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# Evolutionary Algorithm for Estimation of Available Transfer Capability in Deregulated Environment

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**Abstract:** ATC is important index in power markets with large volume of power exchanges taking place in hourly basis. The major issue in the restructuring process is to compute the value of Available Transfer Capability (ATC). In this paper, Evolution Algorithm is used to determine the optimal value of ATC for normal operating condition and line outage condition. In the proposed GA, real power settings of ATC values are taken as control variables and are represented as the combination of floating point numbers. Crossover and mutation operators which can directly deal with the floating point number are used for a more effective genetic operation. The proposed algorithm is tested on IEEE 24 bus Reliability Test System (RTS) and IEEE 118 bus system. GA based method has achieved solutions with good accuracy and satisfactory wide space area search computation.The results are compared with the conventional Repeated Power Flow (RPF) method and the comparison shows the superior performance of GA based approach for ATC computation.

**Key words:** Available Transfer Capability · Evolutionary Algorithm · Repeated Power Flow · NRLF

## INTRODUCTION

Dérégulation in the power industry and market for delivery of energy to the customers has created new challenges for the operation of power systems. In order to facilitate the electricity market operation and trade in the restructured environment, ample transmission capability should be provided to satisfy the demand of increasing power transactions. The conflict of this requirement and the restrictions on the transmission expansion in the restructured electrical market has motivated the development of methodologies to estimate the Available Transfer Capability (ATC) of the existing transmission grids. Operation of a power system requires that all forms of security constraints be met during all possible operating conditions. These include static constraints such as thermal and voltage limits. Violating these constraints may result in severe contingencies including system wide blackout. Therefore, the allowable system operation ranges must be carefully determined. NERC specifies that ATC should be obtained by subtracting from the total transfer capability (TTC) [1], provided the transmission reliability margin and capacity benefit margin are neglected. There are several methods and tools available in the literature to calculate ATC. Various mathematical models [2] have been developed by the researches to determine the ATC of the transmission system based on conventional power system equations. Methods based on DC load flows [3] are faster than the AC load flow [4], since no iterations are involved. Complexity in computation is also less as the number of data to be used is less. The DC-PTDFs [5] are easy to calculate and can give quick estimate of ATC. But the ATC values calculated using them are not very accurate as DC power flow neglect reactive power effects. AC-PTDFs for transfer capability calculation is investigated in [5]. AC-PTDFs are based on derivatives around the given operating point and may lead to unacceptable results when used at different operating points to calculate ATC. Also, neither DC nor AC PTDFs based method considers generator limits and bus voltage limits when used to determine ATC. The continuation power flow(CPF)based methods[6] perform full-scale ac load flow solution for each increment of the load at sink bus, above the base case value, until any of the system operating limits is reached. This method is accurate but due to the

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complexity involved in the computation it is difficult to be implemented for large systems. The optimal power flow based methods [7] determine ATC formulating an optimization problem in order to maximize the power transmission between specific generator and load subject to satisfying power balance equations and system operating limits. The Repeated Power Flow (RPF) method repeatedly solves power flow equations at a succession of points along the specified load generation increment as discussed in references [9, 10]. However, the above based methods are time consuming and may not be suitable for on-line implementation.

Recently, evolutionary computation techniques have been applied to calculate the ATC values. The most important avantage of these techniques [11]is that they use only the objective function information and hence are independent of the nature of the search space such as smoothness, convexity, uni-modality etc. This paper proposes a Real coded Genetic Evolution Algorithm (RGA) for ATC Calculation. RGA is an evolutionary algorithm that uses rather greatly selection and less stochastic approach to solve optimization problems than other evolutionary algorithms. The main features of RGA are its simple structure, convergence property, quality of solution and robustness. It is used for solving complex constrained non-linear optimization problem. The effectiveness of the proposed approach has been demonstrated through IEEE RTS 24 Bus system and IEEE118 Bus system.

**Problem Formulation:** As stated in section I, ATC is defined as the additional power that can be transmitted through a specified interface over and above the already committed transactions. The problem of ATC computation in bilateral and multilateral transaction can be formulated as an optimization problem in which the objective is to maximize the difference between TTC and ETC without violating the constraints

The objective function to be maximized is expressed as

$$f = max\ ATC \qquad (2.1)$$

Where ATC for each bilateral transaction between a seller at bus-m and power purchaser at bus –n satisfies the following power balance relationship:

$$P_{Di} - P_{Di}^{0} = 0\ ,\ \forall_i \in t_k \qquad (2.2)$$

It is subjected to following

Equality and In-Equality constraints:

(I) $$P_{Gi} - P_{Di} - \sum_{j=1}^{nb} |V_i||V_j||Y_{ij}|\cos\left(\delta_i - \delta_j - \theta_{ij}\right) = 0 \qquad (2.3)$$

(ii) $$Q_{Gi} - Q_{Di} - \sum_{j=1}^{nb} |V_i||V_j||Y_{ij}|\sin\left(\delta_i - \delta_j - \theta_{ij}\right) = 0 \qquad (2.4)$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \qquad i= 1,2,\ldots\ldots\ldots ng \qquad (2.5)$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \qquad i =1, 2,\ldots\ldots\ldots ng \qquad (2.6)$$

$$V_b^{\min} \le V_b \le V_b^{\max}, \qquad b =1, 2, \ldots\ldots\ldots nb \qquad (2.7)$$

**Genetic Algorithm:** Genetic algorithms (GA) [8] are generalized search algorithms based on the mechanics of natural selection and natural genetics. Starting with an initial population, the genetic algorithm exploits the information contained in the present population and explores new individuals by generating offspring using genetic operators which can then replace members of the old generation. The commonly used genetic operators are reproduction, crossover and mutation. After several generations, the algorithm converges to the best solution, which hopefully represents the optimum or near optimal solution.

Generally, binary strings are used to represent the decision variables of the optimisation problem in the genetic population, irrespective of the nature of the decision variables. The conventional binary-coded GA has Hamming cliff problems [10] which sometimes may cause difficulties in the case of coding continuous variables. Also, for discrete variables with total number of permissible choices not equal to $2^k$ (where k is an integer) it becomes difficult to use a fixed length binary coding to represent all permissible values. To overcome these difficulties, in this paper continuous variables are represented as floating point numbers and discrete variables are represented as integers. With mixed form of representation, the evaluation procedure and reproduction operator remain the same as that in binary-coded GA, but crossover operation is done variable by variable. Also, the real parameter mutation operator is used. The features of the proposed algorithm are presented in the following subsections.

**Selection Strategy:** Selection plays an important role in Genetic Algorithm, since, it determines the direction of search in the search space. It emphasizes good solutions and eliminates bad solutions while keeping the population size constant. The goal is to allow the “fittest” individuals

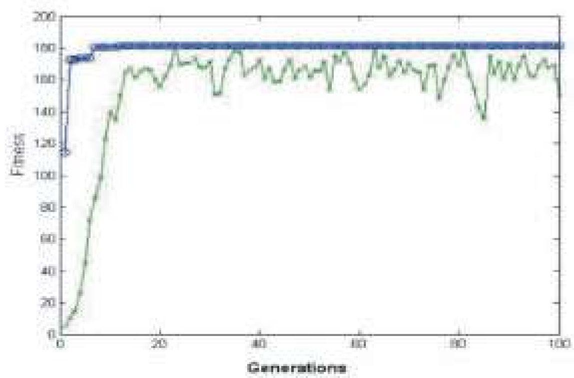


Fig. 1: Convergence for the transaction T3 (Line Outage)

to be selected more often to reproduce. In this work we use "tournament selection" for this purpose. In tournament selection, "n" individuals are selected at random from the population and the best of the "n" is inserted into the new population for further genetic processing. This procedure is repeated until the matting pool is filled. Tournaments are often held between pairs of individuals (tournament size = 2), although larger tournaments can be used.

**Crossover:** The crossover operator is a method for sharing information between chromosomes.Generally, it combines the features of two parent chromosomes to form two offspring, with the possibility that good chromosomes may generate better ones. With hybrid representation, separate crossover operators are applied on the real and integer parts. BLX-α [10] is used for real variables and the standard single point crossover is applied on the integer part. BLX- α uniformly picks new individuals with values that lie in [$u_1$-αI, $u_2$+ αI] where I = ($u_2$- $u_1$) and $u_1$ and $u_2$ represent two parents from a particular variable. The crossover operator is a method for sharing information between chromosomes. Generally, it combines the features of two parent chromosomes to form two offspring, with the possibility that good chromosomes may generate better ones. With hybrid representation, separate crossover operators are applied on the real and integer parts. BLX-α [10] is used for real variables and the standard single point crossover is applied on the integer part. Figure 1 illustrates the BLX- α crossover operation for the one dimensional case. BLX-α uniformly picks new individuals with values that lie in [$u_1$-αI, $u_2$+ αI] where I = ($u_2$- $u_1$) and $u_1$ and $u_2$ represent two parents from a particular variable.

In BLX-α crossover operation, the offspring, $y$ is sampled from the space [$e_1$,$e_2$] as follows:

$$y = \begin{cases} e_1 + r\times(e_2 - e_1) : if \;\; u^{\min} \le y \le u^{\max} \\ repeat \;\; sampling : otherwise \end{cases} \quad (3.1)$$

where

$$e_1 = u_1 - \alpha\times(u_2 - u_1)$$

$$e_2 = u_2 + \alpha\times(u_2 - u_1)$$

r = uniform random number ∈ [0 1]

It is to be noted that $e_1$ and $e_2$ will lie between $u_{min}$ and $u_{max}$, the variable's lower and upper bound respectively. In a number of test problems, it was observed that α = 0.5 provides good results. One interesting feature of this type of crossover operator is that the created point depends on the location of both parents. If both parents are close to each other, the new point will also be close to the parents. On the other hand, if the parents are far from each other, the search is more like a random search.

**Mutation:** The mutation operator is used to inject new genetic material into the population. Mutation changes randomly the new offspring. In this work, "Non Uniform Mutation" operator is applied to the mixed variables with some modifications. First a variable is selected from an individual randomly. If the selected variable is $u_k$ with the range $\left[u^k_{\min}, u^k_{\max}\right]$, two random numbers $r$ and $r_1$ are generated and the result $u^1_k$ is:

$$u^1_k = \begin{cases} u_k + \left(u^k_{\max} - u_k\right).\left(1 - r^{\left(\frac{1-v}{M}\right)^q}\right) & if\; r_1 \le 0.5 \\ u_k - \left(u_k - u^k_{\min}\right).\left(1 - r^{\left(\frac{1-v}{M}\right)^q}\right) & if\; r_1 > 0.5 \end{cases} \quad (3.3)$$

where, $v$ is a generation number, $q$ is a non uniform mutation parameter and $M$ is maximum generation number. If the selected variable is an integer, then the randomly generated floating point number is truncated to the nearest integer. After mutation, the new generation is complete and the procedure begins again with the fitness evaluation of the population.

**Details of Genetic Algorithm Implementation:** When applying GA to calculate the ATC, two main issues need to be addressed:

- Representation of the decision variables and
- Formation of the Fitness function

**Variable Representation:** Each individual in the genetic population represents a candidate solution. For calculating ATC, the change in new load demand of sink bus value ($P_{Di}^{new}$) is taken as a decision variable.This variable is represented as real point numbers in the GA population. The lower and upper bound for decision variable are taken as 1, ($ATC^{max}$) respectively. This bound may vary for different transactions.

**Fitness Function:** Evaluation of the individuals in the population is accomplished by calculating the objective function value for the problem using the parameter set. The result of the objective function calculation is used to calculate the fitness value of the individual. Fitter chromosomes have higher probabilities of being selected for the next generation. The fitness function is given below.

$$F = P_{Di}{}^{new} - P_{Di}{}^{old}$$

**GA Implementation:** In genetic algorithm, individuals are simplified to a chromosome that includes control variables of the problem. The value of an individual is called fitness which is corresponding to the objective function value that should be maximized. The section 5.5.1 discusses the procedure for ATC estimation using genetic algorithm.

**GA Based ATC Estimation:**

- Read the power system data
- Read system line and bus data

**System Data:** From bus, To bus, line resistance, line reactance, half line charging susceptance, off nominal turns ratio, maximum line flow

**Bus Data:** Bus no, Bus type, Real and Reactive powers, Minimum and Maximum values of bus voltages.

- Read data for genetic operations, ie.population size, elitism probability, cross-over probability, mutation probability.
- Read No. of control variables, here the change in new load demand of sink bus value, min and max values of the control variables.
- Read minimum line flow limits, load bus voltage limits.
- Read the sending end (seller bus)m and the receiving bus(buyer bus) n

- Set generation Gen =1.
- Generate population size of chromosomes randomly
- k1=1, chromosome count
- Calculate ATC using Eq(2.1)
- Calculate fitness(k1)=ATC (i.e maximization)
- If ( $K_1$< population size),proceed to next step
- $K_1 = K_1$+1, go to (4), Else to (9)
- Check the termination criteria, i.e. the difference between first chromosome fitness value and last chromosome fitness value will be certain tolerance. If the condition is satisfied stop the process otherwise to step (10)
- Arrange chromosome in ascending order of their fitness values
- Copy elitism probability of chromosome to next generation and perform tournament selection reproduction technique for parent selection
- If ($r < P_c$) perform cross over to obtain children of next generation using the equation from equation 3.1.
- Perform mutation, i.e.If ($r_1$< Pm) perform mutation to inject new information using the following equation, where $r_1$ is a random number between 0 and 1 and $P_m$ is the mutation probability. Finally replace old population by new population by equation 3.3.
- If (gen < gen max)
- Gen=gen+1, go to step (4), Else to step (16)
- Print optimized values, i.e. maximized ATC values for each transaction.

## RESULTS AND DISCUSSION

This section presents the details of the simulation study carried out on IEEE RTS 24 bus and IEEE 118 bus system for ATC computation under normal operating condition and line outage condition using the proposed approach. The data for IEEE RTS 24 bus and 118 bus systems are taken from [15].The reactive power demand at load bus is assumed to be increasing as a percentage of real power increase. The simulation studies were carried out by developing Matlab program and by using Matpower 4.1 software [14]. The results obtained by proposed approach are compared with the conventional method i.e. RPF with power flow using NR to justify its accuracy.

Table 1: Transaction Details for IEEE-24RTS

| Transaction | Source-sink |
|---|---|
| T1 | 23-3 |
| T2 | 21-6 |
| T3 | 22-5 |
| T4 | 23-15 |
| T5 | 22-9 |
| T6 | 23,10 (0.6,0.4)-15,3(0.6,0.4) |

Table 2: ATC values under normal operating condition

| | Transaction | | ATC(MW) | | |
|---|---|---|---|---|---|
| Transaction | Source Bus | Sink Bus | RPF | GA | Limiting element |
| T1 | 23 | 3 | 118.55 | 117.60 | The voltage magnitude at 3rd bus |
| T2 | 21 | 6 | 115.10 | 115.45 | Thermal limit of line 6-10 |
| T3 | 22 | 5 | 219.40 | 219.61 | The voltage magnitude at 3rd bus |
| T4 | 23 | 15 | 867.00 | 867.21 | Thermal limit of line 15-16 |
| T5 | 22 | 9 | 281.90 | 281.74 | The voltage magnitude at 9th bus |
| T6 | 23,10 (0.6,0.4) | 15,3(0.6,0.4) | 428.60 | 427.32 | Thermal limit of line 15-16 |

Table 3: ATC values with line outage of 4-9

| | Transaction | | ATC (MW) | | |
|---|---|---|---|---|---|
| Transaction No. | Source Bus | Sink Bus | RPF | GA | Limiting element |
| T1 | 23 | 3 | 55.80 | 55.23 | The voltage magnitude at 3rd bus |
| T2 | 21 | 6 | 52.30 | 52.24 | Thermal limit of line 6-10 |
| T3 | 22 | 5 | 185.40 | 185.32 | The voltage magnitude at 3rd bus |
| T4 | 23 | 15 | 525.50 | 525.16 | Thermal limit of line 15-16 |
| T5 | 22 | 9 | 175.30 | 174.48 | The voltage magnitude at 9th bus |
| T6 | 23,10 (0.6,0.4) | 15,3(0.6, 0.4) | 284.70 | 283.82 | Thermal limit of line 15-16 |

Table 4: Transaction details for IEEE-118 Bus System

| Transaction | Source-sink |
|---|---|
| T1 | 32-75 |
| T2 | 12-60 |
| T3 | 24-40 |
| T4 | 65-100 |
| T5 | 46-80 |
| T6 | 5,6 (0.6,0.4)-40,60(0.6,0.4) |

Table 5: ATC values under normal operating condition

| | Transaction | | ATC (MW) | | |
|---|---|---|---|---|---|
| Transaction No. | Source Bus | Sink Bus | RPF method | GA method | Limiting element |
| T1 | 32 | 75 | 151.05 | 151.15 | The voltage magnitude at 118th bus |
| T2 | 12 | 60 | 254.30 | 254.37 | The voltage magnitude at 38th bus |
| T3 | 24 | 40 | 239.05 | 239.56 | The voltage magnitude at 38th bus |
| T4 | 65 | 100 | 499.35 | 499.45 | Thermal limit of line 65-100 |
| T5 | 46 | 80 | 527.85 | 527.785 | Thermal limit of line 46-80 |
| T6 | 10,12 (0.6,0.4) | 40,60(0.6,0.4) | 587.05 | 587.14 | The voltage magnitude at 38th bus |

Table 6: ATC with line outage of 76-118

| | Transaction | | ATC (MW) | | |
|---|---|---|---|---|---|
| Transaction No. | Source Bus | Sink Bus | RPF method | GA method | Limiting element |
| T1 | 32 | 75 | 81.05 | 81.34 | The voltage magnitude at 118$^{th}$ bus |
| T2 | 12 | 60 | 189.80 | 189.67 | The voltage magnitude at 38$^{th}$ bus |
| T3 | 24 | 40 | 175.70 | 174.94 | The voltage magnitude at 38$^{th}$ bus |
| T4 | 65 | 100 | 386.95 | 386.38 | Thermal limit of line 65-100 |
| T5 | 46 | 80 | 503.75 | 503.21 | Thermal limit of line 46-80 |
| T6 | 5,6 (0.6,0.4) | 40,60(0.6,0.4) | 524.35 | 524.45 | The voltage magnitude at 38$^{th}$ bus |

**ATC Estimation in IEEE RTS 24 Bus System:** The IEEE RTS 24 bus system consists of 11 generator buses, 13 load buses and 38 transmission lines. The transactions considered here are given in Table 1.

The best result of the GA was obtained with the following control parameters:

- No. of generations: 100;Population size: 60
- Crossover probability: 0.8;Mutation factor: 0.01

**Normal Operating Condition:** The ATC values for different transactions under normal operating condition using the proposed approach are given in Table2. The results are compared with the results of RPF method. Table 2 also shows limiting element for all transactions.

From this Table 2, it is observed that, the ATC values calculated by the proposed approach are very close to the values obtained using RPF method. The GA based algorithm provides wider search area. The time taken by RPF method for the same transaction is comparatively more than GA based method.

**Line Outage (4-9):** In this case, the line connected between bus 4 and bus 9 is removed and corresponding ATC values are computed using the proposed approach. Table 3 shows the values of ATC obtained for the same bilateral transactions with line outage condition. The results are also compared with RPF results.

From Tables 2 and 3 it is observed that ATC values for line outage condition has reduced compared to the non-outage condition. The limiting elements of ATC for all transactions are also given in the above table.

**ATC Estimation in IEEE 118 Bus Systems:** The IEEE 118 bus system consists of 54 generator buses, 64 load buses and 186 transmission lines. The line flow limits for IEEE 118 bus system are given in appendix 3. The bilateral and multi lateral transactions considered here are, shown in Table 4.

The control parameters for the best result of GA are: No. of generations: 100

Population size: 60; Crossover probability: 0.8; Mutation probability: 0.01

**Normal Operating Condition:** The ATC values obtained for the different bilateral and multilateral transactions under normal operating condition using the proposed approach are given in Table 5. The results are compared with the results of RPF method. Table 5 also shows limiting element for all transactions.

From this table, it is observed that, the ATC values calculated by the GA method are very close to the values obtained by RPF method. The computation time taken by RPF method for all the transaction is less in GA based approach.

**Line Outage (80-118):** In this case, the line connected between bus 76 and bus 118 is removed and corresponding ATC values are computed using GA approach. The Table 6 shows obtained ATC values for bilateral and multilateral transaction with line outage condition. The results are compared with RPF results. The limiting element of ATC for all transactions is also given in this table6.

From Tables 2, 3 and 5,6 it is observed that ATC obtained by GA is much closer to the RPF results. Hence this proposed approach is suitable for computing ATC in deregulated environment.

## CONCLUSION

This paper has presented the application of GA for computation of ATC under normal operating condition and line outage. The ATC computation has been tested on IEEE RTS 24 bus and IEEE 118 bus system. The obtained results are compared with the RPF results. Test results show that the proposed method is very effective with good convergence characteristics. Test results also show that for large system like IEEE 118 bus system the ATC estimation using GA based approach provides wide search area. In a real time operation of deregulated power system, the Independent System Operator (ISO) has to estimate ATC values for many possible proposed transactions with in short time. As, GA based approach can estimate ATC value in short time with good accuracy, the ISO can use GA based approach for ATC estimation. Thus the proposed approach provides significant profit to all the market participants in the electricity market.

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