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RBFNN based GSA for optimizing TCSC parameters and location- A secured optimal power flow approach

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Abstract. Your abstract goes here.This paper proposes a hybrid technique for securing optimal power flow (OPF) with installation of Thyristor controlled series compensator (TCSC). The hybrid technique is the combination of Radial Basic Function Neural Network (RBFNN) and Gravitational Search algorithm (GSA). Here, RBFNN-GSA provides the new velocity and the position of the agent resulting in superior results for optimized parameters and location of TCSC as compared to traditional GSA and Fuzzy based GSA algorithm. The location of TCSC depends on the loading factor and apparent power flow index and the secured parameters are optimized by RBFNN-GSA. The proposed method is implemented in MATLAB working platform and the power flow security is evaluated with IEEE 6 bus and IEEE 14 bus transmission systems. The performance of the proposed method is evaluated and compared with the other existing methods. Then, the total generated power, power losses, and cost of the generation are examined by changing the system load. In addition, the contingency of the system is analyzed by reducing the line flow limits and the effectiveness of proposed method is confirmed by the results obtained.

Keywords: apparent power flow index, fuzzy aided GSA, load factor, RBFNN, secured OPF, TCSC

1 Introduction

In a deregulated system, economic and security issues of a power system are required to be coordinated tightly as it strongly influences the operation of the power industry. Optimal power flow (OPF) is a significant application of a fast optimization tool which functionally integrates the power flow with profitable dispatch thus paving the way for the cutback in cost function like the operating expenditure by considering the equality and inequality parameters[9]. Generator MW outputs, transformer taps and phase angles include the accessible controls of OPF[19]. Non-linear technique by means of Newton's method is one of the solution techniques of OPF which appreciably addresses the marginal losses, though comparatively sluggish and faced with the issue of deciding the binding parameters[3]. Whereas the linear programming approach is quick and effective in deciding the binding constraints, it encounters trivial losses and is effectively employed in power world simulator[20]. While carrying out the OPF function, the system safety parameters must not be ignored and have to be invariably taken into account such as the communication capacity limit and the bus voltage limit[11].

Security parameters employ the overall market data put in by the participants, such as the individuality of generating units, availability of communication capacity, production offers and demand bids, automatic deals and reduction in contracts, to name a few[21]. At the outset, the OPF is resolved to assess the maximum protected concurrent transfer capacity of each tie-line between adjoining regions, by considering the security parameters thrust into the tie-lines[10]. Security appraisal is meant for ascertaining whether or not the system functional in an ordinary state is capable of surviving contingencies devoid of any limit infringement[5]. To

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ensure a consistent power system function, it is essential that the safety of the system is duly accounted for in the electrical energy system[22].

FACTS devices are exceedingly employed to effectively cut down the flows in heavily loaded lines, ultimately leading to enhanced power transfer, reduced system damage, augmented solidity of the contractual needs by keeping under check the power flows in the system. Outstanding among the FACTS devices, Thyristor Controlled Series Compensator (TCSC) is endowed with incredible application potential in precisely controlling the power flow on communication line, damping inter area power oscillations, alleviating sub synchronous resonance and stepping up transient solidity[12]. In this regard, there is a host of several stochastic investigation methods like genetic algorithms (GA), evolutionary programming (EP), Tabu search (TS), particle swarm optimization (PSO), simulated annealing (SA), differential evolution (DE), and bacteria foraging (BF) algorithm which have been effectively employed to successfully address the OPF issue with and without utilizing FACTS devices[6, 14].

Some of the useful research works based on TCSC implementation as a damping controller for attainment of secured optimal power flow are depicted in literature. To alleviate small signal oscillations in a multi machine power system, D. Mondal et al.[13] have explored Particle Swarm Optimization for optimal location and setting parameters of SVC (Static Var Compensator) and TCSC (Thyristor Controlled Series Compensator) controllers. Nima Amjady et al.[4] have suggested a solution method for optimal power flow with security constraints (OPF-SC) problem, which was an enhanced version of bacterial foraging (BF) technique. The OPF-SC was a nonlinear programming optimization problem with complex irregular solution space. T. Nireekshana et al.[15] have accounted for determination and enhancement of Available Transfer Capability (ATC) which is significant in power systems deregulated operation. It examines the inclusion of FACTs devices like SVC and TCSC to exploit power transfer transactions during normal and contingency situations. Y. C. Chang[8] had suggested the multi-objective optimal TCSC installation approach that uses the performance index sensitivity factor technique to explore which lines were most required for TCSC installation and with the lines prcised for TCSC installation and the multi-objective function containing of maximum system load ability and minimum TCSC installation cost.

In deregulated power system, the systems functions close to its security limits and their operation is tightly monitored based on prices or in general operating costs. Of late, the economic constraints based enlarged load demand governs the system operations. These considerations have led to secured operation of power systems as an inevitable feature. Without any limit violation security measurement has an imperative role for finding out whether or not the system operating in a normal state can oppose contingencies. In the research work proposed, RBFNN based GSA algorithm is suggested for optimizing the location and size of TCSC and develops the power flow security. The rest of the paper is organized into the following section. In the section 2, the detailed suggested technique is specified. The IEEE 6 and 14 bus systems power loss, generated power, cost and losses are examined in the section 3and conclusion is specified in section 4.

2 Problem formulation of OPF with TCSC

TCSC consists of series compensating capacitor shunted by thyristor controlled reactor. In this system, the controllable reactance is integrated in series to the transmission line and the line impedance is adjusted. With the result, the apparent power flow through the line attains the maximum or minimum value depending upon the loading condition. In this paper, we set out to ascertain the optimal location of TCSC based on their optimal power flow parameters and security constraints. When active and reactive powers of the loads increase at the same time, the loading factor is observed to be proportional. Hence, the values of loading factors are changed from the base case value to maximum without violating the equality and inequality limitations.

Normally, the OPF issue is formulated to minimize the fuel cost for the production. The objective function of fuel cost is included with the inequality constraints of the active power limits of generator. The quadratic equation of fuel cost is furnished by Eq. (1):

Fuel cost,

$$F_c = \sum \left(a_n + b_n P_{ni} + c_n P_{gn}^2 \right) \$/hr, \tag{1}$$

where, F_c stands for the total fuel cost, a_n, b_n and c_n indicate the fuel cost coefficients and p_{gn} represents the active power generated by n^{th} generator. The objective function is employed to ascertain the optimal location of TCSC subject to optimal power flow parameters and security constraints.

2.1 Constraints

The equality and inequality constraints are employed for assessing the optimal power flow with TCSC. A detailed account of these constraints is furnished in the following section.

1. Equality constraints

Real power balancing condition is given by Eq. (2):

$$P_{inj,\,n} = P_{g\,n} - P_{L\,n}. \tag{2}$$

Reactive power balancing condition is furnished by Eq. (3):

$$Q_{inj,\,n} = Q_{gn} - Q_{Ln}, \tag{3}$$

where, $P_{inj,n}$ and $Q_{inj,n}$ characterizes the real and reactive power injected into bus n. P_{gn} and Q_{gn} are real the reactive power produced by n^{th} generator, P_{Ln} and $Q_{L,ni}$ are real and reactive power of n^{th} load bus.

2. Inequality constraints

The generation limits of the generating units are segregated in to upper and lower bounds which are situated in between the real limits. The real and reactive power, voltage magnitude and the reactance constraints of TCSC are detailed as follows:

$$P_{g\,n}^{\min} \le P_{g\,n} \le P_{gn}^{\max}, \tag{4}$$

$$Q_{gn}^{\min} \le Q_{gn} \le Qg_{n}^{\max}, \tag{5}$$

$$V_{n}^{\min} \le V_{n} \le V_{n}^{\max}, \tag{6}$$

$$-\,0.7X_{\text{line}} \le X_{\text{TCSC}} \le 0.2X_{\text{line}}. \tag{7}$$

In the equations given above, $P_{g,n}^{\min}$ and $P_{g,n}^{\max}$ indicate the minimum and maximum power generation limits of n^{th} generator, $Q_{g,n}^{\min}$ and $Q_{g,n}^{\max}$ the minimum and maximum reactive power generation limits, $V_n^{\min}$ and $V_n^{\max}$ the voltage magnitude limits of n^{th} bus and X_{line}, X_{TCSC} are the transmission line and TCSC reactance respectively.

2.2 TCSC optimal location

The utilization of security index is done to set up the TCSC optimally with secured power flow. With a view to place TCSC optimally, the optimal line power flow is taken into account restricted to the maximum power flow limit. When the system load changes, the line flow fluctuations is assessed during this period by means of power flow index which in turn is estimated by loading factor with OPF of the line and maximum flow limits of the line. In this regard, Eq. (8) furnishes the expression of a new index called Apparent Power Flow Index (API) as shown below:

Apparent power flow index,

$$API = \frac{S_{n,\,Opf}}{S_{n,\,\max}}\left(\frac{S_{n,\,L} - S_{n,\,n}}{S_{n,\,L} - S_{n,\,opf}}\right), \tag{8}$$

where, $S_{n,n}$ expresses the power flow of n^{th} line at normal situation, $S_{n,Opf}$ represents the power flow of n^{th} line at OPF, $S_{n,\max}$ signifies the maximum power flow of n^{th} line, and stands for the power flow of line at loading. With the aid of this equation, the apparent power flow index is estimated and the bus possessing the maximum index value is shortlisted as optimal location of TCSC. The relative constraints of the captioned equation are executed on the input of GSA and the best parameters are optimized.

2.3 Selecting TCSC parameters and location using RBFNN based GSA

The optimal location and the injected capacity of TCSC are mainly based on security index such as apparent power flow and voltage stability. These relative constraints are optimized by the proposed technique. When the transmission line is overloaded, the optimal position of TCSC is ably assessed by the proposed method. The injection capacity of TCSC is estimated by means of Eqs. (2) and (3) in terms of the security parameters. Now, the RBFNN based gravitational search technique is appropriately employed as the hybrid technique to successfully address the objective function. The gravitational constant is evaluated by RBFNN network and the efficiency in execution of the search algorithm is incredibly increased. The proposed method is a novel approach to establish secured operation along with economic load dispatch with TCSC installation. The detailed explanation of hybrid approach is given in the next section.

2.3.1 Gravitational search algorithm (GSA)

The GSA has amazingly arrived on the arena as one of the stochastic search techniques rooted on Newtonian laws of gravity and mass interaction[16]. With an eye on successfully tackling the OPF menace, the GSA endowed with inherent potential invariably optimizes the objective function[7]. In GSA, the efficiency of the agents is evaluated by their masses which are deemed as objectives. For the issue in question, these objectives are characterized as a solution or a fragment of the solution. The gravitational forces of attraction between the objects trigger a complete motion towards the objects which possesses heavier masses. The heavier masses attain superior fitness values and the best solution is progressing step by step as against the lesser ones which signify the worst solution. However, in the GS technique, each and every mass has the position in the order such as inertial mass (Mi), active gravitational mass (Ma) and passive gravitational mass (Mp). The mass position amounts to the solution of objective function and the fitness function employed is indicated by the gravitational and the initial masses[17].

2.3.2 RBFNN based GSA

In traditional GSA, agent's moves in every search space of the problem are adjusted by the velocity equation. But the velocity equation of the agents consists of random variable which leads the solution to uncertainty. Sequentially, to manage these uncertainties and to keep away the detonation and deviation, in this section velocity constraint is introduced which is predicted by RBFNN.

Step 1. Initialization process and mass evaluation

Initially, sets of agents are considered and their positions specified and represented as follows:

$$X_i = \left(x_i^1, \cdots, x_i^d, \cdots, x_i^s\right), \tag{9}$$

where, x_i^1 represents the position of the agent, x_i^d the dimension of agent, and x_i^s the search space of the agent. Here, the mass of each agent is evaluated as follows:

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)}. \tag{10}$$

In the above Eq. (10), $m_i(t)$ represents the mass of i^{th} agent and $\sum\limits_{j=1}^{N} m_j(t)$ the mass of total agents in the X^{th} search space. Then the value is evaluated by using the below equation:

$$m_i(t) = \frac{f_i(t) - \text{worst(t)}}{\text{best}(t) - \text{worst}(t)}, \tag{11}$$

where, $f_i(t)$ characterizes the fitness value of i^{th} agent at instant t. best(t) and worst(t) represent the best and worst fitness of all the agents.

Step 2. Calculation of fitness function

In this section, the fitness of the agents is calculated by using the following equation:

$$\text{best}(t) = \min_{j\in\{1,\cdots,N\}} f_j(t), \tag{12}$$

$$\text{worst}(t) = \max_{j\in\{1,\cdots,N\}} f_j(t). \tag{13}$$

Step 3. Evaluation of force and acceleration

For estimating the acceleration of an agent, a set of total force from heavier masses is applied which has to be taken into account as given below:

$$F_i^d(t) = \sum_{j\in k\text{best},\, j\neq i} \text{rand}_j G(t) \frac{m_j(t)\times m_i(t)}{E_{i.\,j}(t)+\beta} \left(x_j^d(t) - x_i^d(t)\right), \tag{14}$$

where, rand_j represents the random number in the interval 0 and 1, the gravitational constant at time t. m_i and m_j represent the masses of i^{th} and j^{th} agents. β is the smallest value, k_{best} the best fitness of first set of K^{th} agents and $K = 0$ is set as initial which is increased linearly to 1 depending on time. Then, the acceleration of i^{th} agent, direction d at time t is selected depending on the law of motion which is described as per the following equation and by substituting values of $F_i^d(t)$ and $M_i^d(t)$ the acceleration equation is modified as in Eq. (16)

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)}, \tag{15}$$

$$a_i^d(t) = \frac{\sum\limits_{j\in k\text{best},\, j\neq i} \text{rand}_j G(t)\, M_j(t)\times M_i(t)\, \left(x_j^d(t) - x_i^d(t)\right) \left\{\sum\limits_{j=1}^{N} m_j(t)\right\}}{m_i(t)\left\{E_{i.\,j}(t)+\beta\right\}}, \tag{16}$$

where, $E_{i,j}(t)$ represents the Euclidean distance between i^{th} and j^{th} agents at time t.

Step 4. Evaluation of velocity and position of agents

Then, the velocity change of the searching strategy of i^{th} agent, direction d at time $t+1$ is specified as:

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1), \tag{17}$$

$$v_i^d(t+1) = \text{rand}_i \left\{v_i^d(t) + a_i^d(t)\right\}, \tag{18}$$

where, rand_i represents the uniform random number which is generated between 0 and 1, $x_i^d(t+1)$, the position of i^{th} agent at time $t+1$ and $v_i^d(t+1)$, the velocity of i^{th} agent at time $t+1$. To avoid the distribution of random number in velocity updating equation, RBFNN is used to calculate the $v_i^d(t+1)$.

Step 5. Evaluation of gravitational constant

From the output of the RBFN network, Eq. (7) is updated. Then, the gravitational constant is determined as follows:

$$G_n = G_0 \left\{\exp\left(-\delta \frac{t}{t_{\max}}\right)\right\}, \tag{19}$$

where, $G_0(t)$ represents gravitational constant at the initial velocity, $G_n(t+1)$ is gravitational constant at n^{th} updated velocity, δ is the constant, t is current iteration and $t_{\max}$ maximum iteration. The initial performance of the GSA is controlled by the values of δ and G_0.

Step 6. Optimal solution and termination

The best solutions which satisfy the objective function are found out. Once the process is finished, the algorithm is ready to give the accurate solutions based on the minimization of the fuel cost and power loss. The selected real power settings are applied to the generator; so the OPF of the system is maintained by the TCSC.

2.3.3 Using RBFNN for updating the velocity of GSA

NN, in essence, represents the artificial intelligence method for evaluating the yield according its training without the necessity for any kind of mathematical model for its configuration. In this regard, RBFNN is unique version of NN encompassing three layers like input layer, hidden layer and output layer. The hidden nodes perform a set of radial basis function and the output nodes carry out linear summation functions as in MLP[18]. Now, the RBFNN is entrusted with the function of dispensing with allocation of random number in velocity updating equation and is employed to evaluate the $v_i^d(t+1)$. The inputs of the RBFNN consist of the current velocity of the agents $v_i^d(t)$ and the acceleration of agents $a_i^d(t)$. Subsequently the output of the system is represented as $v_i^d(t+1)$. Fig. 2 effectively illustrates the structure of the system.

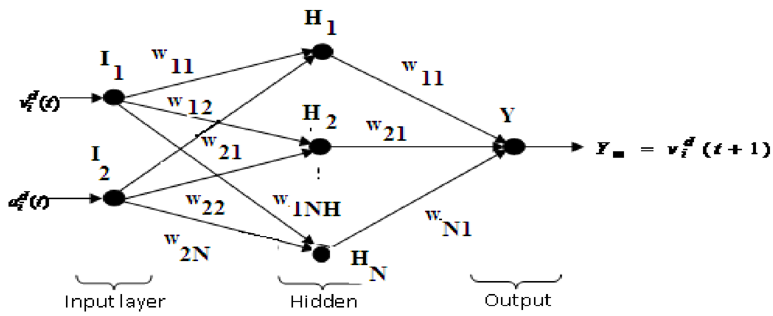

Fig. 1: Structure of RBFNN

Once the training procedure is over, the network is trained sufficiently enough to realize the target yield. And from the yield of innovative technique, the safe power flow of the system is preserved by TCSC with the index of power flow.

3 Results and discussion

In this paper, RBFNN based GSA technique is proposed for securing the OPF with TCSC. Here, the RBFNN is used to enhance the searching performance of the GSA by evaluating the new agent velocity and their positions. TCSC installation in the system leads to greater effectiveness of the proposed method. The performance of proposed method was evaluated by overloading transmission line arbitrarily which leads to optimal placement of TCSC by selecting secured reactance. The line flow limit is utilized to check the violation of line limits after solving the problem which depicts the security limits. The proposed technique is applied to the IEEE standard bench mark 6 bus and14 bus systems respectively. The bus data, line data and the limits of control variables are measured from [1, 2] respectively. The fuel cost coefficient of IEEE 14 bus system is referred from [4]. The Newton Raphson power flow method is used to calculate the power flow solution before and after setting TCSC.

3.1 Performance analysis of the IEEE bench mark bus system

The performance of the proposed technique is validated by comparing it to various cases of without TCSC installed in the system, TCSC installed with traditional GSA and TCSC with fuzzy based GSA applied to the IEEE standard bench mark 6 and 14 bus system and optimal location and parameters of the TCSC are determined and their performances are evaluated.

The performance evaluation is done by two statistical measurements as individual relative error (%) and individual absolute error with formulas illustrated as follow:

$$\text{Individual} \tag{20}$$

$$\text{relative error } (\%) = \frac{(\text{TCSC with other cases} - \text{TCSC with RBFN based GSA})}{\text{TCSC with RBFN based GSA}} \times 100, \tag{21}$$

$$\text{Individual} \tag{22}$$

$$\text{absolute error } = \text{TCSC with othercases} - \text{TCSC with RBFN based GSA}. \tag{23}$$

The error calculations are established by comparing RBFNN based GSA with the other existing method of traditional GSA, Fuzzy-GSA and the condition of system without TCSC installation. By using N-R method, the initial power flow of the system is observed to fetch the values of active power, power loss and generation cost. Increasing the load of the selected line randomly from the normal line flow limits, total active power from the generators, real power losses and generation cost of the systems are evaluated. Evaluation of the given parameters is tested on the system under conditions of with and without TCSC installation.

3.2 IEEE 6 bus system

For IEEE 6 bus system, the location of TCSC as optimized by proposed RBFNN based GSA and also for other methods is between 5 and 6 buses and TCSC injection is calculated as 7.4591. Under the different load varying condition, the powers generated from each generator are tabulated in Tab. 1. The evaluated result of proposed method is compared with other previously existing methods and these values are tabulated in Tab. 3.

Table 1: Active power of IEEE-6 bus generators

Cases		Prior to Loading without TCSC	Subsequent to Loading 6 buses with RBFNN based GSA	TCSC in line of between 5 and
Active power in MW	G_1	62.0081	80.3723	88.0805
	G_2	84.9135	37.2591	58.1641
	G_6	63.4237	96.6153	63.2622

Table 2: Comparison of individual absolute error on IEEE 6 bus for cases without TCSC installed, TCSC installed with GSA and Fuzzy based GSA

Methods	Without TCSC controller	TCSC Installed in the test system	
		Traditional GSA	Fuzzy based GSA
Generated Power	10	5.15	2.135
Power Loss	3.6485	2.29	2.04
Cost of Power	85.703	82.905	35.35

Tabs. 2 and 3 candidly represents the superior performance of the proposed optimization method as it yields better results with respect to generated power, power loss and power cost respectively. Fig. 3 presents Individual relative error (%) comparing RBFNN GSA to cases of existing methods of GSA, Fuzzy GSA and without placing TCSC controller for IEEE 6 bus system.

3.3 IEEE 14 bus system

The fuel cost coefficient values of the system is tabulated in Tab. 4. The evaluated results of proposed method is compared with the existing methods and tabulated in Tab. 5. Under the different load varying condition, the powers generated from each generator are tabulated in Tab. 6.

From the above illustration, the traditional GSA method has the relative error for the total power generated is of about 35%. Whereas for the proposed method without controller the relative error for the power loss and the cost about 23% and 27% respectively. The comparison chart of IEEE 14 bus individual relative

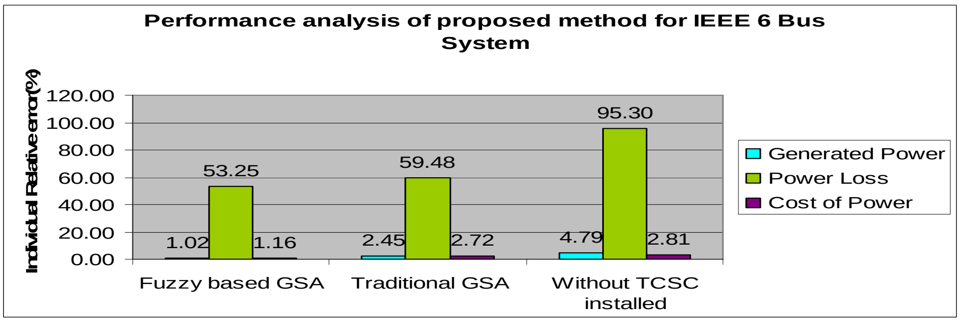

Fig. 2: Comparison and performance analysis by Individual Relative Error of proposed method with cases without TCSC, GSA and Fuzzy based GSA in IEEE 6 bus system

Table 3: Active power profile with respect to secured OPF and performance analysis of proposed method

Methods	Prior to loading	Subsequent to loading without TCSC	Subsequent to loading and TCSC installed in line between 5 and 6 bus		
			GSA	Fuzzy based GSA	RBFNN based GSA
Total active power generation in MW	210	220	215.15	212.135	210
Total real power loss in MW	6.5393	7.48	6.1279	5.8715	3.8315
Total active power generation cost ($/hr)	3122.1627	3136.0769	3133.2793	3085.7303	3050.3739

Table 4: Fuel cost coefficients of generators and synchronous condenser

Buses		$P_{G,\min}$ in MW	$P_{G,\max}$ in MW	a_i	b_i	c_i
Generator	1	30	200	100	15	0.02
	2	20	230	100	10	0.01
Synchronous Condenser	6	40	300	100	30	0.05

Table 5: Active power profile of secured OPF and performance analysis of proposed method

Methods	Prior to loading	Subsequent to loading without TCSC	Subsequent to loading and TCSC installed in line between 5 and 6 bus		
			GSA	Fuzzy based GSA	RBFNN based GSA
Active power generation in MW	258.3396	285.55	259.9853	259.9539	259
Real Power loss in MW	6.5929	8.48	7.95	7.6	6.8227
Active power generation cost ($/hr)	3460.2349	3920.1708	3164.4385	3125.9924	3050.1011

Table 6: Active power of IEEE-14 bus generators

Cases		Prior to loading	Subsequent to loading without TCSC	Subsequent to loading and TCSC installed in line between 5 and 6 bus		
				GSA	Fuzzy based GSA	RBFNN based GSA
Active power in MW	G_1	161.3305	151.3313	146.7308	141.8538	150.54
	G_2	70.48593	79.93441	42.5217	71.3896	53.38314
	G_6	27.17207	53.58641	71.6527	46.7304	54.88227

Table 7: Comparison of proposed method of RBFNN based GSA on IEEE 14 bus by individual absolute error for cases without TCSC installed, TCSC installed with GSA and Fuzzy based GSA

Methods	Without TCSC controller	TCSC Installed in the test system	
		Traditional GSA	Fuzzy based GSA
Generated Power	0.9539	0.9853	26.55
Power Loss	0.7773	1.1273	1.6573
Cost of Power	75.8913	114.3374	870.0697

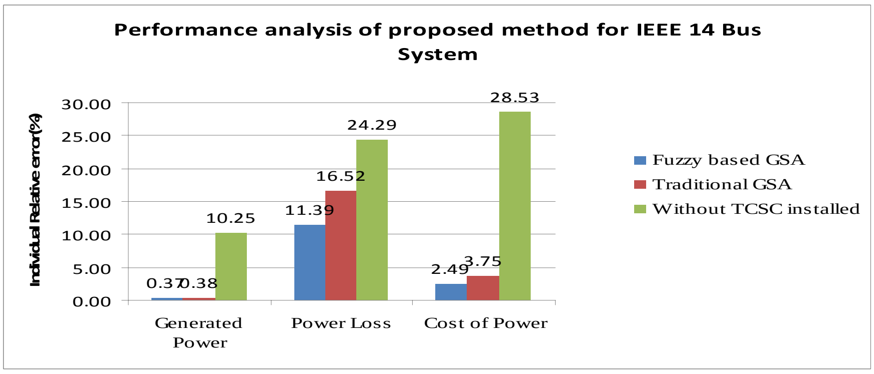

Fig. 3: Comparison and performance analysis by Individual Relative Error of proposed method with cases without TCSC, GSA and Fuzzy based GSA in IEEE 14 bus system

error (%) and bus individual absolute error for various cases with the proposed method is illustrated in Fig. 3 and tabulated in Tab. 7. The optimal location of TCSC here is in line between 13 and 14 buses and optimized TCSC injection is calculated as 0.36892.

In IEEE 6 and 14 bus systems, two weak buses are selected and at the same buses TCSC was placed. From the evaluation, the losses and generation cost are highly reduced by using proposed technique. Likewise, all weak buses and how much amount of losses reduced in those buses after fixing the TCSCs is measured. When installing TCSC the generator power, power loss and the cost of power errors are reduced and the OPF is enhanced. On the whole results validates that apparent power flow index optimizes exact location to install TCSC under normal and network load varying conditions. Therefore, the proposed method is highly effective in reducing power loss & costs and achieving better outputs as compared to without controller installed, traditional GSA, and Fuzzy based GSA techniques.

4 Conclusion

This paper proposes a novel approach and a hybrid technique for attainment of secured optimal power flow with installation of TCSC controller. The hybrid technique is a combination of RBFNN and GSA and its implementation leads to parameters of the TCSC and its locations to be optimized. The effectiveness of the proposed optimization technique is evaluated by comparing the real power generation cost, real power generated and losses with various cases of without TCSC installed, TCSC installed with traditional GSA and Fuzzy based GSA under changing load condition. Also, the power flow security of the proposed method is studied by line outage and reducing the load power limits. Therefore, by locating and sizing the TCSC optimally in normal and loading conditions the secured power flow of transmission system is active. The individual relative and absolute error measurements assert the effectiveness and superiority of proposed method with respect to other existing methods.

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