Paper accepted for presentation at 2009 IEEE Bucharest Power Tech Conference, June 28th - July 2nd, Bucharest, Romania

Optimal Power Flow with Steady-State Voltage Stability Consideration Using Improved Evolutionary Programming

Kritsana Tangpatiphan, *Student Member, IEEE*, and Akihiko Yokoyama, *Member, IEEE*

***Abstract*—This paper presents an Improved Evolutionary Programming (IEP) algorithm for the Optimal Power Flow (OPF) with steady-state voltage stability consideration. The objective function is formulated as a trade-off between an economic concern, i.e. fuel cost and a system security issue, i.e. voltage stability margin. The indicator L is adopted to estimate the steady-state voltage stability margin in this paper. The proposed IEP algorithm borrows an idea of crossover techniques from Real-Coded Genetic Algorithm (RCGA) to enhance the offspring generation process. The IEEE 30-bus system is used as the test system. Three types of cost curves are considered to verify that the proposed algorithm works well with both convex and non-convex objective functions. The results of the proposed method are compared with those of the EP algorithm, which solely relies on the mutation process for offspring generation. Moreover, a series of experiments are conducted to properly tune the main IEP parameters.**

***Index Terms*—Evolutionary programming, optimal power flow, real-coded genetic algorithm, voltage stability.**

I. Introduction

RECENTLY, due to a more complicated structure of the present power systems and competitive environment introduced by deregulation, Optimal Power flow (OPF) which provides effective and efficient exploitation of existing power generations and networks is a reliable solution for operational scheduling. OPF is one of the optimization problems basically aiming at determining the control variables of power system to optimize a selected objective function while satisfying all related constraints simultaneously [1], [2].

Since there have been numerous voltage collapses causing severe blackouts around the world, the consideration of voltage stability in power system operation is essential and should be added into the conventional OPF in order to guarantee a sufficient stability margin for both normal and emergency operations. Generally, a study of voltage stability [3] can be categorized into steady-state and dynamic analyses. Although the dynamic is needed for deep understanding of this phenomenon, the steady-state provides a faster estimation how far the system status is from the voltage collapse point. Therefore, the voltage stability index is very important for the steady-state analysis. Among various voltage stability indices summarized in [4], the indicator L originally developed in [5] is selected to estimate voltage stability margin in this paper. This indicator is widely used in many researches for the steady-state voltage stability estimation as shown in [6] and [7]. When considering the voltage stability in OPF, the optimization problem is formulated as a trade-off between fuel cost minimization and voltage stability margin maximization.

Inherently, OPF is a non-linear, non-smooth, and multimodal optimization problem, i.e. there exist more than one local optimum. Consequently, the application of conventional optimization methods, which are effective only with convex or classical non-convex, and some specified objective functions, cannot easily obtain the desired optimal OPF solution. In this paper, Improved Evolutionary Programming (IEP) is proposed to solve OPF with steady-state voltage stability consideration. IEP is an Evolutionary Programming (EP)-based algorithm [8] with an additional use of a crossover technique, normally applied in Real-Coded Genetic Algorithm (RCGA) [9], [10], to enhance an offspring generation process. Through the processes of EP mutation and RCGA crossover, the offspring is generated either by perturbing its parent on a one-by-one basis or exchanging information between two selected parents.

The effectiveness of the proposed algorithm is tested on IEEE 30-bus system [11] with three different fuel cost curves representing a simplified model and more accurate models of a thermal unit with valve-point loading effect. The results of IEP are also compared with those of EP to make it clear that the proposed method is powerful and reliable. In addition, a study of IEP parameters tuning for the OPF problem is presented and discussed.

II. Problem Formulation

The objective function and all related constraints for the problem are shortly described as follows:

A. Objective function

The minimization of fuel cost of all generating units and indicator L at the weakest bus is considered as the objective function. It can be expressed mathematically as follows:

Kritsana Tangpatiphan is with the Department of Electrical Engineering, the University of Tokyo, Tokyo, 113-8656 Japan (e-mail: kritsana@syl.t.u-tokyo.ac.jp).

Akihiko Yokoyama is with the Department of Advanced Energy, the University of Tokyo, Chiba, 277-8568 Japan (e-mail: yokoyama@syl.t.u-tokyo.ac.jp).

978-1-4244-2235-7/09/$25.00 ©2009 IEEE

$$F=\sum_{i=1}^{NG}F_i(P_{Gi})+\alpha\cdot\text{Max}(L_j)\qquad j=1,2,...,NLB \tag{1}$$

where F is the objective function; $F_i(P_{Gi})$ is the i-th generating unit's fuel cost which is a function of active power generation output (P_{Gi}); NG is the total number of generating units; α is the scaling factor; L_j is the value of indicator L at load bus j; NLB is the total number of load buses.

B. Constraints

All equality and inequality constraints related to the OPF problem are defined as follows:

$$P_{Gi}-P_{Di}-V_i\sum_{j=1}^{N}V_j\left(G_{ij}\cos\theta_{ij}+B_{ij}\sin\theta_{ij}\right)=0 \qquad i=1,2,...,N \tag{2}$$

$$Q_{Gi}-Q_{Di}-V_i\sum_{j=1}^{N}V_j\left(G_{ij}\sin\theta_{ij}-B_{ij}\cos\theta_{ij}\right)=0 \qquad i=1,2,...,N \tag{3}$$

$$P_{Gi,\min}\le P_{Gi}\le P_{Gi,\max}\qquad i=1,2,...,NG \tag{4}$$

$$Q_{Gi,\min}\le Q_{Gi}\le Q_{Gi,\max}\qquad i=1,2,...,NG \tag{5}$$

$$V_{i,\min}\le V_i\le V_{i,\max}\qquad i=1,2,...,N \tag{6}$$

$$T_{i,\min}\le T_i\le T_{i,\max}\qquad i=1,2,...,NT \tag{7}$$

$$\left|S_{Li}\right|\le S_{Li,\max}\qquad i=1,2,...,NL \tag{8}$$

where (2) and (3) are active and reactive power balance equations; (4)-(8) are active and reactive power generation limits, voltage limits, transformer tap setting limits, and line loading limits, respectively; P_{Di} and Q_{Di} are the total active and reactive power demands at bus i; Q_{Gi} is the total reactive power generation at bus i; V_i and V_j are the voltage magnitudes at buses i and j; G_{ij} and B_{ij} are the real and imaginary parts of the ij-th element of the admittance matrix (Y_{bus}); θ_{ij} is the difference of voltage angles between buses i and j; T_i is the tap setting of the i-th transformer; $|S_{Li}|$ is the line loading in MVA at line i; N, NL, and NT are the total numbers of buses, lines, and transformers, respectively. The subscripts $x_{\max}$ and $x_{\min}$ are the upper and lower limits of variable x.

C. Indicator L

The indicator L [5] is a quantitative measure for estimating the voltage stability margin of the current operating point. It is derived from the solution of the power flow equations based on the fact that at the voltage collapse point the Jacobian matrix of load flow becomes singular. The value of indicator L less than 1 can guarantee the voltage stability. To calculate the indicator, firstly the hybrid representation derived from the original admittance matrix (Y_{bus}) is built as follows:

$$\begin{bmatrix}V_L\\ I_G\end{bmatrix}=\begin{bmatrix}Z_{LL} & F_{LG}\\ K_{GL} & Y_{GG}\end{bmatrix}\begin{bmatrix}I_L\\ V_G\end{bmatrix} \tag{9}$$

where V_L, I_L are the voltage and current vectors at the load buses; V_G, I_G are the voltage and current vectors at the generator buses including slack bus; Z_{LL}, F_{LG}, K_{GL}, Y_{GG} are the sub-matrices of the hybrid matrix.

The hybrid representation is obtained by a partial inversion, where the voltages at the load buses are exchanged against their currents. Through the utilization of this representation, the voltage stability indicator L at load bus j can then be calculated as follows:

$$L_j=\left|1+\frac{V_{0j}}{\overline{V_j}}\right|=\left|\frac{S_j+S_{jcorr}}{Y^*_{jj+}\cdot V_j^2}\right| \tag{10}$$

and

$$V_{0j}=-\sum_{i=1}^{NG}F_{ji}\cdot\overline{V}_i\ , \tag{11}$$

$$S_{jcorr}=\left(\sum_{\substack{i=1\\ i\neq j}}^{NLB}\frac{Z^*_{ji}}{Z^*_{jj}}\cdot\frac{S_i}{\overline{V_i}}\right)\cdot\overline{V_j} \tag{12}$$

$$Y_{jj+}=1/Z_{jj} \tag{13}$$

where F_{ji} is the ji-th element of sub-matrix F_{LG}; Z_{jj} is the jj-th element of sub-matrix Z_{LL}; Z^*_{jj} and Z^*_{ji} are the conjugate of jj-th and ji-th elements of sub-matrix Z_{LL}; S_i and S_j are the complex power demands at load buses i and j; V_j is the voltage magnitude at bus j; $\overline{V}_i$ and $\overline{V_j}$ are voltage vectors at bus i and bus j respectively.

Based on (10), the indicator L at load bus j is a function of the term V_{0j} or S_{jcorr} which is influenced by all generator voltages or all active and reactive load demands. The V_{0j} physically indicates the equivalent voltage of all generator buses and S_{jcorr} represents equivalent complex power of all other load buses except bus j. The value of indicator L is in between 0 (no load) and 1 (voltage collapse). The advantages of indicator L are listed as follows:

- It has a simple structure and can be handled easily.
- There is no need of repetitive power flow calculation.
- The weakest bus (Max (L_j)) can be identified.
- The accuracy in predicting is satisfactory.

D. Problem Formulation

According to sections *A*-*C*, the optimization problem has now been formulated:

$$\begin{aligned}&\text{Minimize}\quad (1)\\ &\text{Subject to}\quad (2)\text{-}(8)\end{aligned} \tag{14}$$

E. Constraint Enforcement Strategy

The equality constraints, i.e. power balance equations appeared in (2) and (3) are satisfied by power flow calculation. The inequality constraints appeared in (4)-(8) will be coped by penalty functions. The original constrained optimization problem is now transformed to an unconstrained one by penalizing inequality constraints of active power generation of slack bus, reactive power generation, load bus voltage magnitude, line loading as follows:

$$\begin{aligned}F_{ext}&=\sum_{i=1}^{NG}F_i(P_{Gi})+\alpha\cdot\text{Max}(L_j)+K_p\left[h(P_{slack})\right]\\ &+K_q\sum_{i=1}^{NG}h(Q_{Gi})+K_v\sum_{i=1}^{NLB}h(V_{Li})+K_s\sum_{i=1}^{NL}h(S_{Li})\end{aligned} \tag{15}$$

where, K_p, K_q, K_v, and K_s are penalty weights of active power output of slack bus, reactive power output of generator bus, load bus voltage magnitude, and line loading respectively; $h(P_{slack})$, $h(Q_{Gi})$, $h(V_{Li})$, and $h(S_{Li})$ are the penalty functions of the related variables. Note that the value of penalty function grows with a quadratic form when the constraints are violated and is 0 in the region where constraints are not violated.

The active power generation limits of all generator buses except for slack bus, voltage limits of all generator buses, and transformer tap setting limits are not included in the extended objective function, since these control variables are randomly created within their feasible limits during the proposed algorithm process. In conclusion, (15), already considering all inequality constraints, will be used as the new objective function to be minimized.

III. IEP Algorithm

Evolutionary Programming (EP) is one of the population-based heuristic algorithms, which searches for the optimal solution by evolving a set of candidate solutions, namely individuals, over a number of iterations through the mechanism of natural selection; mutation and selection. It employs only mutation to generate the offspring population. The proposed Improved Evolutionary Programming (IEP) enhances the offspring generation process by adding a crossover technique, normally found in RCGA. Different from the mutation, the crossover generates the offspring by exchanging some parts of candidate solutions (individual) between two selected parents without perturbing their values. The utilization of the appropriate proportion between mutation and crossover can provide better probability of detecting an optimal solution. The main components of IEP algorithm are briefly stated as follows:

A. Individual Representation

An individual represents a candidate solution coded by real number as depicted in Fig. 1. It contains control variables in the optimization problem, i.e. active power outputs of all generator buses excluding slack bus, voltage magnitudes of all generator buses, and transformer tap settings.

P_{G2}		P_{GNG}	V_{G1}		V_{GNG}	T_1		T_{NT}
0.48	…	0.25	1.08	...	0.98	0.99	...	1.01

Fig. 1. Real number coding solution (individual).

B. Initialization

The N individuals in an initial population are randomly initialized using a set of uniform random number distribution ranging over the feasible limits of each control variable.

C. Power Flow Solution and Fitness Calculation

After initialization, power flow solution by Newton-Raphson method is performed for each individual to come up with all variables in the system and then the indicator L for each load bus is computed. At this moment, the weakest bus ($\text{Max}(L_j)$) can be indentified. Lastly, the fitness value of each individual in the population will be calculated to determine their degree of optimality as follows:

$$f_k = 1 / F_{ext,k} \tag{16}$$

where f_k is fitness value and $F_{ext,k}$ is the value of the extended objective function shown in (15) of the k-th individual.

D. Mutation and Crossover

An offspring individual is created by either mutation or crossover based on the crossover acceptance rate (M). If $U[0,1]$ (uniform random number between 0 and 1) > M, the offspring will be created by the mutation operator. Otherwise, it will be created by the crossover technique.

Through mutation, an offspring individual is produced from a parent individual on a one-by-one basis. Each control variable of the k-th offspring is computed as follows:

$$\begin{aligned} c'_{ki} &= c_{ki} + N(0, \sigma_{ki}^2) \\ \sigma_{ki} &= (x_{ki,\max} - x_{ki,\min})\left(\frac{f_{\max} - f_k}{f_{\max}} + a^g\right) \end{aligned} \tag{17}$$

where c'_{ki} and c_{ki} are the i-th control variable of the k-th offspring and parent individual respectively; $N(0, \sigma_{ki}^2)$ is a Gaussian random number with a mean of zero and standard deviation of σ_{ki}; $x_{ki,\max}$ and $x_{ki,\min}$ are the upper and lower limits of the i-th control variable of the k-th parent individual; $f_{\max}$ is the maximum fitness in the parent population; a is the decaying mutation rate, which is a positive constant number slightly less than one; g is the iteration counter.

In crossover, a modified discrete crossover is proposed to generate offspring. Suppose that $C_1 = (c_{11}, \ldots\ldots, c_{1n})$ and $C_2 = (c_{21}, \ldots\ldots, c_{2n})$ are the two parent individuals that are randomly selected for crossover and n is the total number of control variables. The offspring $C' = (c'_1, \ldots\ldots., c'_n)$ is generated as follows:

$$c'_i = \begin{Bmatrix} c_{1i} & if & U[0,1] \le f_1 / (f_1 + f_2) \\ c_{2i} & if & U[0,1] > f_1 / (f_1 + f_2) \end{Bmatrix} \tag{18}$$

where f_1 and f_2 are the fitness of the parent individuals C_1 and C_2; $U[0,1]$ is a uniform random number in the interval [0,1].

Both mutation and crossover in (17) and (18) provide the diversification of offspring generation. During the process of IEP, the offspring individual is generated not only by perturbing the values of control variables from a single parent, but also by exchanging the information from the two selected parents. This can increases the chance of obtaining the optimal solution, and also reduce overall computational time because of a less complicated process of the crossover for offspring generation than that of the mutation.

E. Selection

The parent and offspring populations are combined together forming a combined population and then a new parent population will be selected from the combined one. Tournament scheme is used to perform the selection. By comparing the fitness with other opponent individuals, scoring for each individual in combined population can be obtained and the individuals with the higher score will be chosen to form the new parent population for the next iteration.

F. Termination Criterion

The maximum generation number (G_{max}) is adopted as a termination criterion. The IEP search procedure will be terminated, if this criterion is satisfied.

G. IEP Procedure

The procedure of IEP algorithm is described as follows:

Step 1: Read system data, IEP parameters and set $g = 1$.
Step 2: Initialize individuals in a population.
Step 3: Compute power flow solution, indicator L, and fitness by (16) for all individuals in the initial population.
Step 4: Set best solution (S_b) = the highest-fitness individual.
Step 5: Create an offspring population through mutation by (17) or crossover by (18) based on the parameter M
Step 6: Compute power flow solution, indicator L, and fitness by (16) for all individuals in the offspring population.
Step 7: If the fitness value of the fittest individual in the offspring population is greater than that of S_b, set S_b = the fittest individual in the offspring population.
Step 8: Select the new parent population for the next iteration by the tournament scheme.
Step 9: If $g < G_{\max}$, set $g = g+1$ and go back to Step 5. If not, terminate the process and S_b is the solution of the problem.

IV. Simulation Results and Discussion

The proposed algorithm is tested on IEEE 30-bus system, which consists of 41 lines, 6 generators, and 4 tap-changing transformers to investigate its robustness. The single-line diagram of the system is depicted in Fig. 2. The bus and line data of the system can be found in [11]. The operating range of each transformer is set between 0.9 and 1.1. The prototype program is developed on MATLAB environment and implemented on a personal computer with Intel Pentium IV 3.8 GHz processor and 512 MB memory.

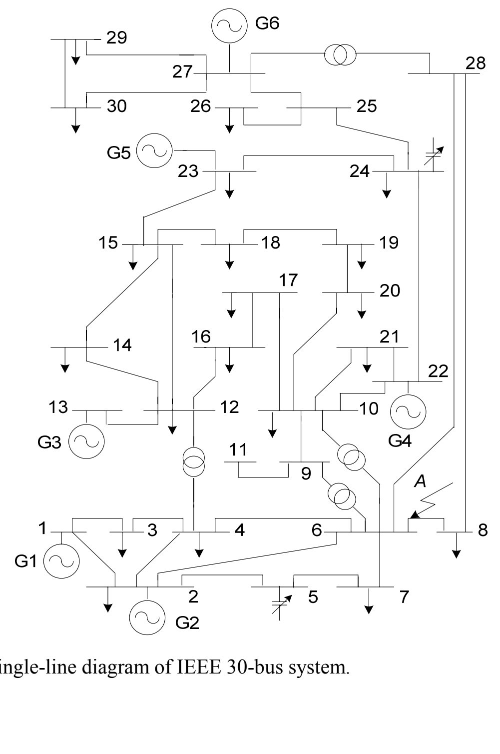

Fig. 2. Single-line diagram of IEEE 30-bus system.

TABLE I
STUDY OF TUNING IEP PARAMETERS

Parameter		Best cost ($/hr)	Avg. cost ($/hr)	Worst cost ($/hr)	Avg. time (s)	Standard deviation
N when (M = 0.4, a = 0.97, G_{max} = 200)	2	575.31	576.40	579.93	9.95	1.09
	4	574.77	575.35	575.81	19.92	0.25
	8	574.52	575.05	575.45	41.12	0.23
	12	574.45	574.96	575.31	83.47	0.20
M when (N = 4, a = 0.97, G_{max} = 200)	0.2	575.03	575.33	575.92	20.85	0.25
	0.4	574.77	575.35	575.81	19.92	0.25
	0.6	575.10	575.72	577.26	18.07	0.62
	0.8	576.02	577.24	579.93	16.05	1.30
a when (N = 4, M = 0.4, G_{max} = 200)	0.9	576.42	582.32	597.47	13.33	6.12
	0.94	576.04	578.22	590.43	16.51	2.99
	0.97	574.77	575.35	575.81	19.92	0.25
	0.99	576.16	581.65	587.08	23.45	3.13

Three different types of generator fuel cost curves, i.e. quadratic cost curve (F_q), piecewise quadratic cost curve (F_p), and quadratic cost curve with sine component (F_s) are considered to represent convex and non-convex generator fuel cost functions. All cost curves are mathematically expressed as follows:

$$F_{qi}(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \tag{19}$$

$$F_{pi}(P_{Gi}) = \begin{cases} a_{1i} + b_{1i} P_{Gi} + c_{1i} P_{Gi}^2 & \text{if } P_{Gi,\min} \le P_{Gi} \le P_{Xi} \\ a_{2i} + b_{2i} P_{Gi} + c_{2i} P_{Gi}^2 & \text{if } P_{Xi} < P_{Gi} \le P_{Gi,\max} \end{cases} \tag{20}$$

$$F_{si}(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin(e_i (P_{Gi,\min} - P_{Gi})) \right| \tag{21}$$

A. Study of IEP Main Parameters

The fuel cost function of all generators is represented by the quadratic curve as shown in (19). The generator data and cost coefficients can be found in Table A.I of Appendix. Three main parameters of the IEP algorithm, i.e. population size (N), crossover acceptance rate (M), and decaying mutation rate (a), are tuned when the OPF problem (i.e. α = 0) is considered. The maximum generation number (G_{max}) is fixed to 200. Table I shows the IEP-based OPF results of 20 independent runs as the IEP parameters are varied.

When the N increases beyond 4, both fuel cost (the best, worst and average costs) and standard deviation are improved slightly whereas the computational time is increased considerably. It implies that the value of N equal to 4 is sufficient to get the acceptable solution for the problem. The increase in the computational time is observed to be linearly proportional to the enlargement of the population size. The optimal value of M is found to be 0.4. This number indicates the suitable proportion between mutation and crossover utilization against the OPF problem. The larger the value of M is, the shorter the computational time will be. This emphasizes that the proposed crossover technique takes less processing time than the mutation. Even if the high reliance on the crossover contributes to computational time saving, the solution is degraded as shown in the table. At the fixed value

TABLE III
OPF AND OPF CONSIDERING STEADY-STATE VOLTAGE STABILITY RESULTS IN ALL CASES

	Case 1		Case 2		Case 3		Case 4
	α = 0	α = 5000	α = 0	α = 5000	α = 0	α = 5000	-
P_{G1} (p.u.)	43.56	43.19	48.93	50.30	48.15	46.76	24.46
P_{G2} (p.u.)	57.17	56.60	40.00	39.95	53.26	53.29	35.51
P_{G3} (p.u.)	16.76	18.67	19.99	19.95	13.30	13.32	33.44
P_{G4} (p.u.)	23.10	22.83	22.99	26.56	24.93	27.75	30.41
P_{G5} (p.u.)	16.22	12.84	18.29	11.31	16.91	9.31	17.09
P_{G6} (p.u.)	34.87	37.70	41.68	43.67	35.46	41.41	50.47
V_{G1} (p.u.)	1.04	1.05	1.00	1.02	1.02	1.05	1.05
V_{G2} (p.u.)	1.04	1.05	1.00	1.02	1.02	1.05	1.05
V_{G3} (p.u.)	1.06	1.10	1.06	1.09	1.02	1.07	1.09
V_{G4} (p.u.)	1.02	1.06	0.99	1.05	1.01	1.04	1.06
V_{G5} (p.u.)	1.03	1.04	1.01	1.04	1.02	1.05	1.07
V_{G6} (p.u.)	1.04	1.05	1.02	1.06	1.02	1.07	1.05
Fuel cost ($/hr)	574.77	575.90	526.96	528.57	604.75	607.15	693.96
Run time (s)	19.92	21.91	20.41	21.86	20.18	21.39	20.75
Indicator L at bus 8	0.051	0.049	0.055	0.052	0.053	0.050	0.048

TABLE II
COMPARISON OF OPF RESULTS (α = 0)

Result	IEP	EP	GA	PSO
Avg. cost ($/hr)	575.37	575.46	576.75	576.69
Worst cost ($/hr)	575.81	575.89	576.91	576.87
Best cost ($/hr)	574.87	575.02	576.64	576.63
Avg. run time (s)	19.92	21.71	-	-

of G_{max}, i.e. 200, the value of a, which provides the lowest fuel cost and smallest standard deviation is found to be 0.97. As appeared in (17), the value of a partially impacts the convergence rate of the proposed algorithm. At the specific value of G_{max}, too small value of a leads to the premature of the solution, but too high value of a results in the slow convergence rate. Since the computational time is strongly related to the convergence rate, the high value of a is more time-consuming than the low one as shown in the table.

After the parameter tuning, the IEP parameters are set as follows: the values of N, M, and a are 4, 0.4, and 0.97 respectively. To investigate the effectiveness of the propose algorithm, Table II shows a comparison of OPF results solved by IEP and those solved by EP, Genetic Algorithm (GA) and Particle Swamp Optimization (PSO). The proposed algorithm can obtain the lower fuel cost than the others. Besides, the computational time of IEP is less than that of EP. Note that the results solved by GA and PSO are reported in [12] and for the reason that GA and PSO are run on the different CPU, the run time of those methods is not inserted in the table.

B. OPF with Steady-State Voltage Stability Consideration

The proposed algorithm with the selected parameters described in the previous session is applied to solve the OPF and OPF with steady-state voltage stability consideration. The following four cases are conducted to test the algorithm.

Case 1: The fuel cost functions of all generators are represented by (19).

Case 2: The cost functions of the *2*-nd and *3*-th generators are replaced by (20). The cost coefficients of the *2*-nd and *3*-th generators can be found in Table A.II of Appendix.

Case 3: The cost functions of the *2*-nd and *3*-th generators are replaced by (21). The cost coefficients of the *2*-nd and *3*-th generators can be found in Table A.III of Appendix.

Case 4: the objective function shown in (1) is modified to minimize only the indicator L at the weakest bus regardless of the economic fuel cost term.

Table III tabulates the results in all cases consisting of control variables, and their corresponding fuel cost, computational time, and indicator L at bus 8. It is important to note that bus 8 is the weakest bus in the test system owing to its largest load demand and the fuel cost of Case 4 is calculated based on the data of the cost function in Case 3. For Cases 1-3, the fuel costs of OPF with voltage stability consideration (α = 5000) slightly rise up from OPF (α = 0). The additional costs of 1.13 $/hr, 1.61 $/hr, and 2.40 $/hr are required in Cases 1, 2 and 3 respectively to increase the voltage stability degree, which is indicated by the lower value of indicator L. Because of indicator L's calculation, the voltage stability-considered case consumes the run time relatively longer than OPF case does. Case 4 provides the smallest value of indicator L among all cases, implying that the operating point obtained by Case 4 possesses the largest voltage stability margin. However, at the same fuel cost data, the fuel cost of Case 4 is significantly more expensive than that of Case 3. This can be realized as the trade-off problem between the economic and system security points of view.

The reason why the indicator L in Case 4 is not notably different from other cases can be explained as the following. Based on (10), to reduce the value of indicator L, the voltage magnitude of generator buses and transformer tap setting near the weakest bus should be lifted up since the indicator L is influenced by voltages (both magnitude and angle) at generator buses and sub-matrix F_{LG}. In other words, if the voltages of generator buses are set higher and transformer-tap setting is adjusted properly, the value of indicator L will drop.

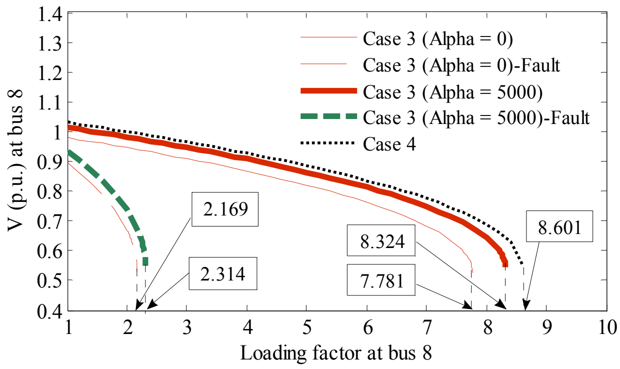

Fig. 3. P-V curves in Case 3 and Case 4.

TABLE IV
RESULTS OF DIFFERENT VALUES OF α IN CASE 3

Value of α	Fuel cost ($/hr)	Indicator L at bus 8	Max. Loading Factor at bus 8
0	604.75	0.0534	7.781
500	605.40	0.0529	7.844
2500	606.09	0.0510	8.149
5000	607.15	0.0497	8.324
50000	630.97	0.0495	8.426
100000	658.03	0.0492	8.477
Case 4	693.96	0.0485	8.601

This can be noticed in Table III that the voltage magnitudes of the cases with voltage stability consideration are set higher than those of the OPF cases. However, the over-increase in voltage magnitudes may cause line overloading and also bring out overvoltage at load buses. In addition, the adjusting of active power generation, which mainly changes the voltage angles of generator buses, has a minor impact on the value of indicator L. Therefore, it is quite difficult to improve the voltage stability by lowering indicator L when the operating point from the OPF has already set the voltage magnitudes of generator buses at a high value or near their upper limits.

The P-V curves at bus 8 based on solutions of Cases 3 and 4 with pre- and post-faults are sketched in Fig. 3. The fault is three-phase grounding at line 6-8 and it is cleared by opening the faulted line. From Fig. 3 and Table III, the lower the value of indicator L is, the larger maximum loading factor will be, and the removal of line 6-8 greatly degrades the system voltage stability. Compared to the OPF case (α = 0), the OPF with voltage stability consideration (α = 5000) can increase the maximum loading factor of roughly 7.0 % under pre-fault and 6.7 % under post-fault. Even though, under pre-fault, the 10.5 % increase of the maximum loading factor from the OPF case can be achieved in Case 4, this improvement leads to very expensive fuel cost as earlier shown in Table III.

Table IV shows an impact of the scaling factor (α) on the fuel cost and indicator L's value in Case 3. When the value of α is beyond 5000, the fuel cost greatly rises up while the indicator L is slightly improved. This signifies that too large value of α results in the unnecessary additional cost without the satisfactory increase in the voltage stability margin.

TABLE V
COMPARISON BETWEEN IEP AND EP RESULTS IN CASE 3 (α = 5000)

Result	IEP	EP
Worst cost ($/hr)	611.51	627.64
Avg. cost ($/hr)	609.03	625.97
Best cost ($/hr)	607.15	624.48
Avg. run time (s)	21.39	24.66
Indicator L at bus 8	0.050	0.050

To emphasize the robustness of the proposed algorithm against the highly non-convex optimization problem, the comparison of results obtained using IEP and EP algorithms to solve the problem of Case 3 (α = 5000) is shown in Table V. It is obvious that the proposed algorithm (IEP) outperforms the conventional EP in both finding the optimal solution and saving the computational time. This again supports the idea that the additional crossover can enhance the EP performance.

V. CONCLUSIONS

This paper investigates the applicability of the IEP for solving OPF with steady-state voltage stability consideration. The problem is formulated as a combination between the financial and voltage stability issues. Before applying the proposed algorithm to solve the problem, its main parameters are properly studied and tuned. The results show that IEP is capable of finding the optimal solution for both the convex and non-convex optimization problems. Furthermore, it has the better performance than the conventional EP.

VI. APPENDIX

The generator data of IEEE 30-bus system used in Case 1, Case 2, and Case 3 are given in Table A.I, Table A.II and Table A.III respectively. The values of penalty weights used in (15) are given in Table A.IV.

TABLE A.I
GENERATOR DATA IN CASE 1

Bus no.	Active power limit		Cost coefficient		
	Min (MW)	Max (MW)	a ($/hr)	b ($/MW/hr)	c ($/MW^2/hr)
1	0	80	0	2.00	0.02000
2	0	80	0	1.75	0.01750
13	0	40	0	3.00	0.02500
22	0	50	0	1.00	0.06250
23	0	30	0	3.00	0.02500
27	0	55	0	3.25	0.00834

TABLE A.II
COST COEFFICIENTS OF 2-ND AND 3-TH GENERATORS IN CASE 2

Bus no.	Active power generation		Cost coefficient		
	Min (MW)	Max (MW)	a ($/hr)	b ($/MW/hr)	c ($/MW^2/hr)
2	0	40	0	1.5	0.005
	40	80	0	2	0.02
13	0	20	0	2.0	0.01
	20	40	0	3.5	0.03

TABLE A.III
COST COEFFICIENTS OF *2*-ND AND *3*-TH GENERATORS IN CASE 3

Bus no.	Active power limit		Cost coefficient				
	Min (MW)	Max (MW)	*a*	*b*	*c*	*d*	*e*
2	0	80	0	2.5	0.01	35	0.118
13	0	40	0	3.7	0.022	21	0.236

TABLE A.IV
PENALTY WEIGHTS OF EXTENDED OBJECTIVE FUNCTION

Penalty weight	Value
K_p, K_q, K_v	1000
K_s	5000

VII. REFERENCES

[1] J. A. Momoh, *Electric Power System Applications of Optimization*, New York: Marcel Dekker, 2001.

[2] A. J. Wood and B. F. Wollenberg, *Power Generation, Operation, and Control*, New York: John Wiley & Sons, 1996.

[3] P. Kundur, *Power System Stability and Control*, New York: McGraw-Hill, Inc., 1994.

[4] C. Reis and F. P. Maciel Barbosa, "A Comparison of Voltage Stability Indices," *in Proc. 2006 IEEE MELECON Electrotechnical Conf.*, pp. 1007-1010.

[5] P. Kessel and H. Glavitsch, "Estimating the Voltage Stability of a Power System," *IEEE Trans. Power Delivery*, vol. PWRD-1, no. 3, pp. 346-354, July 1986.

[6] R. Billinton and S. Aboreshaid, "Voltage Stability Consideration in Composite Power System Reliability Evaluation," *IEEE Trans. Power Systems*, vol. 13, no. 2, pp. 655-660, May 1998.

[7] S. Kim, T. Y. Song, M. H. Jeong, B. Lee, Y. H. Moon, J. Y. Namkung, and G. Jang, "Development of Voltage Stability Constrained Optimal Power Flow (VSCOPF)," in *Proc. 2001 IEEE PES Summer Meeting*, vol. 3, pp. 1664-1669.

[8] J. Yuryevich and K. P. Wong, "Evolutionary Programming Based Optimal Power Flow Algorithm," *IEEE Trans. Power Systems*, vol. 14, no. 4, pp. 1245-1250, Nov. 1999.

[9] F. Herrera, M. Lozano, and J. L. Verdegay, "Tackling Real-Coded Genetic Algorithms: Operators and Tools for Behavioral Analysis," *Artificial Intelligence Review*, vol. 12, no. 4, pp. 265–319, 1998.

[10] G. Zwe-Lee and H. Hou-Sheng, "Real-coded mixed-integer genetic algorithm for constrained optimal power flow," in *Proc. 2004 IEEE TENCON Conf.*, vol. 3, pp. 323- 326.

[11] R. Zimmerman, E. Murillo-Sánchez, and D. Gan, "MATPOWER: a MATLAB Power System Simulation Package," 2006.

[12] N. Mo, Z. Y. Zou, K. W. Chan, and T. Y. G. Pong, "Transient stability constrained optimal power flow using particle swarm optimization," *IET Generation Transmission and Distribution*, vol. 1, no. 3, pp. 476-483, May 2007.

VIII. BIOGRAPHIES

Kritsana Tangpatiphan (S'08) received the B.Eng. in Electrical Engineering, Thammasat University, Thailand, in 2002 and M.Eng. in electric power system management from Asian Institute of Technology (AIT), Thailand, in 2004. Currently he is pursuing the Ph.D. degree at the University of Tokyo, Japan, with MEXT scholarship. His interests include the application of artificial intelligence techniques to power system optimization problems. He is a student member of IEEJ and IEEE.

Akihiko Yokoyama (M'78) was born in Osaka, Japan, on October 9, 1956. He received B.S., M.S. and Dr. Eng from the University of Tokyo, Tokyo, Japan in 1979, 1981 and 1984, respectively. He has been with Department of Electrical Engineering, the University of Tokyo since 1984 and currently a professor in charge of Power System Engineering. He is a member of IEEJ, IEEE and CIGRE.