Chapter 6

Novel approach of Teaching Learning Based Optimization to compute value of optimized Available Transfer Capability for manifold transactions

6.1 Introduction

The Available Transfer capability has been renowned as most noteworthy for congestion management in electrical power system. Due to physical and financial limitations, the transmission line capability has been fixed for a particular transmission line. New erection of transmission line has not been possible because of economical and environment limitation. Hence, Available Transfer Capability (ATC) computation has been made compulsory to keep system stable and healthy. The optimized ATC has been identified as an integral part of modern energy management systems.

Therefore, the Available Transfer capability (ATC) calculation has been recognized as a vital part of modern power system. The higher power demand due to industrial development may leads to over loading of other healthy lines and results in unstable system. In this chapter, a novel approach, Teaching Learning Based Optimization (TLBO) has been proposed for optimized ATC computation.

The two important groups, evolutionary algorithms (EA) and swarm intelligence (SI) based algorithms has been involved in the population-based trial-error-based algorithms.

The Algorithms like Genetic algorithm (GA), PSO, Evolution Programming, ANT colony Optimization (ACO), Artificial Bee Colony (ABC), Fire Fly (FF) etc are the popular evolutionary algorithm. Some natural phenomena based algorithm like Harmony algorithm, Gravitational search Algorithm (GSA), Biogeography-Based Optimization (BBO), Flower Pollination Algorithm (FPA), etc. has been well accepted in optimization field of the power system. Above listed evolutionary and swarm intelligence based algorithms are probabilistic algorithms. Hence, it requires some ordinary controlling parameters like size of the population, the number of generations, elite size, etc.

Over and above the common control parameters, some algorithms require their own control parameters based on algorithm-specific task. The mutation probability, crossover probability, selection operator are the parameters required in GA; the inertia weight, social and cognitive parameters in PSO; number of onlooker bees, employed bees, scout bees and limit in case of ABC; harmony memory consideration rate, pitch adjusting rate, and the number of improvisations uses in algorithm.

Likewise, the other algorithms need the tuning of respective algorithm-specific parameters. The specific parameter is a prime factor to be considered for proper tuning of the algorithm-specific parameters. The false tuning of algorithm-specific parameters tend to increase the computational pains or solution will stick to local optima.

To overcome the above-mentioned problems, Rao et al. (2011) [93] established the teaching-learning-based optimization (TLBO) algorithm [94] which has been free from tuning of algorithm-specific parameters. In this new concept, only common controlling parameters like size of population and number of generations are required tuning for its functioning. The TLBO algorithm [95] has been more popular among the researchers due to its accuracy in the field of optimization. The TLBO has been applicable to other optimization problem [96] of electrical power system.

This algorithm has been inspired from teaching-learning methodology [97]. It based on the impact of a teacher on the outcome of the students or learner. In this chapter the optimization ATC value has been calculated with the help of TLBO methods. The best possible value has been obtained with this method.

Teaching learning based optimization (TLBO) has been extended in the present chapter to work out optimized ATC for secure and stable operation of power system and demonstrated on the IEEE 30 bus and 75 UPSEB system. The system consisting of total 41 lines has been evaluated for a given IEEE 30 bus system and 98 lines for 75 bus UPSEB system.

6.2 Elementary of Teaching Learning Based Optimization

Teaching learning-based optimization algorithm is extremely powerful, yet simple algorithm proposed by Rao et. al (2011) [93] that improves populations over several iterations through the concept of teaching learning process between the teacher and the students in a class [95]. The algorithm maintains a constant population of students, where each student represents a candidate solution to an optimization problem. The design variables are considered as subjects offered to the students. The candidate solution comprises of design variables, and the objective function value represents the knowledge of the particular student. TLBO has been successfully employed by various researchers in solving economic power dispatch problem [98], [99], optimal power flow [100], mitigation of transmission losses [100], etc. The process of TLBO has been divided into two parts namely; the teacher phase and the learner phase which are described below:

The algorithm has two segments of learning through :

- **Teacher Phase (known as teacher segment)**
- **Learner Phase (known as learner segment)**

In Teaching Learning Based Optimization (TLBO),two groups of learners has been deemed as population and different subject recommended to the learners are taken as design variables. The outcome of learners result has been known as fitness value of the optimization problem. The teacher is the best solution from the entire population. The objective function consisting of design variables and the best solution is the best value of an objective function of the particular optimization problem. The population-based TLBO simulates the teaching-learning process of the classroom. The basics working of TLBO has been based on two process, namely "Teacher phase" and "Learner phase". The detail regarding these two phase as follows:

6.2.1 Teacher Phase

A learner learns through the teacher in the first step of this algorithm. In this step, the teacher tries to give best of the subject to the learner as per his/her capability in the class. The aim of the teacher is to improve the average result of the class from an initial level to his own level. However, in actual practice, the level of learners depends on other aspects like their aptitudes and commitment to learn.

If m is the number of subject (i.e Design variable), L is the number of learner (i.e size of population, $k = 1, 2...L$) and $N_{j,i}$ is the mean result of the learners in the particular subject j ($j = 1, 2, ...m$) for any iteration, i. The best overall result $Y_{total-kbest,i}$ taking in to account all the subject together obtained in the total population of the learners can think about the best learner *kbest*. Though teacher is the best learned person who educates learners so they can have the best results. The algorithm will identify the best learner as a teacher. The distinction between the existing mean result of each subject and the corresponding result of the teacher for each subject is given by Eq.(6.1).

$$\text{Mean Diff}_{j,k,i} = r_i(Y_{j,kbest,i} - T_F N_{j,i}) \tag{6.1}$$

Where,

$Y_{j,kbest,i}$ =Result of learner in subject j.

T_F = the teaching factor which decides the value of mean to be changed.

r_i = the random number in the range [0, 1].

The value of TF can be either 1 or 2. The value of T_F is decided randomly with equal probability as,

$$T_F = round(1 + rand(0, 1)(2 - 1) \tag{6.2}$$

T_F is not a parameter of the TLBO algorithm. The value of T_F is not given as an input to the algorithm and its value is randomly decided by the algorithm using Eq.(6.2).

The standard value of T_F can be decided 1 or 2 by performing algorithm on standard functions. Based on the Mean Diff.$_{j,k,i}$, the existing solution is updated in the teacher phase according to the following expression Eq.(6.3).

$$Y'_{j,k,i} = Y_{j,k,i} + \text{Mean Diff.}_{j,k,i} \tag{6.3}$$

Where, $Y'_{j,k,i}$ is the updated value of $Y_{j,k,i}$ and $Y'_{j,k,i}$ is accepted if it gives better function value.

At the end of the teacher phase all the accepted function values are maintained and these values become the input to the learner phase. The learner phase depends upon the teacher phase.

6.2.2 Learner Phase

In this second segment of the algorithm, the learners enhance their data by dealing among themselves. A learner interacts arbitrarily with another learner for augmenting their information. The exchange of knowledge between learners will improve the results. If population size is n then following is the explanation of learner phase in detail.

In this thesis, TLBO has been slightly modified in teaching and learning phase. In teaching phase, the decision variables may go beyond the limits when the transfer of knowledge from teacher to students takes place. This is also observed in the learning phase during the interaction between the learners. To alleviate this difficulty, each time, the decision variable values are compared with their limiting values, whenever there is a transfer of knowledge in teaching as well as in learning phase.

If S and T are the two learners selected randomly such that $Y'_{total-S,i} \neq Y'_{total-T,i}$ (where $Y'_{total-S,i}$ and $Y'_{total-T,i}$) are the updated function value of $Y'_{total-S,i}$ and $Y'_{total-T,i}$ of S and T respectively at the end of teacher phase given by Eq(6.4).

If $Y'_{j,S,i} \leq Y'_{j,T,i}$

$$Y'_{j,S,i} = Y'_{j,S,i} + r_i Y'_{j,S,i} - Y'_{j,T,i} \tag{6.4}$$

if $Y'_{j,T,i} \leq Y'_{j,S,i}$

$$Y''_{j,S,i} = Y'_{j,T,i} + r_i Y'_{j,T,i} - Y'_{j,Q,i} \tag{6.5}$$

if $Y'_{j,T,i} \leq Y'_{j,S,i}$

$$Y''_{j,S,i} = Y'_{j,S,i} + r_i Y'_{j,S,i} - Y'_{j,T,i} \tag{6.6}$$

if $Y'_{j,S,i} \leq Y'_{j,T,i}$

$$Y''_{j,S,i} = Y'_{j,T,i} + r_i Y'_{j,T,i} - Y'_{j,Q,i} \tag{6.7}$$

$Y''_{j,S,i}$ is accepted if it gives a better function value. The Eq.(6.4) and Eq.(6.5) are for minimization problems. In the case of maximization problems, the Eq.(6.6). and Eq.(6.7) are used.

6.2.3 Steps for Teaching Learning Based Optimization

The steps for Teaching Learning Based Optimization (TLBO) has been listed as under:

1. Declaration of number of population (student), Number of Design variable and termination criteria, maximum and minimum limits of each decision variable, iteration count i, maximum number of iterations, i_{max}
2. Assess initial population.
3. Compute Mean of each Design variable.
4. Recognize the best solution and the values of variables.
5. With the help of best solution, modify the other values of variables by: Mean Diff.$_{j,k,i}$ = $r_i(Y_{j,kbest,i} - T_F N_{j,i})$ $Y'_{j,k,i} = Y_{j,k,i} +$ Mean Diff.$_{j,k,i}$.
6. Check whether the solution $Y'_{j,k,i}$ is better than $Y_{j,k,i}$.
7. If "Yes", accept and replace the previous.
8. If "No", reject and keep the previous.
9. Select two solutions arbitrarily and modify them by comparing with each other.
10. Check whether the solution is better than previous.
11. If "Yes" then accept the solution. Check termination criteria and print final result.
12. If "No" then keep previous solution Check termination criteria and go to step(3).

6.2.4 Elitist TLBO

To improve the performance of the algorithm the concept of elitism has been introduced by the evolutionary and swarm intelligence algorithms. In such method after every generation, some of the generations which are good in quality are stored as an elite solution.

To the improvement of results, the worse solution is replaced by elite solution during each and every generation.

In the TLBO algorithm, after changing the worst solutions with elite solutions at the end of learner phase, if the duplicate solutions exist then it is necessary to modify the duplicate solutions in order to avoid trapping in the local optima. The duplicate solutions are modified by a mutation on haphazardly selected dimensions of the duplicate solutions before executing the next generation.

6.3 Problem formulation of Available Transfer capability

In open access power electrical network, the power demand has been increased due to industrial revolution. Due to multiple transactions from source to destination,the transmission line has been operated beyond its capability. Hence, the computation of accurate optimized ATC calculation has been recognized as key role to mitigate congestion in power system .

In this section, the optimized ATC has been evaluated by varying generation at generator bus for a specific loading condition with the help of Teaching Learning Based Optimization (TLBO). The main objective function as per Equation- 6.8 taken here is to maximize ATC for manifold transactions at three different load bus. The objective function can be defined as under:

6.3.1 Proposed Algorithm

1. Run load flow for the base-case with data file.

2. Interpret line flows.

3. Create populations for source buyer and supplier bus, through GA.

4. Alteration of bus data by inclusion of new transactions generated through GA.

5. Run a load flow to derive the optimized value of ATC (Available Transfer Capability) for all randomly generated population.

6. Convergence condition is verified (Is the transaction accomplished?)

7. Check, if the answer to step (6) is No, go to step (3).

8. If the answer to step (6) is Yes, print the result pertaining to the optimized value of ATC for a transaction between source and destination bus.

6.3.2 Objective Function

$$Max(f_n(x)) = Max(ATC_n^{i-j}(P, PTCDF)) \tag{6.8}$$

Subjected to $P_{min} \leq P \leq P_{max}$
Where,

i, j=line index,

n= Number of Transaction,

P= Power Generation at generator bus,

$PTCDF$= Power Transmission Congestion Distribution Factors

6.4 System Studies and Results

This work has been demonstrated on IEEE 30 bus test system and 75 bus UPSEB system.

6.4.0.1 IEEE 30 bus system

The maximum capability of each transmission line has been assumed to be 200 MW for the IEEE 30 bus test system. All the five generator at bus 2,5,8,11 and 13 act as source bus. The load has been connected to bus number 3,10 and 25. The load has been served by varying generation at source bus with the optimized value of ATC. In this work, the generation at generator buses has been taken as decision variables for the optimization techniques. The generation at generator bus varies for the computation of optimized ATC. Total 41 transmission lines has to be valuated with the help of the Teaching Learning Based Optimization (TLBO).

The comparison between optimized ATC value without and with elitism has been shown by Table : 6.2 for IEEE 30 bus test system. The optimized ATC has been obtained along-with generation at different generator bus for 100 iterations for a specific load with the help of TLBO method. The output with elitism and without elitism has been

Table 6.1: Parameters for TLBO for IEEE 30 bus

Sr.no	Parameter	Value
1	Population Size (Number of Learners)	10
2	Number of Design Variables	05
3	Maximum Iterations	100

Table 6.2: Comparison of Optimized ATC value without and with Elitism using TLBO for IEEE 30 bus test system

MW Loading			Optimized ATC with out Elitism	Optimized ATC with Elitism
L_1	L_2	L_3		
10	15	22	96.81611	98.137137
12	19	25	87.526012	87.595117
20	10	21	96.184557	97.200168
5	13	9	91.34115	91.437211
22	46	10	65.266502	65.876792
39	9	19	92.986787	92.986787
12	49	23	71.536459	73.924609
3	10	13	93.685566	95.390785
10	23	49	68.251734	69.035156
30	9	46	80.882574	80.924229

presented graphically in Fig: 6.4.0.1 and Fig: 6.4.0.1 respectively for a specific load. The parameters has been used in TLBO algorithm as shown in Table:6.1 for IEEE 30 bus test system.

After running algorithm the optimized value of ATC without Elitism is shown in Table:6.2 The noise (Imperfectness) in output results has been damp out with Elitism strategy. The results with Elitism strategy has been shown in Fig: 6.4.0.1. The optimized ATC with the specific load can be revealed as per Table: 6.2.

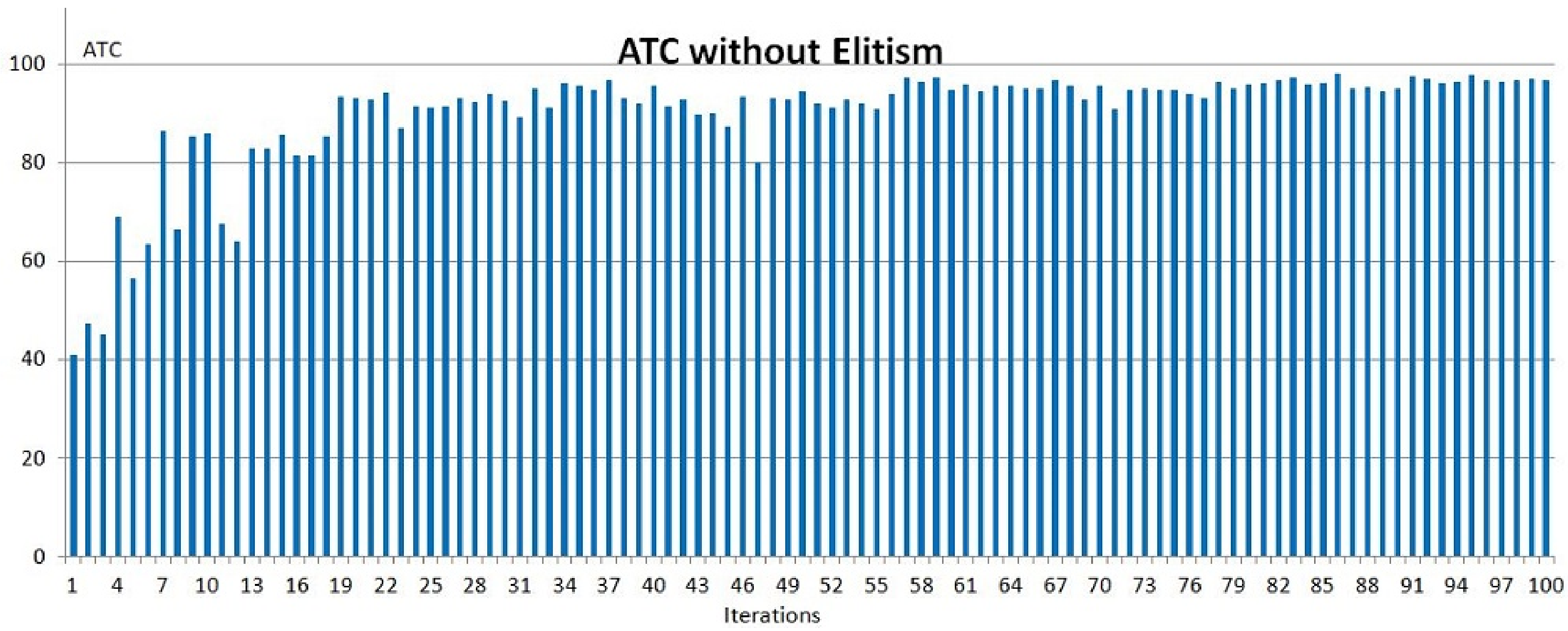

Figure 6.1: Optimized value of ATC using TLBO without Elitism strategy for IEEE 30 bus test system for the 1_{st} loading condition

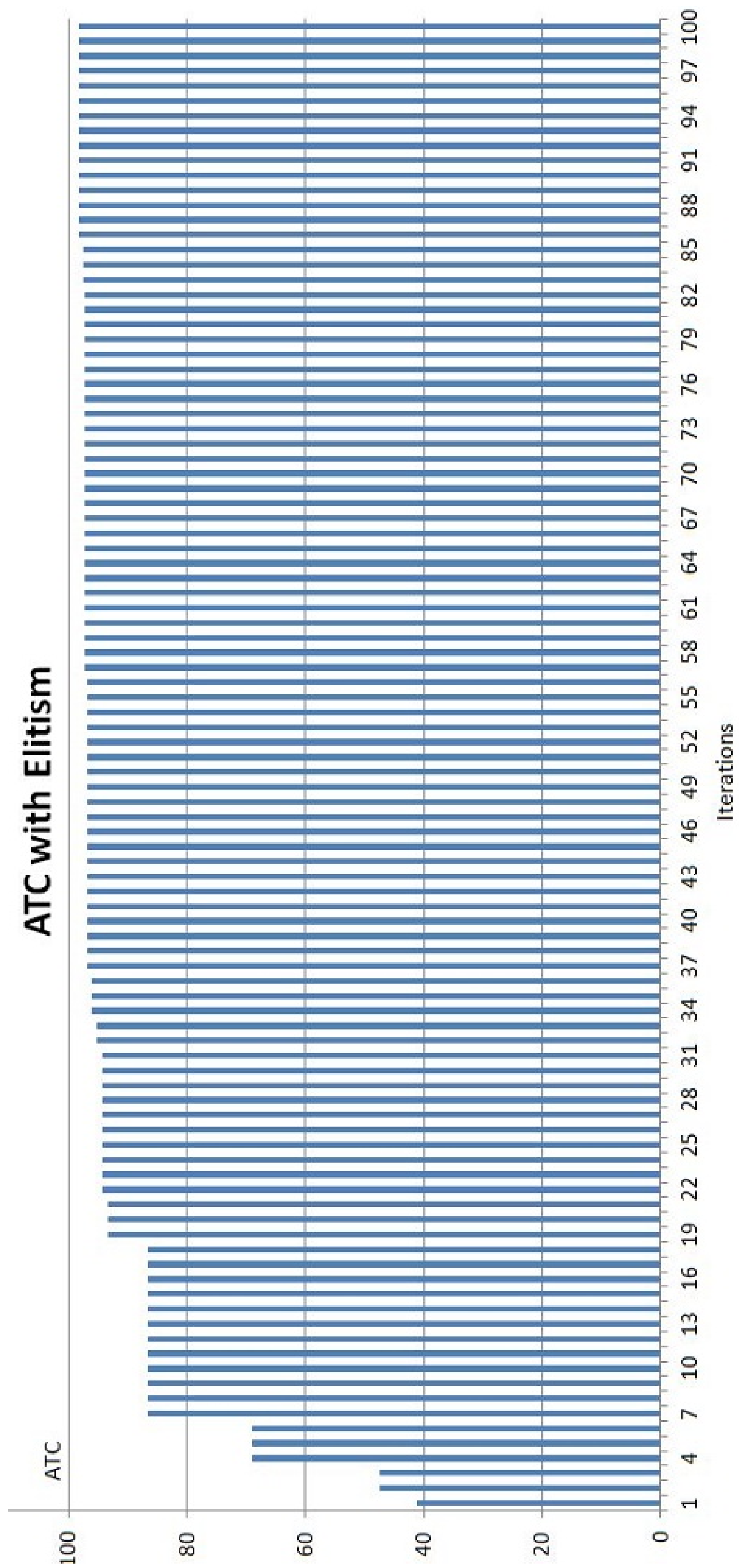

Figure 6.2: Optimized value of ATC using TLBO with Elitism strategy for IEEE 30 bus test system for the 1_{st} loading condition

Table 6.3: Parameters for TLBO for 75 bus UPSEB System

Sr.no	Parameter	Value
1	Population Size (Number of Learners)	10
2	Number of Design Variables	14
3	Maximum Iterations	100

6.4.0.2 UPSEB 75 bus system

For UPSEB 75 bus system, maximum capability of each transmission line has been shown different as per Annexure-B .The load has been connected to bus number 17,21 and 26 as shown in Table: 6.4. The load has been governed by 15 generator buses. The generator bus number 2 to 15 has been taken as decision variables for the optimization problem. Hence, there are 14 decision variables are used in PSO algorithm. The load has been served by the generation at different generator bus for a specific load on load bus to determine optimized ATC. The Objective function has been evaluated for 98 transmission lines. The algorithm will drive the load in such a way that the ATC value should be optimized. The optimized value of ATC has been computed with proposed algorithm. The obtained value of ATC without Elitism is revealed as per Table:6.4 The parameters used in TLBO method has been listed in Table : 6.3.

The graphical representation is shown in Fig. 6.4.0.2 without elitism policy.

The problem of losing good result has been resolved by the TLBO with elitism strategy. The good results has been stored and may be replaced if next value is greater then stored value. The results after Elitism strategy shown in Fig:6.4.0.2. The optimized ATC with the valid transaction can be revealed as per Table:6.4.

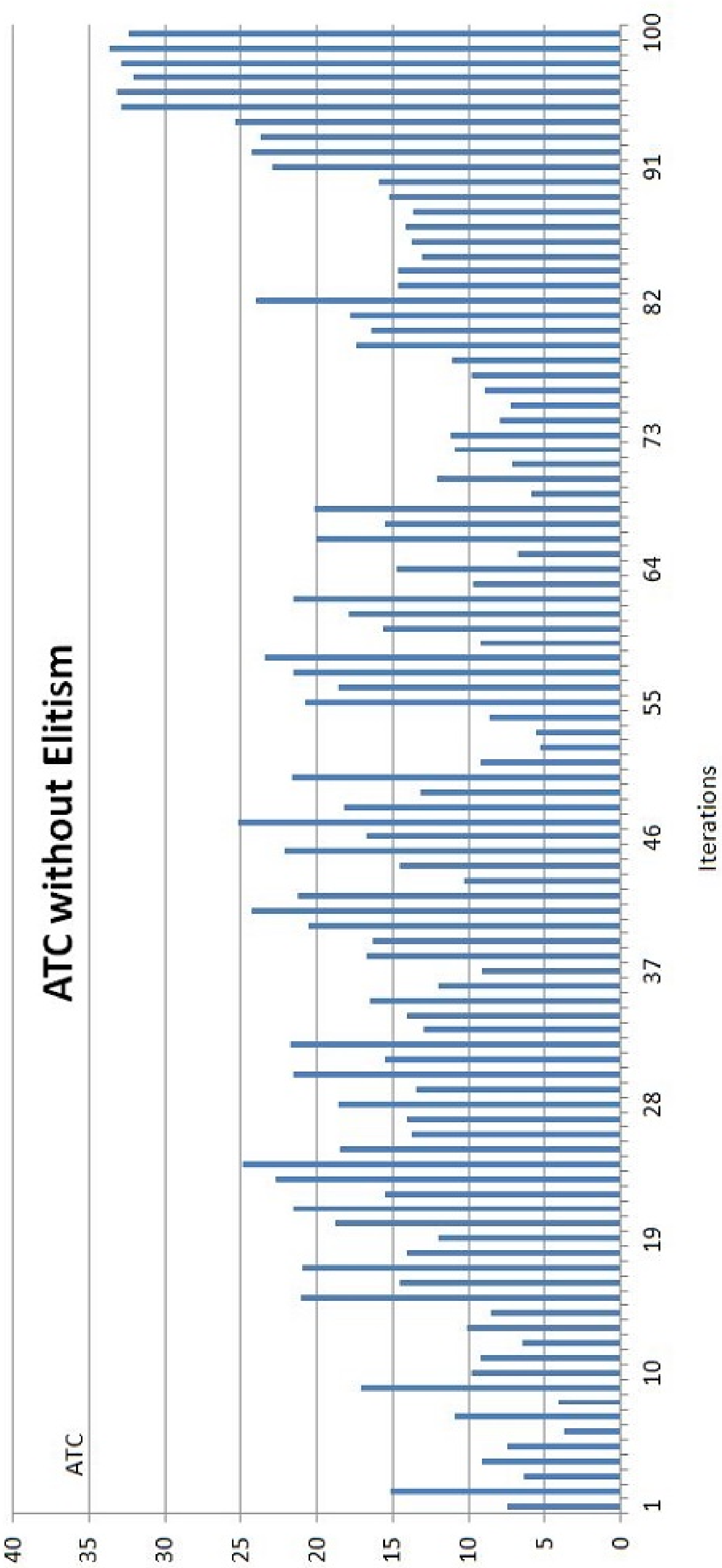

Figure 6.3: Optimized value of ATC using TLBO without Elitism strategy for 75 bus UPSEB system for the 1_{st} loading condition

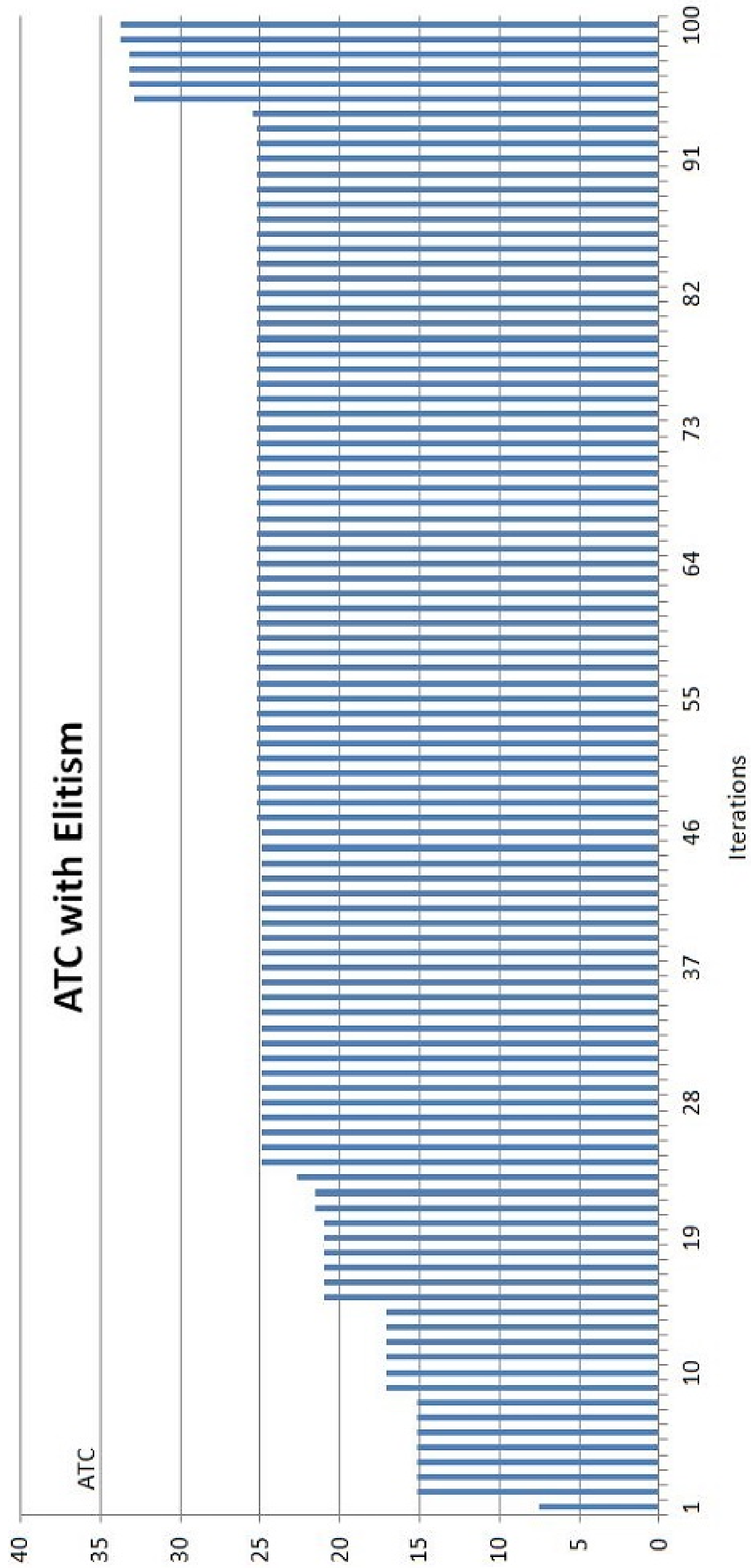

Figure 6.4: Optimized value of ATC using TLBO with Elitism strategy for 75 bus UPSEB system for the 1_{st} loading condition

Table 6.4: Comparison of Optimized ATC value without and with Elitism using TLBO for UPSEB 75 bus system

MW Loading			Optimized ATC with out Elitism	Optimized ATC with Elitism
L_1	L_2	L_3		
10	15	22	32.375882	33.710236
12	19	25	38.7497	43.592904
20	10	21	31.157661	44.62184
5	13	9	40.95659	52.690426
22	46	10	33.238222	34.820826
39	9	19	42.592949	42.592949
12	49	23	38.043749	39.651079
3	10	13	41.551803	41.998509
10	23	49	27.597725	27.597725
30	9	46	31.561307	31.561307

6.5 Conclusion

In this chapter, a novel method for the reckoning of Available Transfer Capability (ATC) using Teaching Learning Based Optimization (TLBO) was developed for safe and steady operation of power system. The present work has been demonstrated on two different systems namely; IEEE 30 bus test system and 75 bus UPSEB system. It is concluded from above tables and graphs that the TLBO gives nearly same value for optimized ATC value with and without elitism strategy. With this novel approach, the optimized value of ATC can be computed with the best value of the objective function as compared to other methods.