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Reducing Losses in a Deregulated Power System with Teaching Learning Based Optimization Algorithm

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Abstract-The robust Newton–Raphson method is suggested to solve the power flow equations. Newton power flow algorithms do not automatically minimize objective function such as real power losses. Hence, this paper presents teaching learning based optimization (TLBO) approach to minimize power lossesby the optimal allocation of reactive power sources considering placement and value in restructured power systems while at the same time satisfying various equality and inequality constraints. Reconstruction of power industries has brought fundamental changes to both power system operation and planning. Moreover,proper location of capacitors and finding the best combination among a large number of potential combinations are important for maintaining a stable and secure operation of a deregulated system, which benefits the system with reducing the total reactive power generation cost, minimizing the total power losses, and increasing available real power transfer capabilities. Therefore, the independent system operator (ISO) does not worry about compensating power losses. This study reviews the method of minimization of power losses, then we investigate the deregulated environment without losses. Next, a new evolutionary method is applied on IEEE 30 bus test system. And its superior performance is compared to particle swarm optimization(PSO) and Genetic Algorithm (GA). Simulationresults have been presented in order to show the effectiveness of the proposed approach for reactive power planning. They must produce reactive power for keeping magnitude bus voltages in their proper magnitudes.

Keywords-losses, teaching learning based optimization, particle swarm optimization, deregulatedpower system.

1. INTRODUCTION

Optimal allocation of Var sources, such as capacitor banks, Static Var Compensators (SVC), and STATicCOMpensators (STATCOM), is a critical component in reactive power planning or Var planning. Traditionally, the locations for placing new Var sources were either simply estimated or directly assumed. Recent research has presented some rigorous optimization-based methods to address reactive power planning. Due to the complicated objective functions, constraints, and solution algorithms, reactive power planning is identified as one of the most challenging problems in power systems. Most of these programs are capable of solving the power flow program for tens of thousands of interconnected buses[1]. Most of the problems in the world have an objective function. And they have more than one way to approach the best answers. Also, user friendly computer programs are developed to handle all AC and DC equipments of power system. So it causes engineers to attract to optimization problem. Optimization techniques are worldwide used in several fields of science such as economic and engineering science. The main purpose of these techniques is to find the variables for maximizing or minimizing an objective function.On the other hand, the power flow problem is originally motivated within planning environments where engineers considered different network configurations necessary to serve an expected future load. Later, it became an operational problem as independent system operatoris required to monitor the real-time status of the network in terms of voltage magnitudes and circuit flows. Today, the power flow problem is widely recognized as a fundamental problem for power system analysis, and there are many advanced, commercial power flow programs to address it. Here, the aim is to achieve an appropriate blend between maximum stability and minimum losses. Firstly, we obtain the power flow solution by the Newton Raphson method for the IEEE30 buses system. Secondly, a new evolutionary algorithm is employed to perform automatically all types of operations needed for finding the total combinations, and obtaining the feasible combinations, then, estimating the losses for all the combinations, next, identifying the minimum loss configuration which might be a local or global minimum from among the feasible combinations, in the end, making a search to find the global optimum for losses minimization. Resent day power systems are being operated closer to their stability limits due to economic constraints. Also, maintaining a stable and secure operation of a power system is very important and challenging issue. By approaching to global optimum point, stability of deregulated system and reducing the total reactive power generation cost are guaranteed. Also the transmission lines are at maximum flow. Recently, deregulation has been a hot issue in electric power industries. The power industrial companies have been moving into a more competitive environment. This enables an end to the era of monopoly. So the system operator is responsible for system operation and enhancing the system reliability. In a deregulated electric power system in which a competitive electricity market can influence system reliability, system analysts are rapidly recognizing that they cannot ignore market risks[2]. In the last decade, several optimization algorithms have been proposed to solve a set of well-known optimization problems. They can be classified into two groups: classical optimization methods and evolutionary optimization methods. Methods in the first group are based on the mathematical theory, such as, Golden Mean, Conjugate Gradients, Modified Newton Method, Linear and Quadratic Programming and etc. Algorithms in the second group are inspired by natural phenomena and the behavior of living organisms. The main strength of these algorithms is their random motion and avoiding from trapping into local optima in finding the global optimum. Genetic Algorithm (GA), Particle Swarm Optimization (PSO)and Teaching–Learning-Based Optimization (TLBO) are well known optimization algorithms in the second category. GA uses the theory of Darwin based on the survival of the fittest[3]. PSO implements the foraging behavior of a bird for finding migration path or food resources[4] . TLBO simulates the tutorial system in a classroom. Some drawbacks of the classical optimization methods are lack of convergence guarantee, the long running time, computational complexity and weakness in dealing with problems[5]. To overcome these deficiencies, many researchers have attained to this file of research area to improve the evolutionary algorithms (EAs). Due to the large number of EAs and their different performance, all of EAs are not suitable for solving any kind of problems. The convergence and performance of EAs are the two important criteria. Some of the EAs have Good convergence, although they have worse performance. In general, it is difficult to balance the performanceand convergence. If the users do not have correct comprehension about algorithms, they could not choose the best ones. So, we investigate, which algorithms has a better solution at a lesser computational effort for to minimizing power lossesand achieving the optimal power flow. The widely used method of solving power flow problems are Gauss–Seidel, decoupled, and Newton- Raphson power flow algorithms. They are often run for a planning or operations study. It is worthwhile to note that, the Newton Raphson power flow is the most robust power flow algorithm used in this study and practice. However, one drawback to its use is the fact that the terms in the Jacobian matrix must be recalculated each iteration.A comparison of the convergence characteristics of the Gauss–Seidel, decoupled, and Newton power flow algorithms shown that the Newton method has the better procedure converges to the optimum answer[6].

This solution algorithm is used because of its speed of solution and the fact that it is reasonably reliable in convergence without losses of accuracy when solving power flow problems. after solving power flow problem, the authors endeavor, have been focused on, finding an efficient algorithm which can be minimized the losses and finded optimal location of Var sources and achieved faster solutions in restructured power systems. also have reasonable storage and computation time requirements. Besides this, we compar e the three algorithms TLBO, PSO and GA for the same IEEE 30 bus system. And TLBO has received widespread attention as possible techniques to obtain the global optimum for the reactive power planning problem.

The rest of this paper is organized as follows: A description of power flow problem is presented in Section 2. Then a detailed of PSO to minimize the power losses is given in Section 3. The analysis of the TLBO to reduced the losses in the restructured power systems is given in Section 4. Simulation and numerical results are compared in Section 5. Finally, a conclusion is given in Section 6.

2. POWER FLOW

As we know, all voltages and currents in the electrical circuit can be found by either of the following two methods, based on either the Kirchhoff's Current law or Kirchhoff's Voltage Law. When node currents are specified, the set of linear equations can be solved for the node voltages. However, in a power system, powers are known rather than currents.The power flow equations are nonlinear and must be solved by iterative techniques. And the power flow equation is formulated in polar form[6]. In solving a power flow problem, the system is assumed to be operating under balanced conditions. Power flow studies are necessary for planning, economic scheduling, and control of an existing system as well as planning its future expansion. The problem consists of determining the magnitudes and phase angle of voltages at each bus and active and reactive power flow in each line. Four quantities are associated with each bus. These are voltage magnitude |V|, phase angle δ, real power P, and reactive power Q[7]. Using a suitable mathematical algorithm, a feasible solution can be obtained.power flow diagram of a example N-buses power system with one generator and how the power is flowed into load shown in Fig. 1. The system has N loads.

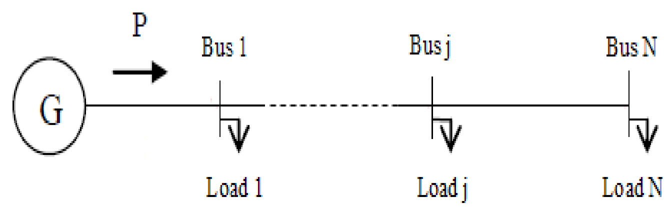

Fig. 1 Example power system to show power flow.

We want the system behavior in dc mode. because the losses become minimum. It is commonto set the voltage magnitude to 1.0 per unit or close to the voltage magnitude of the slack bus. and the resistor of system is zero. The main output ofsuch a solution is the power flow on all transmission and/or distribution devices. Thepower flow on each device is checked against the device flow capability to determineif the device will stay within operationally accepted limits.Generally, a power flow study assumes knowledge of bus loading and generationschedule at all busses except one.It means that, power flow uses the knowledge of demand at each bus, theparameters for each piece of equipment (dependent current sources, dependentvoltage sources, ideal transformers, resistances, reactances, and capacitances), andthe power capability of each piece of equipment or device to determine a solution tothe power flow equations[7].Moreover, solving a set of equations with losses is much more difficult to solve this set of equations than with no losses. This set of equations with losses involves the computation of the network loss in order to establish the validity of the solution in satisfying the constraint equation. The approach to the solution of this problem is to incorporate the power flow equations as essential constraints in the formal establishment of the optimization problem. This general approach is known as the *optimal power flow*.An optimal solution can be selected from the feasible region to obtaina desired objective by adjusting the optimal setting for the controllablevariables with respect to various constraints. The optimal power flowis a static constrained nonlinear optimization problem, and itsdevelopment has closely followed advances in numerical optimizationtechniques and computational methods. firstly, the main target is meeting constraints. Secondly, finding the optimal point of an objective function.

Optimal power flow is formulated mathematicallyas a general constrained optimization problem as

$$minimize\ f(v,x) \quad (1)$$

$$subjet\ to \quad = \begin{cases} g(v,x) = 0 \\ h(v,x) \leq 0 \end{cases} \quad (2)$$

where v is the set of controllable variables in the system; x is the set of dependent variables. And they can be voltage magnitudes at load buses, voltage phase angle at every bus, Var source installed at bus i, and Line flows; objective function(1) is scalar; equalities in (2) are the conventional powerflow equations and occasionally include a few special equalityconstraints such as the limit of the number of potential Var compensators;and inequalities in (2) represent the physical limitson the control variables$v$, physical limits of the state variables x ; and the operating limits on the powersystem.

The power system could collapse when supply does not equal demand.Generator active power output should be equal to load active power. Also, generator reactive power output and load reactive power should be equal. When the reactive power required by the transmission system becomes inadequate,we say that the power system goes through a voltage collapse.the voltage will collapse andthe whole power system will go down.Generally, failure of the power flow is a sign that the power system is not secure and should be alarmedto operators[8].

Power flow constraints can be expressed as follows:

$P_g^i - P_l^i - P(V,\delta) = 0$activepowerbalance (3)

$Q_g^i + Q_c^i - Q_l^i - P(V,\delta) = 0$reactivepowerbalance (4)

$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max}$ active power generation limits (5)

$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}$reactivepowergenerationlimits (6)

$V_i^{min} \leq V_i \leq V_i^{max}$ bus voltage limits (7)

$|LF_l| \leq LF_l^{max}$lineflowlimits (8)

Where P_g^i is generator active power output;P_l^i is load active power;Q_g^i is generator reactive power output;Q_c^i is Var source installed at bus;Q_l^i is load reactive power;V_i is bus voltage; and LF_l is transmission line flow.

The limits on Q_c^i is calculated based on the latest update to the voltage magnitudes and angles. After this calculation, check to see if the required reactive generation is within limits. If it is not within limits, set it at the appropriate limit and release the constraint that $V_i$is fixed. Thatis, $V_i$andQ_g^iexchange roles. This changes the type of the bus from voltage controlled (PV) to PQ[6].(The type PQ bus would identify any bus for which generator active and reactive power output are known. This includes any bus with no generation. The type PV bus is typically a bus with a generator connected to it. The two main control actions available at a generator plant enable control of P_{gi} and V_i. Since these values are controlled, they should be specified as known.)

During subsequent iterations, continue to check the reactive power needed tosupport the voltage desired. Whenever the required reactive power falls withinacceptable limits, change the bus type to PV. This process may occur morethan once during a solution.In the next section of this article optimal reactive power planning based on losses is studied. The planning problem is studied using reactive power injection in each bus and PSO, GA, and TLBO are also used for solving optimization problem.

3. PARTICLE SWARM OPTIMIZATION

Most of the population based search approaches are motived by evolution as seen in nature. It is assumed that the behavior of nature is always optimum in its performance. Particle swarm optimization is motivated from the simulation of social behavior. Kennedy and Eberhart developed a PSO algorithm based on the behavior of individuals of a swarm in 1995 . It modeled the flocking behavior seen in many species of birds or fishes. In simulations, the operation begins with a random selection, continues with a search for optimal solutions through earlier iterations, and evaluates the quality of the solutions through their fitness. Each individual in PSO swarm approaches to the optimum or a quasioptimum through its present velocity, previous experience, and the experience of its neighbors[9]. The PSO hires particles form the colony to explore the D-dimensional search space of problem. Suppose that the th particle locates at $Xi = (xi1, xi2, \dots, xiD)$ $(i = 1, 2, \dots, n)$ in the searching space. We could calculate the particle's fitness by putting its position into a designated objective function. Because, the goal of optimization is minimizing the lossses, when the fitness is lower, the corresponding is better. The th particle's flying velocity is also a *D*-dimensional vector, denoted as$Vi = (vi1, vi2, \dots, viD), (i = 1, 2, \dots, n)$.

Vector pbedescribes the local best position discovered by the th particle. Further, best position of the colony is represented by the symbol G_q. it called gbe. Pbe and gbe must be updated at each iteration throughout the optimization process. Because they are important components in the searching process, in which every individuals try to improve its position toward reaching gbt. To do so, a fitness function should be defined to evaluate the location of each particle at each step. The velocity and position of the th particle are updated iteratively based on:

$$v_i^{k+1} = \omega\, v_i^k + c_1\, r_1\, (pbest_i^k - x_i^k) + c_2\, r_2\, (gbest^k - x_i^k) \quad (9)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}\Delta t \quad (10)$$

where $k$represents the iterative number, $\omega$is the inertia weight. and c_1 and c_2 are learning rates that $(c_1 + c_2 \leq 4)$, r_1 and $r_2$are random numbers between 0 and 1, Δt is the time step value,

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Finally $Vi \in [Vmin, Vmax]$, where $Vmin$ and $Vmax$ are the designated vectors. A unit time step $(\Delta t = 1)$is used throughout the present work. The termination criterion for the iterations is determined according to whether the max generation or a designated value of the fitnessis reached.
To modify the position of each individual, it is necessary to calculate the velocity of each individual, which is obtained from (5). In this velocity updating process, the values of parameters such as should be determined in advance[9]. In this paper, the weighting function is defined as follows:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter\_max} \times iter \quad (11)$$

Where ω_m and ω_n are initial and final weights, respectively. and $iter\_m$ represents maximum iteration number and it is current iteration number.
Initial population of position and velocity of particles is generated randomly as follows:

$$X = rand \times (x_{i,min} + x_{i,max}) + x_{i,min} \quad (12)$$
$$vel = rand \times (v_{min} + v_{max}) + v_{min} \quad (13)$$

where $x_{i,min}$, $x_{i,max}$ are minimum, maximum reactive power sources. further, v_{min} and v_{max} describe minimum and maximum velocity limit of particle, respectively.
In power flow program the losses can bewritten as follows:

$$P_{loss} = Pgt - Pdt \quad (14)$$
$$Pgt = \sum Pg \quad (15)$$
$$Pdt = \sum Pd \quad (16)$$

Where Pgt is sum of the active powers of voltage controlled (PV) buses. and Pdt is the total real powers consumed by PQ buses.
When applied PSO to large-scale power systems, a slow convergent rate may occur, due to a number of variables and uncertain parameters.it does not succeed in finding the global solution. and it traps into local extremes. But in comparison to the GA, the performance of PSO is better. Some of advantages are simple concepts, easy implementation, and quickly. Despite having these features, it often experiences inappropriate convergence due to the local optima, lake of diversity of particles. All of which would be corrected as introducedTLBO.

4. TEACHING LEARNINGBASEDOPTIMIZATION

Teaching learning based optimization (TLBO), proposed by Rao et al in 2011. It is a recently developed population based optimization technique. TLBO algorithm describes the process of teaching and learning, where a student at first learns through the teacher and then through the interaction with the other learners[5]. The grade points of the students are viewed as output of the algorithm, which depends on the quality of a teacher. In TLBO, the group of learners are considered as population and different design variables are considered as different subjects offered to the learners and learners' result is analogous to the fitness value. The best solutionis considered as the teacher (best learner) who helps the learnersto raise their grade points. Sufficient information exchange among the students and between the students and the teacher in order to enhance their knowledge which in turn helps raisingtheir grade points. TLBO algorithm is divided into two phases: (i) Teacher phase and (ii) Learner phase.

a. Teaacher phase

The teacher phase is responsible for the global search of the algorithm . The teacher endeavour to increase the mean of the student's results to his or her level. But in real practice this is not possible and a teacher can only move the average of a class up to some extent depending on the capability of the class. Let M^i be the mean and Ta^i be the teacher at each iteration$i$. Ta^i would make effort to take the mean to his/her level. To find the M_i, at first the whole fitness value (student's mark) of each individual is evaluated[10]. As mention before M^i is updated by the fitness function. Afterward, the population (students) are sorted from best to worst based on their fitness functions (grade points). The best result obtained so far is considered as Ta^i. So the solution is updated according to the difference between teacher's knowledge level and the mean of the class at any iteration of i, shown by following equation:

$$deltaX\_Ta^i = rand() \times (Ta^i - F \times M^i) \quad (17)$$
$$F = round(1 + rand(1,1)) \quad (18)$$

where is a teaching factor that determines the value of mean to be changed. The value of can be either 1 or 2, which is update a heuristic step and decided randomly. and rand() is a random number in the range [0,1]. This difference modifies the existing solution according to the following expression.

$$X\_Ta^{i+1}_{new} = X\_Ta^i_{old} + deltaX\_Ta^i \quad (19)$$

In this study, equation (14) is the fitness function and the aim is to optimize the losses. We defined equation (14) in Newton Raphson program.

b. Student phase

This phase is generally used to enhance the local search ability of the algorithm. A learner interacts randomly with other learners for upgrading his/her knowledge by two different ways: one through input from the teacher and the other through interaction between themselves or with a more knowledgeable learner. By the interaction existed among learners, a learner learns something new if the other learner has more knowledge than him/her. So, we have got two $deltaX\_S$. As a result of which, the knowledge of the particular learner is updated. It assumed X_S_i and X_S_j are two randomly selective learners, where $i \neq j$. To solve the single objective problem, the achieved objective functions of$X_S_i$and X_S_j are compared. then learning phase can be expressed by the following equation:

$$deltaX\_S = rand() * (X\_S_j - X\_S_i) \text{if } f(X\_S_j) < f(X\_S_i) \quad (20)$$

$$deltaX\_S = rand() * (X\_S_j - X\_S_i) \text{if } f(X\_S_j) > f(X\_S_i) \quad (21)$$

$$X\_S_i^{new} = X\_S_i^{old} + deltaX. \quad (22)$$

X_S^n is better than the existed one then it is accepted. It should be noted that the output solutions of the learner phase are the input solutions for the next phase.TLBO Compared to the PSO has much more profound intelligent background and could be performed more easily.

Based on its advantages, the TLBO is applied to IEEE 30 bus system to achive the optimal losses.The optimal location of Var sources, such as capacitor banks areoptimized in this paper, in order to decrease the cost, losses values simultaneously.

5. RESULTS AND DISCUSSIONS

The IEEE- 30 bus system is used to demonstrate the data preparation and the use of power flow programs by the Newton Raphson method. The IEEE 30-bus sample system is depicted in Fig. 2. The system is assumed to be operating under balanced condition and is represented by a single phase network[11]. For implementing TLBO and PSO techniques to minimize power losses, and to choose the optimal location of reactive sources , the maximum number of iterations of 100 is taken in the simulation study. The program is developed inMATLAB 8.6 to solve problem and tested on a core 5 processor of2.20 GHz with 4 GB RAM personal computer.

The optimum population size of each algorithm is related to the dimensions of the search space and complexity of the problem. A population that is either too large or very small may not be able to reach an optimal solution, especially in complex problems. In this study, the different population sizes were selected and the problem was carried out in 30 independent runs to evaluate how the population size effects on the performance of TLBO and PSO. The statistical information of total losses, as well as the average CPU time and frequency of convergence for 20, 50, 100, 150 population sizes, are shown in Table. 1.

A population size of 50 resulted in a more consistent solution, but when the number of population sizes increased from 50 to 150 the global best solution could not handle all the individuals and reach a better global solution in the busy population. Table. 1 shows that a population size of 50 resulted in obtaining global solutions more robustness. Increasing the population size beyond this value did not produce any substantial enhancement rather, it increases the execution time which is not attractive in the real-time studies. In addition, Table. 1 shows that the TLBO method was consistently the least costly. It is clear that the worst mean and the best solutions of TLBO were close to each other, which confirms the robustness of the proposed method. The bold numbers in Table 1, show that the population size of 50 resulted in achieving global solutions. It should be pointed out that due to the stochastic nature of the evolutionary algorithm, 30 independent trail runs were made to extract the statistical information. The results of PSO and TLBO such as the placement of reactive power sources, and the value of reactive generation and the losses objective function value as shown in Table. 2, and Table.3, respectively. The ten arbitrary different results is chosen. The population size of 50 and the maximum number of iterations of 100 are taken in this case.

Voltages are all within their limits of 0.95–1.07 pu; the reference bus is scheduled at 1.0 pu. All reactive power limits are being met and all line flows are within their MW limits. And it is obvious that the reactive power losses are small. Also, the voltage can be controlled by an exciter at a generatorbus, or by a FACT device[6],[11].

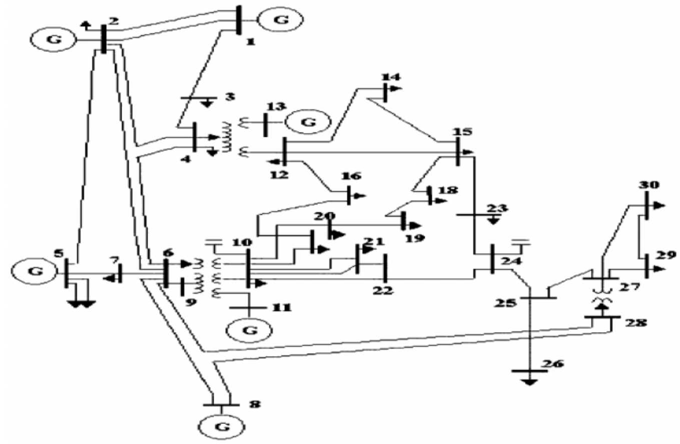

Fig. 2. 30- bus IEEE sample system.

Table.1 Effect of population size on PSO and TLBO.

		Total losses (MW)			
Population size	Method	Best value	Mean value	Worst value	Average CPU time (sec)
20	TLBO PSO	17.4591 17.5481	17.5691 17.5942	17.6091 17.6402	580. 232674 542. 667675
50	**TLBO PSO GA**	**17.3738 17.4591 18.9979**	**17.4067 17.5133 NA**	**17.4994 17.5685 NA**	**863. 759827 851. 110550 NA**
100	TLBO PSO	17.3738 17.4592	17.4509 17.5147	17.5279 17.5701	1215. 829924 1206. 334548
150	TLBO PSO	17.3738 17.4592	17.4585 17.5187	17.5412 17.5782	1371. 675109 1315. 928633

Table. 2 the optimal solutions which are found by PSO.

iteration	Location of reactive sources			The value of reactive power generation (M var)			Global solution (MW)
1	11	8	4	83	61	19	17.4985
2	7	2	5	34	79	8	17.5595
3	2	5	23	76	83	8	17.5015
4	5	9	17	82	36	3	17.5189
5	7	2	28	3	10	10	17.4881

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6	2	40	13	83	25	5	17.5685
7	4	17	18	10	16	3	17.4994
8	13	18	19	81	1	13	17.4712
9	3	6	21	38	11	10	17.4593
10	4	8	28	69	20	17	17.4591

Here, an objectivefunction is losses. Because of being single objective, it has convergence characteristic. A study of Fig. 3, shows that under the sample objective function the convergence rate of TLBO is faster than PSO in earlier generations. It is further noted that the population for all the individuals is generated randomly within the upper and lower limits. So different results may be created. And the best, average and worst results of the TLBO algorithm are very close to each other to indicate the robustness.

Table. 3 the optimal solutions which are found by TLBO.

iteration	Location of reactive sources			The value of reactive power generation (M var)			Global solution (MW)
1	11	17	9	82	3	36	17.3933
2	18	13	19	1	81	13	17.3912
3	20	28	7	10	10	3	17.3881
4	3	13	18	28	48	5	17.4496
5	3	24	18	10	1	14	17.3979
6	6	18	25	32	9	5	17.4034
7	17	4	18	6	10	3	17.4994
8	21	3	6	10	38	11	17.4291
9	3	24	4	15	8	22	17.3895
10	21	4	26	11	34	3	17.3738

Fig. 4 and Fig. 5 and Fig.6, show that the cost convergence characteristics of the GA, PSO, and TLBO respectively. By comparing the results of three methods, it can be found that premature convergence of GA compared to the PSO with respect to TLBO degraded their performance, reduced its capability that would have resulted in a higher probability of being trapping in local optima. It can be seen from results of the simulation that the solutions from the proposed TLBO were better that the other methods.From Fig. 6, it is clear that the value of loss function converges smoothly to the optimum solution without any sudden oscillations even for the large-scale system with several local optima. This feature proves the convergence reliability of the proposed TLBO algorithm. For further analysis, success rate is calculated. The success rate is defined as($\frac{Trail_S}{Trail_T} \times 100$) in this paper where $Trail_T$is the total number of the tests carried out and$Trail_S$is the number of the successful tests to converge to the best solution. results of the success rate are provided in Table. 4. The Table. 4, shows the TLBO algorithm has satisfactory success rate and is robust.

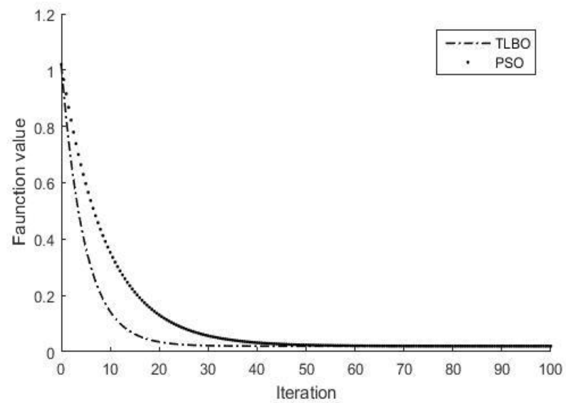

Fig.3 comparison between characteristics of PSO and TLBO

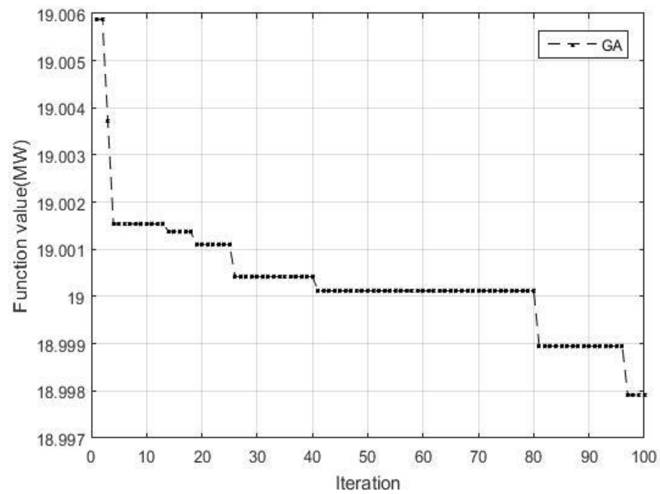

Fig. 4. Convergence graph of loss objective function by the use of GA

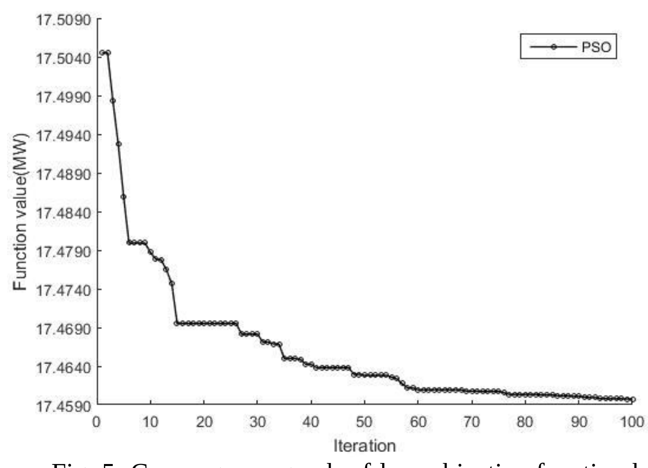

Fig. 5. Convergence graph of loss objective function by the use of PSO

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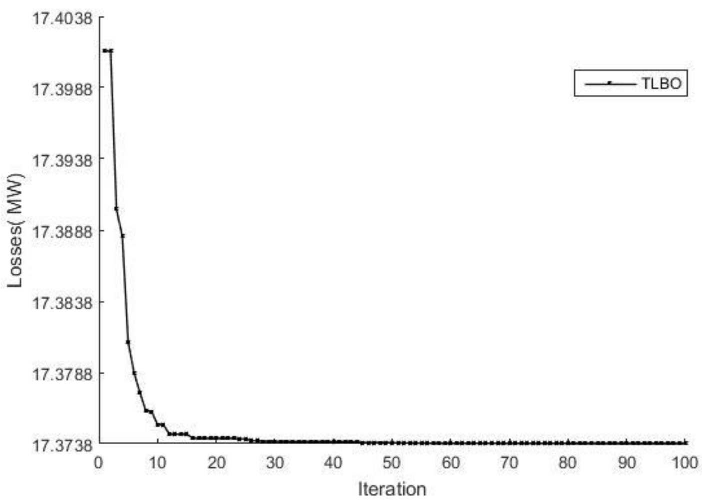

Fig. 6. Convergence graph of losses objective function by the use of TLBO.

Table. 4. Success rate of the TLBO out of 30 trails

Best of the loss value	Range of the loss value	17.3738-17.4338	17.4338-17.4938	17.4938-17.5538	17.5538-17.6138
	Success rate	96%	4%	0%	0%

6. CONCLUSION

The power flow problem, became an operational problem as independent system operator is required to monitor the real-time status of the network in terms of voltage magnitudes and circuit flows. Today, the power flow problem is widely recognized as a fundamental problem for power systems. This paper presented approach firstly obtains the power flow solution by the Newton-Raphson method. Using Newton Raphson to determine the magnitudes and phase angle of voltages at each bus and active and reactive power flow in each line. Next the TLBO algorithm have been applied to solve the optimization problem of optimal placement of capacitor banks in restructured power systems in order to optimize the losses.They must produce reactive power for keeping magnitude bus voltages in their proper magnitudes.by optimal planning, we could reduce the total reactive power generation cost. And the more active power can transfer. It means that, the transmission lines are at maximum flow. Also, Ensuring stableoperation, and maintaining stability and power quality.

TLBO has several advantages, especially due to its capability to handle constraints. It deals with the steady state analysis of an IEEE 30 buses power system in during normal operation. Newton method is mathematically superior to the other method like as Gauss-Seidel method and is less porn to divergence will ill-conditioned problem. For large power system, the Newton-Raphson method is found to be more efficient and practical. The comparative study was done in terms of the solution quality, computational efficiency, and the robustness. The simulation results showed that the proposed TLBO method not only provides more optimal solutions for the reactive power planning in a proper computational time, but also gives solutions with satisfactory constraints. moreover, the TLBO algorithm found solutions with lower loss in comparison with PSO and GA. PSO needs learning factors and the inertia weight which exact adjustment of these parameters is a difficult task for handling. However, TLBO does not require any parameters to be adjusted hence the implementation of TLBO is simpler. The TLBO algorithm takes advantage of two different phases, the teacher phase, and the learner phase. The proposed TLBO approach improve both the velocity and accuracy of the convergence and to avoid premature convergence to the local optima.

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