# Total Transfer Capability Enhancement Using Hybrid Evolutionary Algorithm

**Peerapol Jirapong***

*Department of Electrical Engineering, Faculty of Engineering, Chiang Mai University, Chiang Mai 50200, Thailand*

**Corresponding author. E-mail: peerapol@doe1.eng.cmu.ac.th*

## ABSTRACT

***In this paper, a new hybrid evolutionary algorithm (HEA) based on evolutionary programming (EP), tabu search (TS) and simulated annealing (SA) is proposed to determine the total transfer capability (TTC) of power transfers between different control areas in deregulated power systems. The HEA simultaneously searches for real power generations except slack bus in a source area, real power loads in a sink area and generation bus voltages. Multi-objective optimal power flow (OPF) including TTC, system real power loss and penalty functions is used to evaluate the feasible maximum TTC value and minimal power loss within real and reactive power generation limits, thermal limits, voltage limits and stability limits. The proposed algorithm is tested on the modified IEEE 24-bus reliability test system (RTS) and compared to other heuristic optimization methods. Test results indicate that TTC calculation using the HEA algorithm could enhance TTC far more than the other methods, leading to an efficient utilization of the existing power systems.***

**Key words:** Hybrid Evolutionary Algorithm, Optimal Power Flow, Total Transfer Capability

## INTRODUCTION

Available transfer capability (ATC) is a measure of the transfer capability remaining in a physical transmission network for further commercial activity over and above already-committed uses (NERC, 1996). It is required to be calculated for each control area and posted on a public communication system to enhance the open-access of a transmission network by providing a market signal of the capability of transmission systems to deliver electric energy (FERC, 1996). Mathematically, ATC is defined as the total transfer capability (TTC) less the transmission reliability margin (TRM), and less the sum of the capacity benefit margin (CBM) and the existing transmission commitments (ETC).

Total transfer capability (TTC) is the main component for the ATC computation. TTC is defined as the amount of electric power that can be transferred over the interconnected transmission network in a reliable manner while meeting all of a specific set of defined pre- and post-contingency system conditions (NERC, 1996). Determination of TTC has been an area of active research in recent years. Wide varieties of mathematical methods such as linear ATC (LATC) (Ejebe et al., 2000), continuation power flow (CPF) (Ejebe et al., 1998) and repetitive power flow (RPF) (Gravener and Nwankpa, 1999) methods have been developed for calculating TTC. The LATC is based on linear incremental dc power flow approximation, ignoring voltage and reactive power effects. Therefore, it may lead to unacceptable error, especially in a stressed system with insufficient reactive power support and voltage control. To increase a certain power transfer, CPF and RPF methods use a common loading factor for a specific cluster of generators and loads which may lead to a conservative TTC value because these methods do not result in the optimal generation, loading and generator bus voltages.

In addition, optimal power flow (OPF) based methods which can be implemented by many optimization techniques such as transfer-based security constrained OPF (Ou and Singh, 2002), neural networks (Luo et al., 2000) and sequential quadratic programming (Shaaban et al., 2003) have been proposed for TTC calculations with various degrees of success. These methods require convexity of objective function to obtain the optimal solution. However, the OPF problem is generally nonlinear and non-convex optimization problem and, as a result, many local solutions may exist especially in highly-nonlinear systems. Therefore, conventional optimization methods may converge to local optimal solutions or diverge altogether (Lai, 1998; Wong et al., 2003).

With the advent of evolutionary computation (EC), EC-based methods, which use the mechanic of evolution to find the global optimal solution of complex optimization problems, have been successfully applied to various areas of power systems such as economic dispatch, reactive power planning and OPF problems (Back et al., 1997; Lai, 1998). In this paper, a new hybrid evolutionary algorithm (HEA) is proposed to determine TTC of power transactions between different control areas without violating system constraints. The proposed method is tested on the modified IEEE 24-bus reliability test system (RTS) and compared to evolutionary programming (EP) (Ongsakul and Jirapong, 2004), tabu search (TS), hybrid TS and simulated annealing (TS/SA) (Ongsakul and Bhasaputra, 2002) and improved EP (IEP) (Ongsakul and Tantimaporn, 2006) methods.

## PROBLEM FORMULATION

Multi-objective OPF including TTC, transmission system real power loss and penalty functions in (1) is used to evaluate the feasible TTC value that can be transferred from a specific set of generators in a source area to loads in a sink area within real and reactive power generation limits, thermal limits, voltage limits and steady-state stability limits.

Maximize
$$F = \sum_{i=1}^{ND\_SNK} P_{Di} - \sum_{i=1}^{N} (P_{Gi} - P_{Di}) - PF \tag{1}$$

Subject to
$$P_{Gi} - P_{Di} - \sum_{j=1}^{N} V_i V_j Y_{ij} \cos\left(\theta_{ij} - \delta_i + \delta_j\right) = 0 \tag{2}$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^{N} V_i V_j Y_{ij} \sin\left(\theta_{ij} - \delta_i + \delta_j\right) = 0 \tag{3}$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad \forall i \in NG \tag{4}$$
$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad \forall i \in NG \tag{5}$$
$$V_i^{\min} \le V_i \le V_i^{\max} \qquad \forall i \in N \tag{6}$$
$$\left|S_{Li}\right| \le S_{Li}^{\max} \qquad \forall i \in NL \tag{7}$$
$$VCPI_i \le 1 \qquad \forall i \in N \tag{8}$$
$$\left|\delta_{ij}\right| \le \delta_{ij}^{crit} \qquad \forall i \in NL \tag{9}$$

Where

| | |
|---|---|
| $F$: | multi-objective function, |
| $PF$: | penalty function, |

*Input Variables*

| | |
|---|---|
| $P_{Gi}^{\min}$, $P_{Gi}^{\max}$ : | lower and upper limits of real power generation at bus *i*, |
| $Q_{Gi}^{\min}$, $Q_{Gi}^{\max}$ : | lower and upper limits of reactive power generation at bus *i*, |
| $V_i^{\min}$, $V_i^{\max}$ : | lower and upper limits of voltage magnitude at bus *i*, |
| $S_{Li}^{\max}$ : | *i*th line or transformer loading limit, |
| $\delta_{ij}^{crit}$ : | critical angle difference between bus *i* and *j*, |
| $Y_{ij}$, $\theta_{ij}$ : | magnitude and angle of the ijth element in bus admittance matrix, |
| *N, NL*: | number of buses and branches, |
| *NG, ND*: | number of generator and load buses, |
| *NG_SCE*: | number of generator buses in a source area, |
| *ND_SNK*: | number of load buses in a sink area, |

*State Variables*

| | |
|---|---|
| $V_i$, $V_j$ : | voltage magnitudes at bus *i* and *j*, |
| $\delta_i$, $\delta_j$ : | voltage angles of bus *i* and *j*, |
| $P_{V1}$, $Q_{G1}$ : | real and reactive power generations at slack bus, |

*Output Variables*

| | |
|---|---|
| $P_{Gi}$, $Q_{Gi}$ : | real and reactive power generations at bus *i*, |
| $P_{Di}$, $Q_{Di}$ : | real and reactive loads at bus *i*, |
| $\left|S_{Li}\right|$ : | *i*th line or transformer loading, |
| $VCPI_i$: | voltage collapse proximity indicator at bus *i*, and |
| $\left|\delta_{ij}\right|$ : | angle difference between bus *i* and *j*. |

Voltage collapse proximity indicator (VCPI) is used to directly determine voltage collapse conditions within voltage stability limits. The procedure for calculating VCPI can be found in Chebbo et al., (1992). Angle stability constraints considered can be either static (Singh et al., 2001) or dynamic (Yue et al., 2003). This paper considers only static angle stability constraint. Critical angle displacement is used as a criterion to determine steady-state angle stability limit. For a reasonable level of typical heavy line loading situations, it is assumed that angle difference between bus *i* and *j* across a transmission line is kept within a critical angle difference, which is 44° as recommended in Taylor (1994). Voltage and angle stability limits are treated as OPF variables in (8) and (9), respectively. During the optimization, inequality constraints of state variables including bus voltage magnitudes and real power generation at slack bus and output variables including reactive power generation and line or transformer loading are enforced, using a penalty function in (10).

$$PF = k_p \cdot h(P_{G1}) + k_q \cdot \sum_{i=1}^{NG} h(Q_{Gi}) + k_v \cdot \sum_{i=1}^{N} h(V_i) + k_s \cdot \sum_{i=1}^{NL} h\left(\left|S_{Li}\right|\right) \tag{10}$$

$$h(x) = \begin{cases} \left(x - x^{\max}\right)^2 & if\ x > x^{\max} \\ \left(x^{\min} - x\right)^2 & if\ x < x^{\min} \\ 0 & if\ x^{\min} \le x \le x^{\max} \end{cases} \tag{11}$$

Where

$k_p, k_q, k_v, k_s$: penalty coefficient for real power generation at slack bus, reactive power generation of all PV buses and slack bus, bus voltage magnitude and line loading, respectively, and

$x^{min}, x^{max}$ : lower and upper limits of variable $x$.

A multilateral transaction trading between source and sink areas is considered. Mathematically, a multilateral transaction involving several sellers and buyers can be expressed as:

$$\sum_{i \in S} P_{Gi} - \sum_{j \in B} P_{Dj} = 0 \tag{12}$$

Where

$P_{Gi}$ : real power generation at bus i in a source area excluding slack bus,

$P_{Dj}$ : real power load at bus j in a sink area,

$S$ : set of sellers who sell the power to buyers, and

$B$ : set of buyers who buy the power from sellers.

The sum of real power loads in the sink area at the point of maximum power transfer is defined as the TTC value. Contingency analysis is also considered in the proposed model. Considering base case configuration, let $TTC_0$ be the maximum amount of power transfer without contingency constraints. Similarly, let $TTC_k$ be the maximum amount of power transfer under the contingency $k$. Therefore, a feasible contingency TTC value is given in (13).

$$TTC = \underset{k}{Min}\{TTC_0,\ TTC_k\} \tag{13}$$

## HYBRID EVOLUTIONARY ALGORITHM

To improve the robustness of EC techniques, a new hybrid evolutionary algorithm (HEA) integrating EP, TS and SA methods is proposed. The HEA algorithm has special features and merits described as follows.

(i) Multiple population search with various mutation operators is designed to enhance search diversity and improve population update, providing higher quality of solutions than those from single population search.

(ii) Reassignment strategy is carried out to fuse and exchange the search information of all subpopulations so that premature convergence caused by consistency of individuals in a single population will be alleviated.
(iii) Selection with a probabilistic updating strategy based on TS algorithm and annealing schedule of SA is applied to avoid dependency on fitness function and to avoid being trapped in local optimal solutions.
(iv) The algorithm can easily facilitate parallel implementation on parallel computers to reduce the elapsed time without sacrificing the quality of solution.

The proposed HEA algorithm is used to simultaneously search for real power generations in a source area excluding slack bus, generation bus voltages and real power loads in a sink area for determining the feasible TTC value. A flowchart of the HEA algorithm is shown in Figure 1, which can be explained as follows.

**Representation of solution:** Each individual consists of OPF control variables coded by real number. The whole population $P$ is divided into $M$ subpopulations according to the number of mutation operators used. The pth individual in a population is represented by a trial vector in (14).

$$S_p = [P_{Gi}, V_{Gi}, P_{Dj}] \tag{14}$$

Where
$S_p$: trial solution vector of the $p$th individual in a population, and
$V_{Gi}$: voltage magnitude of generator at bus $i$ including slack bus.

**Initialization:** Each element of the trial vector is initialized randomly within its search space by using uniform random number distribution in (15).

$$x_i = x_i^{\min} + u \cdot (x_i^{\max} - x_i^{\min}) \tag{15}$$

Where
$x_i$ : ith element of the individual in a population,
$x_i^{\max}$, $x_i^{\min}$ : lower and upper limits of the $i$th element of the individual, and
$u$: uniform random number in the interval [0,1].

**Power flow solution:** During iterations, a full AC Newton-Raphson (NR) power flow analysis is used to check the feasibility of each individual solution.

**Fitness function:** The objective function in (1) is taken as the fitness function of the HEA algorithm.

**Cooling schedule procedure:** The initial temperature of each subpopulation is expressed in (16). The temperature is cooled down by the temperature annealing function or cooling schedule in (17).

$$T_{0,m} = -(F_{\max,m} - F_{\min,m}) / \ln p_r \tag{16}$$

$$T_{r,m} = \lambda^{(r-1)} \cdot T_{0,m} \tag{17}$$

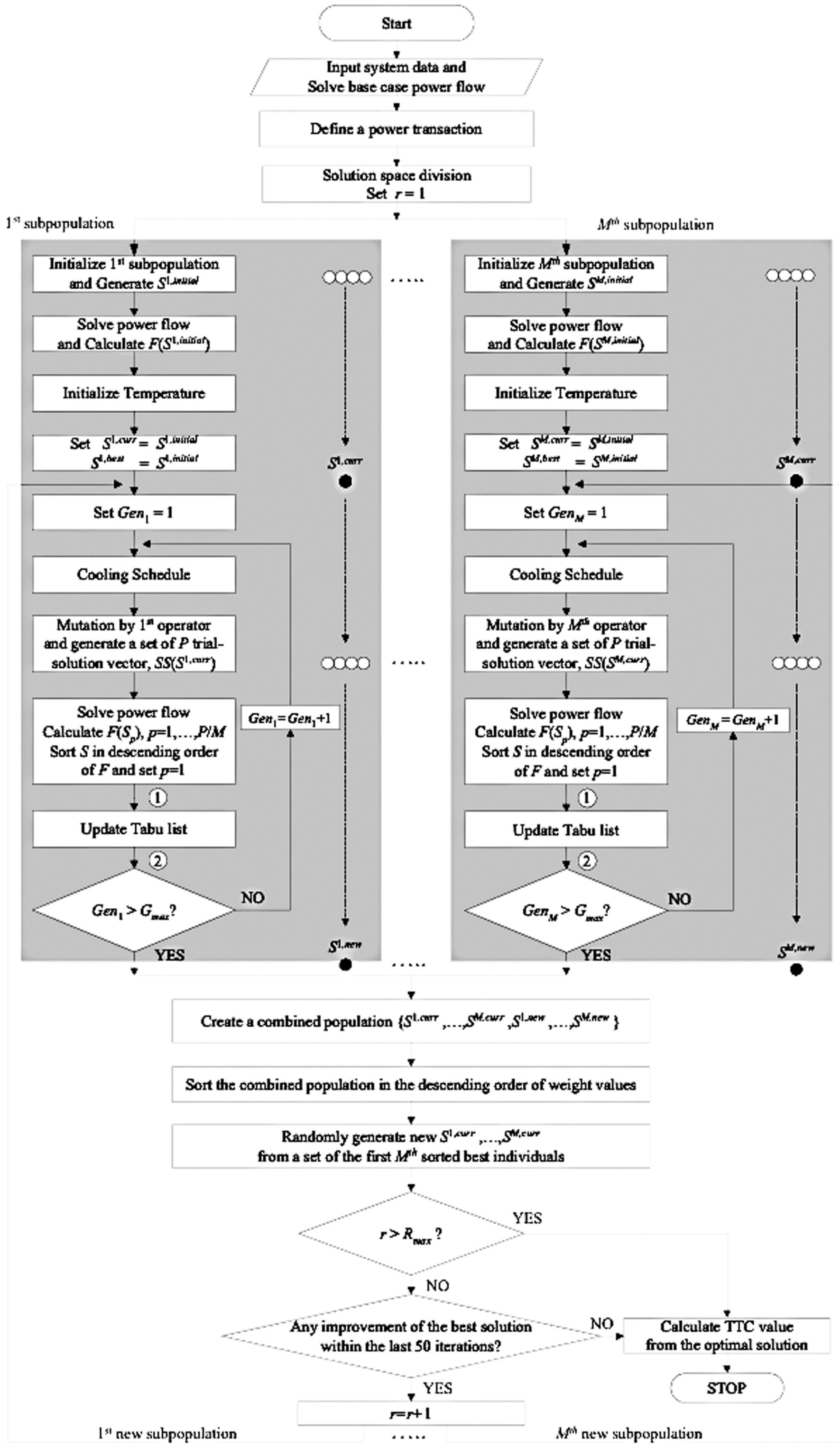


**Figure 1.** Flowchart of the HEA algorithm.

Where
$T_{0,m}$: initial temperature of the *m*th subpopulation,
$F_{min,m}$: objective value of the worst individual in the *m*th subpopulation,
$F_{max,m}$: objective value of the best individual in the mth subpopulation,
$p_r$: probability of accepting the worst individual with respect to the best individual.
$T_{r,m}$: annealing temperature of the *m*th subpopulation after the *r*th reassignment,
$\lambda$: rate of cooling, and
$r$: iteration counter of reassignment.

**Mutation:** In different subpopulations, different mutation operators are used to create new offspring subpopulation so that many hybrid operators are applied to enhance the search diversity. Two mutation operators including Gaussian and Cauchy combined with cooling schedule of SA are applied. Each element of the offspring individual is calculated in (18).

$$x'_{k,i} = x_{k,i} + \sigma_{k.i} \cdot \xi_m \tag{18}$$

$$\sigma_{k,i} = T_{r,m} \cdot a^{(r-1)} \cdot (x_i^{\max} - x_i^{\min}) \tag{19}$$

Where
$x'_{k,i}$: *i*th element of the *k*th offspring individual,
$x_{k,i}$: *i*th element of the *k*th parent individual,
$\sigma_{k,i}$: mutation step size for the ith element of the *k*th individual,
$\xi_m$: mutation operator of the *m*th subpopulation e.g. $N(0,1)$, $C(0,1)$, etc.,
$N(0,1)$: Gaussian random number with mean 0 and standard deviation 1,
$C(0,1)$: Cauchy random number with parameter $t$=1, and
$a$: positive number slightly less than one.

**Tabu list:** Tabu list is a finite length one-in one-out first-in first-out structure, which records a set of current best solutions visited. A new trial vector is placed on top of the list and the oldest trial vector is taken out of the list.

**Aspiration criterion:** The aspiration criterion adopts a probabilistic acceptance criterion of SA in (20). The tabu restriction is overridden if the aspiration criterion is satisfied. When the probabilistic acceptance criterion is higher than a uniform randomly generated variable in the interval [0,1], the tabu restriction is overruled.

$$p_{k,m} = 1/(1 + \exp(-\Delta / T_{r,m})) \tag{20}$$

Where
$p_{k,m}$: probabilistic acceptance criterion of the kth offspring individual within the *m*th subpopulation, and
$\Delta$: difference of objective values between the kth offspring individual and its corresponding parent individual.

**Reassignment strategy:** Tournament scheme is used to select new current parent population from the combined population of current parent ($S^{1,curr}$,…, $S^{M,curr}$) and new offspring ($S^{1,new}$,…, $S^{M,new}$) individuals of all subpopulations (Ongsakul and Tantimaporn, 2006). Each individual in the combined population is assigned a weight value according to the competition in (21).

$$w_k = \sum_{t=1}^{Nt} \begin{cases} 1 & if\ F_k > F_r \\ 0 & otherwise \end{cases} \tag{21}$$

Where

$w_k$: weight value of the *k*th individual in the combined population,

$F_k$: fitness value of the *k*th individual in the combined population,

$F_r$: fitness value of the *r*th opponent randomly selected from the combined population based on $r = \lfloor 2 \cdot M \cdot u + 1 \rfloor$, and

$N_t$: number of competitors.

After sorting the combined population of 2*M* individuals in the descending order of weight values, each new current parent solution individual of all subpopulations will be randomly selected from a set of the first *M*th sorted best solution individuals.

**Termination criteria:** There are three termination criteria in the proposed HEA algorithm. The first termination criterion is set as the maximum number of generations of each subpopulation and the second termination criterion is the number of reassignment required. The algorithm will be stopped if there is no improvement of the best fitness within 50 generations as the third termination criterion.

## CASE STUDY AND TEST RESULTS

The modified IEEE 24-bus RTS, which is partitioned into 3 areas as shown in Figure 2, is used to demonstrate the TTC calculation using the proposed HEA method. The modified system data are given in Ou and Singh (2002). A multilateral transaction from area 1 to 2 with contingency constraints is considered. Only the outage of the largest generator in each area and the outage of tie lines are included in the contingency list. The HEA algorithm is implemented using MATLAB version 6.5 on an AMD Athlon64 3200+ computer with 512 MB memory. Parameter settings of the HEA algorithm suggested in Back et al. (1997) and Lai (1998) are utilized. Test results from HEA are compared to those from EP, TS, TS/SA and IEP methods.

Normal case TTC using HEA method is 716.82 MW. Considering the pre-specified contingency constraints as shown in Table 1, contingency TTC value using HEA is 635.44 MW without violating system constraints, which is 0.75%, 0.97%, 0.73% and 0.37% higher than those from EP, TS, TS/SA and IEP methods, respectively. In addition, the TTC value is decreased by 11.35% compared to that without contingency constraints or normal case. The critical contingency case is the interconnected line 14-11 between those two areas outage. Even though test results indicate a marginal improvement of HEA over the other methods, the higher TTC for power transfer of HEA than the other methods could lead to a substantial cost savings of daily energy trading between different control areas under deregulated power systems.

The comparisons of TTC results and CPU times evaluated by EP, TS, TS/SA, IEP and HEA methods from 30 runs are shown in Table 2. Test results indicate that single-population search of EP, TS and TS/SA is less effective than multi-population search of IEP and HEA methods. The proposed HEA method can obtain better results on the best, average and the worst TTC values than those from the other optimization methods because HEA algorithm uses the selection mechanism with a probabilistic updating strategy based on TS and SA algorithms to avoid dependency on fitness function and to escape from the entrapment in local optimal solutions. Furthermore, the variation of the HEA best solution is smaller as evidenced by a smaller standard deviation than the other methods, leading to a more-stable HEA algorithm.

CPU times of IEP and HEA methods are higher than those from EP, TS and TS/SA because the best solutions of IEP and HEA are obtained based on the acceptance probability, which depends on the improvement of the offspringís objective value and the annealing procedure of SA algorithm. In addition, the reassignment strategy requires additional computing effort. However, both IEP and HEA methods can easily facilitate parallel implementation, reducing elapsed time without sacrificing the quality of solution.

To compare the convergence characteristic, IEP and HEA algorithms utilize a probabilistic updating strategy based on annealing schedule of SA, resulting in more generations required and slower convergence characteristic than EP, TS and TS/SA methods as shown in Figure 3. However, the convergence speed of HEA is improved by introducing a flexible memory of search history of TS to prevent cycling and to avoid entrapment in local optima compared to IEP algorithm.

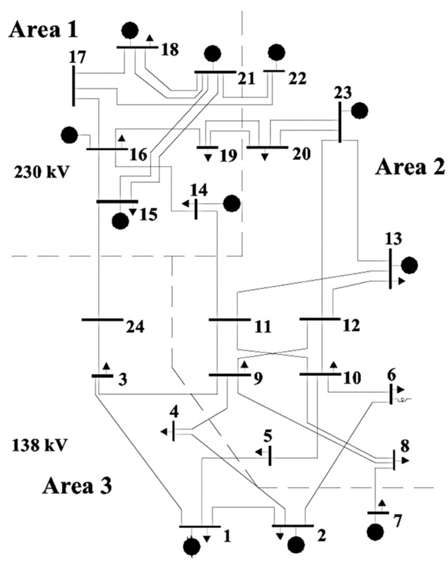


**Figure 2.** Diagram of the modified IEEE 24-bus RTS.

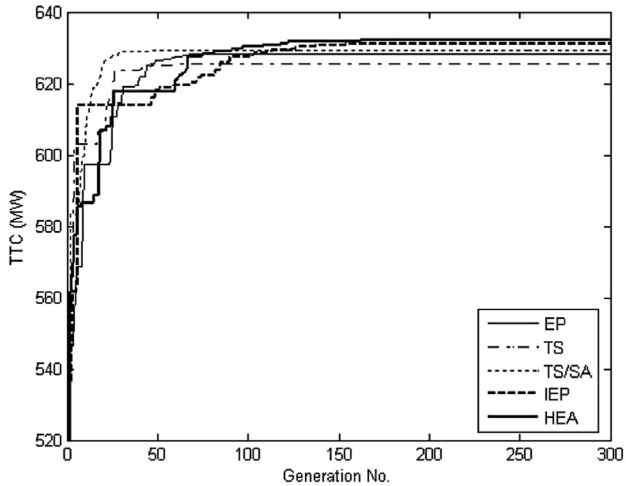


**Figure 3.** Convergence characteristic of solutions.

**Table 1.** TTC level and contingency TTC value of multilateral transaction on the modified IEEE 24-bus RTS.

| Case | TTC Level (MW) | | | | |
|---|---|---|---|---|---|
| | EP | TS | TS/SA | IEP | HEA |
| Normal | 713.99 | 714.90 | 716.01 | 714.80 | 716.82 |
| Largest gen. in area 1 outage | 717.19 | 714.12 | 715.00 | 715.02 | 716.26 |
| Largest gen. in area 2 outage | 731.23 | 727.36 | 729.04 | 743.25 | 743.77 |
| Line 21-22 outage | 711.75 | 699.90 | 710.35 | 713.15 | 715.68 |
| Line 17-22 outage | 714.68 | 707.01 | 716.65 | 716.98 | 718.24 |
| Line 19-20 outage | 700.56 | 701.32 | 707.64 | 705.99 | 717.52 |
| Line 14-11 outage | 630.73 | 629.30 | 630.83 | 633.11 | 635.44 |
| Contingency TTC Value (MW) | 630.73 | 629.30 | 630.83 | 633.11 | 635.44 |

**Table 2.** Optimal solutions of multilateral transaction on the modified IEEE 24-bus RTS.

| TTC Value (MW) | EP | TS | TS/SA | IEP | HEA |
|---|---|---|---|---|---|
| Best | 630.73 | 629.3 | 630.83 | 633.11 | 635.44 |
| Average | 619.74 | 593.36 | 612.02 | 622.89 | 624.86 |
| Worst | 570.5 | 524.53 | 552.84 | 606.91 | 607.91 |
| Standard Deviation | 14.84 | 31.51 | 19.98 | 7.14 | 6.83 |
| CPU Time (minute) | 0.38 | 0.43 | 0.35 | 0.56 | 0.45 |

## CONCLUSION

In this paper, the proposed HEA algorithm is effectively implemented to determine TTC value of power transactions between different control areas. Test results indicate that the HEA algorithm can effectively re-dispatch real power generations except slack bus in a source area, increment of real power loads in a sink area and optimal setting of generation bus voltages, leading to an efficient utilization of the existing power systems. In addition, the algorithm can consider additional voltage and angle stability limits, resulting in a higher trading level of energy transactions in secured power systems.

## ACKNOWLEDGEMENTS

The author gratefully acknowledges Dr. Weerakorn Ongsakul for his supervision, invaluable guidance and constant encouragement. This work is supported in part by the Royal Thai Government.

## REFERENCES

Back, T., U. Hammel, and H.P. Schwefel. 1997. Evolutionary computation: comments on the history and current state. IEEE Trans. Evolutionary Computation 1(1): 3-16.

Chebbo, A.M., M.R. Irving, and M.J.H. Sterling. 1992. Voltage collapse proximity indicator: behaviour and implications. IEE Proceedings-C. 139(3): 241-252.

Ejebe, G.C., J. Tong, J.G. Waight, J.G. Frame, X. Wang, and W.F. Tinney. 1998. Available transfer capability calculations. IEEE Trans. Power Syst. 13(4): 1521-1527.

Ejebe, G.C., J.G. Waight, M.S. Nieto, and W.F. Tinney. 2000. Fast calculation of linear available transfer capability. IEEE Trans. Power Syst. 15(3): 1112-1116.

Federal Energy Regulatory Commission (FERC). 1996. Open Access Same-Time Information System and Standards of Conduct. Order No. 889.

Gravener, M.H., and C. Nwankpa. 1999. Available transfer capability and first order sensitivity. IEEE Trans. Power Syst. 14(2): 512-518.

Lai, L.L. 1998. Intelligent system applications in power engineering: evolutionary programming and neural networks. New York: Wiley.

Luo, X., A.D. Patton, and C. Singh. 2000. Real power transfer capability calculations using multi-layer feed-forward neural networks. IEEE Trans. Power Syst. 15: 903-908.

North American Reliability Council (NERC). 1996. Available Transfer Capability Definitions and Determination. Princeton: New Jersey.

Ongsakul, W., and P. Bhasaputra. 2002. Optimal power flow with FACTS devices by hybrid TS/SA approach. Int. J. of Elect. Power & Ener. Syst. 24(10): 851-857.

Ongsakul, W., and P. Jirapong. 2004. Calculation of total transfer capability by evolutionary programming. Proc. IEEE Region 10 Conf. TENCON. 3: 492-495.

Ongsakul, W., and T. Tantimaporn. 2006. Optimal power flow by improved evolutionary programming. Int. J. of Elect. Power Comp. & Syst. 34: 79-95.

Ou, Y., and C. Singh. 2002. Assessment of available transfer capability and margins. IEEE Trans. Power Syst. 17(2): 463-468.

Shaaban, M., W. Li, Z. Yan, Y. Ni, and F.F. Wu. 2003. Calculation of total transfer capability incorporating the effect of reactive power. Int. J. Elect. Power Syst. Res. 64: 181-188.

Singh, S.N., K.S. Verma, and H.O. Gupta. 2001. Optimal power flow control in open power market using unified power flow controller. Proc. IEEE Power Eng. Soc. Summer Meeting 3: 1698-1703.

Taylor, C. W. 1994. Power System Voltage Stability. New York: McGraw-Hill Inc.

Wong, K.P., J. Yuryevich, and A. Li. 2003. Evolutionary programming based load flow algorithm for systems containing unified power flow controllers. Proc. Inst. Elect. Eng. Gen. Transm. Dist. 150(4): 441-446.

Yue, Y., J. Kubokawa, T. Nagata, and H. Sasaki. 2003. A solution of dynamic available transfer capability by means of stability constrained optimal power flow. Proc. IEEE. Bologna Power Tech. Conf. 2: 8-15.