainly on the social insect, especially ant, metaphor [3]. Each individual exchanges information through pheromones implicitly in ACO. Eberhart and Kennedy developed particle swarm optimization (PSO) based on the analogy of swarms of birds and fish schooling [4]. Each individual exchanges previous experiences in PSO. These research efforts are called swarm intelligence [5, 6]. This paper focuses on PSO as one of the swarm intelligence techniques.

2. BASIC PARTICAL SWARM OPTIMIZATION

Swarm behavior can be modeled with a few simple rules. Schools of fishes and swarms of birds can be modeled with such simple models. Namely, even if the behavior rules of each individual (agent) are simple, the behavior of the swarm can be complicated. Reynolds utilized the following three vectors as simple rules in the researches on boid.

- Step away from the nearest agent
- Go towards the destination
- Go to the center of the swarm

The behavior of each agent inside the swarm can be modeled with simple vectors. The research results are one of the basic backgrounds of PSO.

Boyd and Richerson examined the decision process of humans and developed the concept of individual learning and cultural transmission [2]. According to their examination, people utilize two important kinds of information in decision process. The first one is their own experience; that is, they have tried the choices and know which state has been better so far, and they know how good it was. The second one is other people's experiences, i.e., they have knowledge of how the other agents around them have performed. Namely, they know which choices their neighbors have found most positive so far and how positive the best pattern of choices was.

Each agent decides its decision using its own experiences and the experiences of others. The research results are also one of the basic background elements of PSO. According to the above background of PSO, Kennedy and Eberhart developed PSO through simulation of bird flocking in a two-dimensional space. The position of each agent is represented by its x, y axis position and also its velocity is expressed by vx (the velocity of x axis) and vy (the velocity of y axis). Modification of the agent position is realized by the position and velocity information.

Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest) and its x, y position. This information is an analogy of the personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gbest) among pbests. This information is an analogy of the knowledge of how the other agents around them have performed. Each agent tries to modify its position using the following information:

- The current positions (x, y),
- The current velocities (vx, vy),
- The distance between the current position and pbest
- The distance between the current position and gbest

This modification can be represented by the concept of velocity (modified value for the current positions). Velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 * (pbest_i - s_i^k) + c_2 rand_2 * (gbest - s_i^k) \quad (1)$$

where v_i^k is velocity of agent i at iteration k, w is weighting function, c_1 and c_2 are weighting factors, $rand_1$ and $rand_2$ are random numbers between 0 and 1, s_i^k is current position of agent i at iteration k, $pbest_i$ is the pbest of agent i, and gbest is gbest of the group. Namely, velocity of an agent can be changed using three vectors such like boid. The velocity is usually limited to a certain maximum value. PSO using (1) is called the Gbest model. The following weighting function is usually utilized in (1):

$$w = w_{\max} - ((w_{\max} - w_{\min})/(iter_{\max})) * iter \quad (2)$$

Where $w_{\max}$ is the initial weight, $w_{\min}$ is the final weight, $iter_{\max}$ is maximum iteration number and iter is current iteration number.

The meanings of the right-hand side (RHS) of (1) can be explained as follows [7]. The RHS of (1) consists of three terms (vectors). The first term is the previous velocity of the agent. The second and third terms are utilized to change the velocity of the agent. Without the second and third terms, the agent will keep on "flying" in the same direction until it hits the boundary. Namely, it tries to explore new areas and, therefore, the first term corresponds with diversification in the search procedure. On the other hand, without the first term, the velocity of the "flying" agent is only determined by using its current position and its best positions in history. Namely, the agents will try to converge to their pbests and/or gbest and, therefore, the terms correspond with intensification in the search procedure. As shown below, for example, $w_{\max}$ and $w_{\min}$ are set to 0.9 and 0.4. Therefore, at the beginning of the search procedure, diversification is heavily weighted, while intensification is heavily weighted at the end of the search procedure such like simulated annealing (SA). Namely, a certain velocity, which gradually gets close to pbests and gbest, can be calculated. PSO using (1) (2) is called inertia weights approach (IWA).

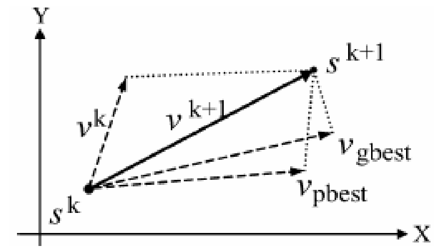

Figure-1. Concept of modifications of a Searching point by PSO.

s^k = current searching point
s^{k+1} = modified searching point
v^k = current velocity
v^{k+1} = modified velocity
v_{pbest} = velocity based on pbest
v_{gbest} = velocity based on gbest

The current position (searching point in the solution space) can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (3)$$

Figure-1 shows a concept of modification of a searching point by PSO, and Figure-1 shows a searching concept with agents in a solution space. Each agent changes its current position using the integration of vectors as shown in Figure-1.

PSO algorithm

Step 1: Generation of initial condition of each agent. Initial searching points (s_i^0) and velocities (v_i^0) of each agent are usually generated randomly within the allowable range. The current searching point is set to pbest for each agent. The best evaluated value of pbest is set to gbest, and the agent number with the best value is stored.
Step 2: Evaluation of searching point of each agent. The objective function value is calculated for each agent. If the value is better than the current pbest of the agent, the pbest value is replaced by the current value. If the best value of pbest is better than the current gbest, gbest is replaced by the best value and the agent number with the best value is stored.
Step 3: Modification of each searching point. The current searching point of each agent is changed using (1), (2), and (3).
Step 4: checking the exit condition. The current iteration number reaches the predetermined maximum iteration number, then exits. Otherwise, the process proceeds to step 2.

The features of the searching procedure of PSO can be summarized as follows:

- As shown in (1), (2), and (3), PSO can essentially handle continuous optimization problems.

- PSO utilizes several searching points, and the searching points gradually get close to the optimal point using their pbests and the gbest.
- The first term of the RHS of (1) corresponds with diversification in the search procedure. The second and third terms correspond with intensification in the search procedure. Namely, the method has a well-balanced mechanism to utilize diversification and intensification in the search procedure efficiently.
- The above concept is explained using only the x, y axis (two-dimensional space). However, the method can be easily applied to n-dimensional problems. Namely, PSO can handle continuous optimization problems with continuous state variables in an n-dimensional solution space.

Shi and Eberhart tried to examine the parameter selection of the above parameters [7, 8]. According to their examination, the following parameters are appropriate and the values do not depend on problems:

$c_i = 2.0,\ w_{\max} = 0.9,\ w_{\min} = 0.4,$

The values are also proved to be appropriate for power system problems [9, 10]. The basic PSO has been applied to a learning problem of neural networks and Schaffer f6, a famous benchmark function for GA, and the efficiency of the method has been observed [4].

3. MATHEMATICAL MODEL OF OPF PROBLEM

The OPF problem is to optimize the steady state performance of a power system in terms of an objective function while satisfying several equality and inequality constraints. Mathematically, the OPF problem can be formulated as given:

$$\text{Min } F(x,u) \tag{4}$$

$$\text{Subject to } g(x,u) = 0 \tag{5}$$

$$h(x,u) \le 0 \tag{6}$$

where x is a vector of dependent variables consisting of slack bus power P_{G_1}, load bus voltages V_L, generator reactive power outputs Q_G, and the transmission line loadings S_l, Hence, x can be expressed as given:

$$x^T = [P_{G_1}, V_{L_1} ... V_{L_{NL}}, Q_{G_1} ... Q_{G_{NG}}, S_l ... S_{l_{nl}}] \tag{7}$$

where NL,NG and nl are number of load buses, number of generators and number of transmission line, respectively.
u is the vector of independent variables consisting of generator voltages V_G, generator real power outputs P_G except at the slack bus P_{G_1}, transformer tap settings T, and shunt VAR compensations Q_C. Hence u can be expressed as given:

$$u^T = [V_{G_1} .. V_{G_{NG}}, P_{G_2} .. P_{G_{NG}}, T_1 .. T_{NT}, Q_{C_1} .. Q_{C_{NC}}] \tag{8}$$

Where NT and NC are the number of the regulating transformers and shunt compensators, respectively. F is the objective function to be minimized. g is the equality constraints that represents typical load flow equations and h is the system operating constraints.

Objective functions

In this paper, the objective(s) (J) is the objective function to be minimized, which is one of the following:

(i) Objective function-1 (Fuel cost minimization)

It seeks to find the optimal active power outputs of the generation plants so as to minimize the total fuel cost. This can be expressed as:

$$J = \sum_{i}^{NG} f_i (\$/h) \tag{9}$$

where f_i is the fuel cost curve of the i[th] generator and it is assumed here to be represented by the following quadratic function:

$$f_i = a_i P_{G_i}^2 + b_i P_{G_i} + c_i (\$/h) \tag{10}$$

where a_i, b_i, and c_i are the cost coefficients of the i^{th} generator.

(ii) Objective function-2 (Voltage profile improvement)

Voltage profile is one of the quality measures for power system. It can be improved by minimizing the load bus voltage deviations from 1.0 per unit. The objective function can be expressed as

$$J = \sum_{i \in NL} |V_i - 1| \tag{11}$$

(iii) Objective function-3 (Voltage stability enhancement)

Voltage profile improvement does not necessary implies a voltage secure system. Voltage instability problems have been experienced in systems where voltage profile was acceptable [11]. Voltage secure system can be assured by enhancing the voltage stability profile throughout the whole power system.

An indicator L-index is used in this study to evaluate the voltage stability at each bus of the system. The indicator value varies between 0 (no load case) and 1 (voltage collapse) [12-14]. One of the best features of the L-index is that the computation speed is very fast and so can be used for on-line monitoring of power system. Enhancing the voltage stability and moving the system far from voltage collapse point can be achieved by minimizing the following objective function:

$$J = L_{\max} \tag{12}$$

where $L_{\max}$ is the maximum value of L-index as:

$$L_{\max} = \max\{L_K, K = 1,....., NL\} \tag{13}$$

(iv) Objective function-4 (Real power loss minimization)

The optimal reactive power flow problem to minimize active losses can be formulated as:

$$\begin{aligned} &\min \quad J = f(Z) \\ &s.t \quad g(Z) = 0 \\ &\quad\quad Z_{\min} \le Z \le Z_{\max} \end{aligned} \tag{14}$$

Where $f(\cdot)$ is the objective function for active losses.

$g(\cdot)$ Nonlinear vectors function representing power flow equations.

$Z = [x\ u]^T$ Vector of decision variables whose components are the vector of state variables x (voltage phase angles and magnitudes, etc.) and the vector of discrete control variables u (generator terminal voltages, tap position of OLTC transformers, number of connected shunt compensation devices etc.).

$Z_{\min}$ and $Z_{\max}$ vectors modeling operational limits on state and control variables

4. SIMULATION RESULTS

The simulation results of the proposed basic PSO method for different objective functions (i.e., fuel cost minimization, voltage profile improvement, voltage stability enhancement, and real power loss minimization) have been applied to IEEE-30 bus system with NR-load flow, Newton-OPF and Interior Point Method. It is chosen as it is a benchmark system, have more control variables and provide results for comparison of the proposed methods. The approach can be generalized and easily extended to large-scale systems.

The IEEE-30 bus system consists of six generators, four transformers, 41 lines, and nine shunt capacitors. In all these different PSO methods, the total control variables are 25: six unit active power outputs, six generator bus voltage magnitudes, four transformer tap settings, and nine bus shunt admittances. The basic PSO methods have been run for 20-populations and for 150-iterations.

To test the ability of the proposed PSO-IPM hybrid algorithm for solving optimal power flow problem to reduce specified objective function, it was applied on selected bus system. Four objective functions are considered for the minimization using the proposed hybrid algorithm namely cost of generation, voltage profile improvement, voltage stability enhancement and real power loss minimization.

Figures 2 to 5 show the convergence characteristics of the three OPF methods under the selected objective function. It can be observed that IPM-PSO converges to a minimum value than PSO-Newton and PSO-NR methods.

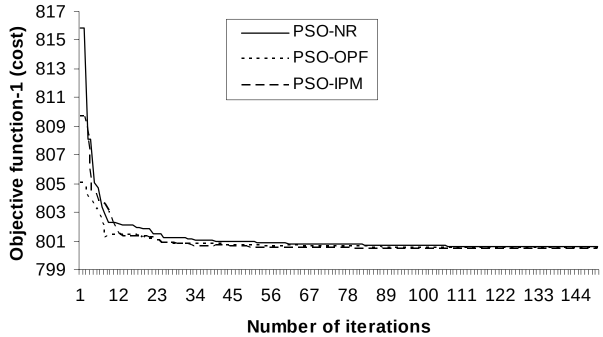

Figure-2. Convergence characteristics of objective function-1.

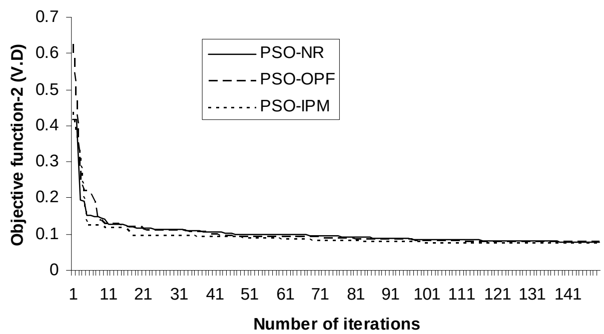

Figure-3. Convergence characteristics of objective function-2.

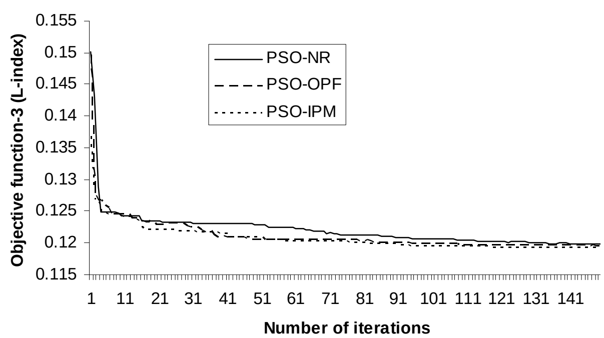

Figure-4. Convergence characteristics of objective function-3.

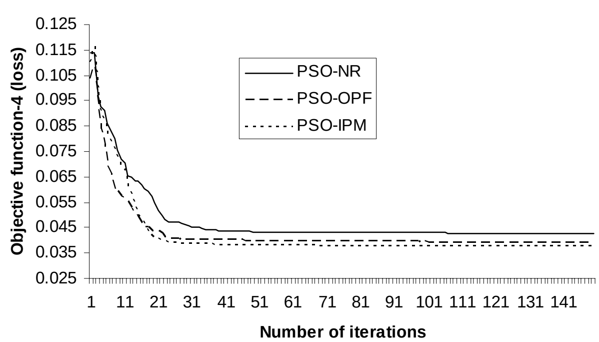

Figure-5. Convergence characteristics of objective function-4.

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The best results for different PSO methods combined with NR-load flow, Newton-OPF, and Interior Point method are compared and results are tabulated in Table-1. In this table, the optimal settings of the control variables and various performance parameters with four objective functions are presented. From this table, it was found that all the state variables satisfy lower and upper limits. From the results it is evident that proposed IPM-PSO hybrid method outperforms in achieving minimum of the specified objective when compared with other optimization methods.

Table-1. Optimal settings of control variables of IEEE 30-bus system.

Control Variables	**Objective function-1** (cost)			**Objective function-2** (V.D)			**Objective function-3** (L-index)			**Objective function-4** (loss)		
	PSO-NR	**PSO-Newton**	**PSO-IPM**	**PSO-NR**	**PSO-Newton**	**PSO-IPM**	**PSO-NR**	**PSO-Newton**	**PSO-IPM**	**PSO-NR**	**PSO-Newton**	**PSO-IPM**
P_1	1.7818	1.7855	1.7812	1.5031	1.7786	1.4490	1.5337	1.6118	1.5662	0.8069	0.7733	0.7716
P_2	0.4896	0.4909	0.4905	0.4794	0.5727	0.6128	0.3552	0.6899	0.2000	0.8000	0.8000	0.8000
P_5	0.2149	0.2135	0.2144	0.1972	0.1709	0.3061	0.3832	0.3084	0.3008	0.5000	0.5000	0.5000
P_8	0.2187	0.2152	0.2185	0.2482	0.2098	0.3000	0.1579	0.1060	0.1000	0.3000	0.3000	0.3000
P_{11}	0.1200	0.1200	0.1200	0.2335	0.1200	0.1200	0.2827	0.1205	0.4000	0.1200	0.4000	0.4000
P_{13}	0.1000	0.1000	0.1000	0.2603	0.1709	0.1334	0.2018	0.1000	0.3468	0.3500	0.1000	0.1000
V_1	1.0867	1.0851	1.0858	1.0089	0.9945	0.9978	1.0614	1.0538	1.0361	1.0673	1.0593	1.0681
V_2	1.0663	1.0653	1.0663	1.0126	1.0041	0.9982	1.0248	1.0225	1.0333	1.0599	1.0528	1.0641
V_5	1.0352	1.0352	1.0350	1.0171	1.0165	1.0155	1.0494	1.0514	1.0300	1.0383	1.0321	1.0453
V_8	1.0409	1.0396	1.0393	0.9977	1.0025	1.0053	1.0458	1.0539	1.0494	1.0409	1.0357	1.0672
V_{11}	1.1000	1.0650	1.0488	1.0323	1.0109	1.0221	1.1000	1.0338	1.0935	1.0456	0.9728	1.0409
V_{13}	1.0186	1.0296	1.0308	0.9847	1.0271	1.0232	1.0353	1.0489	1.0301	1.0332	1.0609	1.0323
T_{11}	1.0421	0.9955	0.9833	1.0422	1.0155	1.0334	1.1000	1.0124	1.0392	0.9661	0.9750	1.0111
T_{12}	0.9734	1.0004	1.0185	0.9960	0.9842	0.9831	1.0467	1.0127	1.0583	1.1000	1.0116	0.9841
T_{15}	0.9291	0.9507	0.9557	0.9504	1.0238	1.0083	0.9967	1.0780	1.0453	0.9739	1.1000	0.9595
T_{36}	0.9750	0.9768	0.9757	0.9701	0.9853	0.9748	0.9883	0.9887	0.9877	1.0117	0.9863	0.9809
Q_{C10}	0.0295	0.0518	0.0936	0.0657	0.0548	0.0542	0.1000	0.1000	0.1000	0.1000	0.0596	0.0176
Q_{C12}	0.0240	0.0594	0.0631	0.0394	0.0495	0.0109	0.1000	0.1000	0.1000	0.1000	0.0319	0.0596
Q_{C15}	0.0226	0.0466	0.0000	0.0443	0.0561	0.0421	0.0783	0.1000	0.1000	0.0577	0.0532	0.0552
Q_{C17}	0.0743	0.0794	0.0677	0.0382	0.0315	0.0291	0.0959	0.1000	0.1000	0.0677	0.0733	0.0705
Q_{C20}	0.0586	0.0409	0.0479	0.1000	0.0780	0.1000	0.1000	0.1000	0.1000	0.0368	0.0440	0.0414
Q_{C21}	0.0786	0.0513	0.0764	0.1000	0.0896	0.0893	0.1000	0.1000	0.1000	0.0978	0.1000	0.1000
Q_{C23}	0.0579	0.0277	0.0263	0.0484	0.0372	0.0411	0.0847	0.0999	0.1000	0.0179	0.0000	0.0254
Q_{C24}	0.0437	0.0649	0.0842	0.0861	0.1000	0.0999	0.0997	0.1000	0.1000	0.0663	0.0873	0.0662
Q_{C29}	0.0225	0.0258	0.0252	0.0282	0.0449	0.0263	0.0351	0.0272	0.0329	0.1000	0.0000	0.0314
Cost ($/h)	800.5894	800.4797	800.4235	818.0057	811.2806	819.7407	838.2179	821.7634	861.3162	924.2717	932.8452	932.4037
V.D	0.9711	0.9179	0.9389	0.0794	0.0761	0.0745	1.0149	1.0212	1.0231	0.8649	0.4042	0.9952
L- Index	0.1239	0.1258	0.1247	0.1330	0.1329	0.1326	0.1198	0.1195	0.1192	0.1267	0.1330	0.1234
Ploss (pu)	0.0911	0.0911	0.0906	0.1229	0.0847	0.1158	0.0805	0.1026	0.0798	0.0429	0.0393	0.0376

5. CONCLUSIONS

In this paper, the basic PSO method is combined with Newton's method, and interior point method for the optimal power flow/volt-var optimization. The results obtained on IEEE 30-bus system showed that the hybrid method based on PSO-IPM gives the best results compared to the other methods proposed in this paper. It has been demonstrated that the proposed method can be easily applied large systems.

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REFERENCES

[1] Reynolds C. 1987. Flocks, herds, and schools: A distributed behavioral model. Computer Graphics. 21(4): 25-34.

[2] Boyd R. and Richerson P.J. 1985. Culture and the evolutionary process. Chicago: University of Chicago Press, USA.

[3] Colorni A, Dorigo M and Maniezzo V. 1991. Distributed optimization by ant colonies. Proceedings of 1st European Conference on Artificial Life. Cambridge, MA: MIT Press. pp. 134-142.

[4] Kennedy J. and Eberhart R. 1995. Particle swarm optimization. Proceedings of IEEE International Conference on Neural Networks (ICNN'95) Perth, Australia: IEEE Press. IV: 1942-1948.

[5] Bonabeau E, Dorigo M and Theraulaz G. 1999. Swarm intelligence: From natural to artificial systems. Oxford: Oxford University Press.

[6] Kennedy J and Eberhart R. 2001. Swarm intelligence. San Mateo, CA: Morgan Kaufmann.

[7] Shi Y and Eberhart R. 1998. A modified particle swarm optimizer. Proceedings of IEEE International Conference on Evolutionary Computation (ICEC'98). Anchorage: IEEE Press. pp. 69-73.

[8] Shi Y and Eberhart R. 1998. Parameter selection in particle swarm optimization. Proceedings of the 1998 Annual Conference on Evolutionary Programming. San Diego: MIT Press.

[9] Fukuyama Y. *et al*., 2000. A particle swarm optimization for reactive power and voltage control considering voltage security assessment. IEEE Trans Power Systems. 15(4): 1232-1239.

[10] Naka S, Genji T, Yura T and Fukuyama Y. 2003. A hybrid particle swarm optimization for distribution state estimation. IEEE Trans Power Systems. 18(1): 60-68.

[11] Overbye T. and DeMarco C. 1991. Voltage Security Enhancement Using Energy Based Sensitivities. IEEE Trans. On Power Systems. 6(3): 1196-1202.

[12] Kim S. and Song T., *et al*., 2001. Development of Voltage Stability Constrained Optimal Power Flow (VSCOPF). Power Engineering Society Summer Meetings, 2001 IEEE. 3: 15-19 July, pp. 1664-1669.

[13] Tuan T.Q., *et al*., 1994. Emergency load shedding to avoid risks of voltage instability using indicator. IEEE Trans. On Power Systems. 9(1): 341-347.

[14] Kessel P. and Glavtisch H. 1986. Estimating the voltage stability of a power system. IEEE Trans. on Power Delivery. 1(3): 346-354.