International Journal on Electrical Engineering and Informatics - Volume 8, Number 2, June 2016

Enhanced Secured Optimal Power Flow by TCSC Parameter Optimization using RBFNN based GSA

Sheila Mahapatra, A.N Jha, and B.K Panigrahi,

Abstract: Attainment of enhanced secured optimal power flow (OPF) has been established as one of the vital requirement of power system operation in a deregulated structure. This paper establishes a novel hybrid technique which is yielded by combining Radial Basic Function Neural Network (RBFNN) and Gravitational Search Algorithm (GSA). The new velocity and position of agents are less deviated by implementing RBFNN based GSA leading to realization of optimized Thyristor controlled series compensator (TCSC) parameters wherein the results are also compared with traditional GSA method and Fuzzy based GSA algorithm. The superiority of performance is established by comparing the proposed hybrid technique with the previously existing method. The Hybrid method proposed is implemented in MATLAB working platform and results are tested on standard IEEE 30 bus transmission system. The total generated power, power loss and cost of generation are evaluated with variation of system load and reduction in line power limit evaluates the system response to contingency.

Keywords: Secured optimal power flow (OPF), TCSC, RBFNN based GSA, Fuzzy aided GSA, Apparent power flow index

1. Introduction

The optimal power flow in a deregulated power system structure emphasizes to integrate the power flow with economic dispatch thereby leading the way to reduction in cost function like operating expenditure by accounting for equality and inequality constraints [20]. The attainable controls of OPF include Transformer taps setting, Generator MW outputs and bus voltages [1]. The non-linear methods have the shortcomings of insecure convergence whereas Newton's based method may not converge in case of unsuitable initial conditions [2].The linear programming approach is very constructive in deciding the constraints but it encounters the problem of inconsequential losses while being implemented using power world simulator[3].

The optimal power flow problem concentrates on its aptness to ascertain security evaluation whether or not the system functional is capable of sustaining contingencies deprived of any limit violation [4].Security and adequacy are two pivotal components for reliable operation of any interconnected power network. These two features ensure a reliable power system operation. To ensure a consistent power system function, it is essential that the safety of the system is duly accounted for in the electrical energy system [5].

Existing transmission lines are congested and are often operated close to or even exceeding their limits due to increased demand, unexpected outages and increased power consumption and trades. Implementation of FACTS devices provides a viable solution to significantly reduce the flow in loaded lines, reduced system damage and restoring stability.

Various heuristic algorithms such as genetic algorithm(GA), Particle Swarm optimization (PSO)[17],evolutionary programming, simulated annealing and bacterial foraging have been formulated and implemented to obtain OPF with and without utilizing FACTS controllers [6,21,22]. These techniques have ensured to overcome the demerit of classical algorithms specially, PSO and DE due to its innovative approach and searching capability. However, these techniques do have their limitations in solving complex multimodal problems by being easily trapped into local optima. Furthermore, their searching performance depends on the appropriate parameter settings [19].

In a multimachine power system, E.S. Ali *et al.* [7] have suggested Bacteria Foraging Optimization Algorithm (BFOA) based Thyristor Controlled Series Capacitor (BFTCSC) for the control of oscillations. The suggested design of TCSC over an extensive range of loading

Received: September 7th, 2015. Accepted: June 3rd, 2016

DOI: 10.15676/ijeei.2016.8.2.10

conditions was devised as an optimization problem with an eigen value based objective function. To explore for optimal controller parameters BFOA was used. In order to display the superior competence of the suggested BFOA in tuning TCSC controller, the presentation of the suggested technique has been assessed with the presentation of Genetic Algorithm (GA). Concurrent tuning of the BFTCSC provides robust damping performance over a broad range of operating conditions in compare to optimized TCSC controller based on GA (GATCSC).

Using Back Propagation Neural Network (BPNN), S. Nagalakshmi *et al.* [8] have offered an approach for on-line assessment of load ability limit for pool model with Thyristor Controlled Series Compensator (TCSC). The optimal location, setting of TCSC and load ability limit for different load patterns in off-line are found out by means of Differential Evolution (DE) algorithm. Their approach employs AC load flow equations with constraints on real and reactive power generations, transmission line flows, magnitude of bus voltages and TCSC setting. At all buses, the input parameters to BPNN were real and reactive power loads. Data for training the BPNN was produced through Optimal Power Flow (OPF) solution by means of DE and the trained BPNN was checked with unseen load patterns. For the choice of best optimal input features Sequential Forward Selection (SFS) belonging to greedy wrapper method was applied. Simulations were carried out on 39 bus New England test system and IEEE 118 bus system. Solution accuracy and computation time were examined. The effects attained show that, for on-line evaluation of load ability limit of pool model with TCSC, BPNN was precise with minimal Mean Squared Error (MSE) and less computation time.

In double auction power market, Prashant Kumar Tiwari *et al.* [9] have suggested an investment cost recovery based competent and dependable optimization approach to optimal allocation of thyristor controlled series compensator (TCSC). By appropriate location and rating of single TCSC in the system, the optimization method has been applied with an objective to maximizing the social welfare and minimizing the tool investment cost. The efficiency of suggested approach for location of TCSC has been compared with some presented methods of single TCSC placement, in terms of its contact on social welfare, TCSC investment recovery and optimal generation with load patterns. The effects have been attained on 5-bus system, modified IEEE 14-bus system and 246-bus Indian practical Northern Regional Power Grid (NRPG) system.

The work presented in this paper aims at proposing a novel hybrid algorithm of RBFNN aided GSA to optimally locate TCSC controller for solving OPF by arriving at an optimal profile of active and reactive power generation in such a way that the net operating cost of the system is minimized while retaining the network within security limits. The most substantial feature of GSA is that gravitational constant adjusts the accuracy of the search, so it accelerates the solution process [23]. The hybrid method of RBFNNGSA proposed will further improve the system performance.

2. TCSC Implementation in OPF Problem Formulation

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. The variation in loading condition leads to the apparent power flow through the line reach the maximum or minimum value. The work asserts TCSC to be optimally placed and also accounting for optimal power flow parameters and security constraints. Hence, the values of loading factors are changed from the base case value to maximum value without violating the equality and inequality limitations.

The most pivotal issue in OPF formulation is 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 Equation 1:

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

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.

A. 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.

- *Equality constraints*

Real power balancing condition is given by equation 2:

$$P_{inj,n} = P_{gn} - P_{Ln} \tag{2}$$

Reactive power balancing condition is furnished by equation 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.

- *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:

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

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

$$V_n^{\min} \le V_n \le V_n^{\max} \tag{6}$$

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

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, $Q_{gn}^{\min}$ and $Q_{gn}^{\max}$ 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.

B. TCSC optimal location and Parameter Selection

Secured power flow is achieved by setting the TCSC optimally with proper utilization of security index. With a view to place TCSC optimally, the optimal line power flow is taken into account restricted to the maximum power flow limit. Fluctuations in the line flow is assessed by changing system load by means of Apparent 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, equation 8 furnishes the expression of power flow index as shown below:

Apparent power flow index, $API = \frac{S_{n,Opf}}{S_{n,\max}}\left(\frac{S_{n,L} - S_{n,n}}{S_{n,L} - S_{n,opf}}\right)$ (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 $S_{n,L}$ stands for the power flow of n^{th} 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.

3. Computational Methods Employed

The optimal location and the injected capacity of TCSC are mainly based on security index of apparent power flow which is optimized by the proposed techniques by overloading the transmission lines. The injection capacity of TCSC is estimated by means of Equations (2) and (3) in terms of the security parameters. The computational methods of traditional GSA, Fuzzy based GSA and RBFNN based gravitational search technique is appropriately employed to successfully address the objective function. The gravitational constant is evaluated by Fuzzy based GSA followed by proposed technique of RBFNN network and the efficiency in execution of the search algorithm is incredibly increased as compared to traditional GSA. The proposed method is a novel approach to establish secured operation along with economic load dispatch with TCSC installation. The detailed explanation of traditional GSA and both the hybrid approach of Fuzzy based GSA and proposed technique of RBFNN GSA is give in this section.

A. 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 [10]. With an eye on successfully tackling the OPF menace, the GSA endowed with inherent potential invariably optimizes the objective function [11]. 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 (M_i), active gravitational mass (M_a) and passive gravitational mass (M_p). The mass position amounts to the solution of objective function and the fitness function employed is indicated by the gravitational and the initial masses [12].

B. Hybrid Methods based on Traditional GSA Algorithm

B.1. Fuzzy based GSA

In classical GSA, velocity equation dictates agent's movements in search space of the problem. But the velocity equation of the agents consists of random variable which leads the solution to an uncertain way. Sequentially, to manage these uncertainty in solutions and to keep away the detonation and deviation, velocity constraint is introduced which is predicted by fuzzy logic. The inputs of the fuzzy system are the current velocity of the agents $v_i^d(t)$ and the acceleration of agents $a_i^d(t)$. The block diagram of fuzzy logic controller with respect to input and output is given as in figure 1.

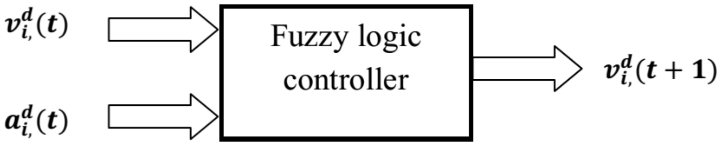

Figure 1: Structure of fuzzy system.

B.2 RBFNN based GSA

The proposed method of RBFNN based GSA is described in detail in this section where now the velocity constraint to substantially reduce deviation is predicted by RBFNN instead of Fuzzy logic as done earlier. The working procedure of the RBFNN based GS algorithm is described below which consists of three basic steps of initialization, fitness evaluation and generating an updating function.

Step 1: Initialization Process

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

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

Where, x_i^1 represents the position of the agent, x_i^d the demission of agent, and x_i^s the search space of the agent.

Step 2: Evaluation of Mass

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

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

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 3: Calculation of fitness function

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

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

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

Step 4: Evaluation of Force

For estimating the acceleration of an agent, a set of total force from heavier masses is applied which has to be taken into account in accordance with the procedure of law of gravity as per Equation 16 given below:

$$F_i^d(t) = \sum_{j \in kbest,\, j \neq i} rand_j G(t) \frac{M_j(t) \times M_i(t)}{E_{i.j}(t) + \beta} \left(x_j^d(t) - x_i^d(t) \right) \tag{14}$$

Where, $rand_j$ represents the random number in the interval 0 and 1, $G(t)$ 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 decreased linearly to 1 depending on time.

Step 5: Determination of acceleration

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:

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

By substituting the values of $F_i^d(t)$ and $M_i(t)$ the acceleration equation is modified as given below:

$$a_i^d(t) = \frac{\sum_{j \in kbest,\, j \neq i} rand_j G(t) M_j(t) \times M_i(t) \left(x_j^d(t) - x_i^d(t) \right) \left\{ \sum_{j=1}^{N} m_j(t) \right\}}{m_i(t) \left\{ E_{i.j}(t) + \beta \right\}} \tag{16}$$

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

Step 6: 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:

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

$$v_i^d(t+1) = rand_i \left\{ v_i^d(t) + a_i^d(t) \right\} \tag{18}$$

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 $t+1$.

Step 7: Modifying the velocity function by using RBFNN

To avoid the distribution of random number in velocity updating equation, RBFNN is used to calculate the $v_i^d(t+1)$.

Step 8: Evaluation of Gravitational Constant

From the output of the RBFN network, equation (7) is updated. Then, the gravitational constant $G(t+1)$ 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 the initial velocity, $G_n(t+1)$, the n^{th} updated velocity, δ , the constant, t , the current iteration and $t_{\max}$, the maximum iteration. The initial performance of the GSA is controlled by the values of δ and G_0.

Step 9: Optimal Solution and Termination

The best solutions which satisfy the objective function are found out and the algorithm is ready to give 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. The power flow parameters of the TCSC power flow depend on the injected voltage magnitude and angle. The flow chart of RBFNN based GS algorithm is illustrated in figure 2.

B.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 [13]. 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 $v_i^d(t+1)$. Figure 3 effectively illustrates the structure of the system. The detail description of RBNN is explained in the subsequent section.

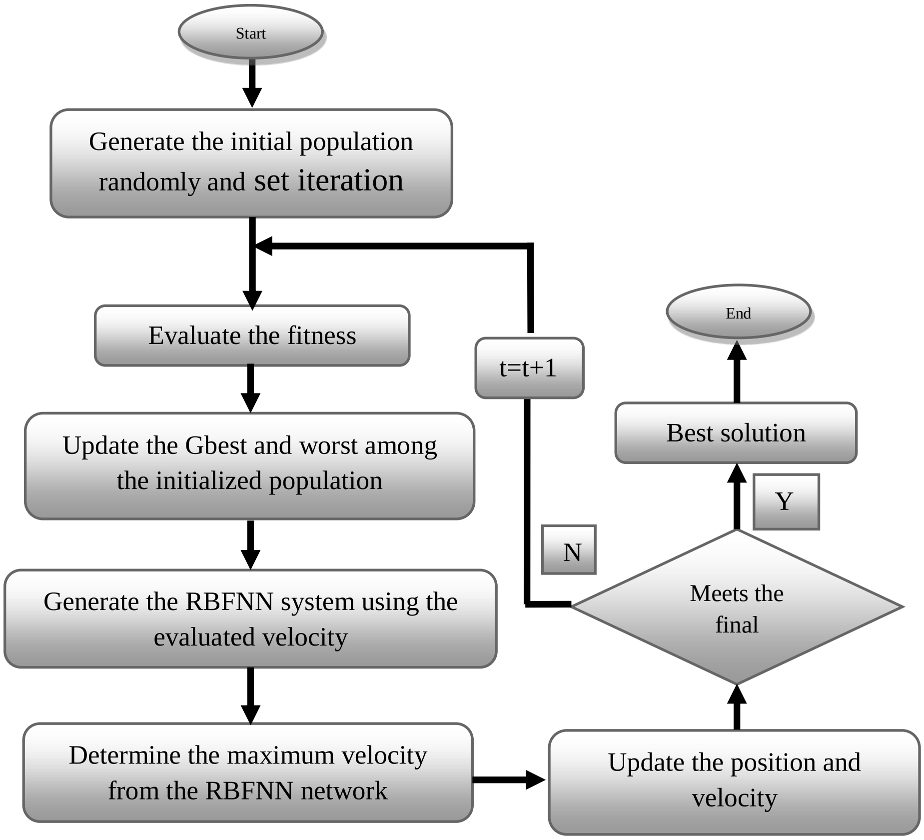

Figure 2. Flow chart of RBFNN based GSA

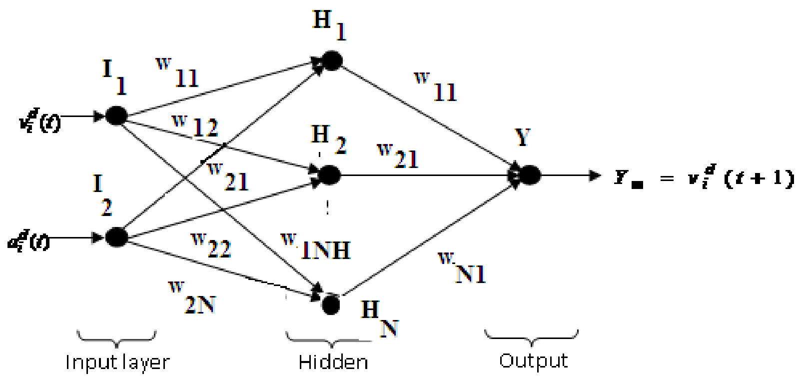

Figure 3: Structure of RBFNN

Steps for back propagation training algorithm
Step 1:

Here, the input layers, hidden and output layer weights of the neural network are randomly initiated. Now, the neuron weights of the hidden layer & output layer are specified in the particular interval $\left[w_{\min}, w_{\max}\right]$. The input layer weights to the hidden layer weights are specified as $(w_{111}, w_{112}, \ldots w_{11n})$. Also, the hidden layer weights to the output layer weights are specified as the $(w_{211}, w_{212}, \ldots w_{2n})$.

Step 2: The network is learnt, according to the input and the corresponding target.

Step 3: The back propagation error of the target (output) Y_m is calculated as follows:

$$BP_{Error}^{m} = (Y_m^{NN})_T - (Y_m^{NN})_{out} \tag{20}$$

Where, $\left(Y_m^{NN}\right)_T$ represents the network target of the m^th^ node and $(Y_m^{NN})_{out}$, the current output of the m^th^ node network.

Step 4: The current output of the network is evaluated as follows:

$$(Y_{m`}^{NN})_{out} = f(Y_m) + \sum_{n=1}^{N} W_{mp} Y_m^{NN}(n) \tag{21}$$

Where, $f(Y_m)$ represents the bias function in the m^{th} node respectively.

$$Y_m^{NN}(n) = \frac{1}{1 + \exp(-w_{11n} Y_m - w_{111} Y_m)} \tag{22}$$

The above equation represents the activation function of output and hidden layer. The bias function of radial bias function is described as follows:

$$f(Y_m) = \sum_{k=1}^{N} w_{mk} H_p(Y_m) \tag{23}$$

Where, N represents the number of neuron, w_{mi}, the weight of the i^{th} neuron, $H_k(Y_m)$, the response of the p^{th} neuron of the hidden layer.

$$H_p(Y_m) = \exp\left(\frac{-\left\| y_m - C_p \right\|^2}{R_p} \right) \tag{24}$$

In the above equation, $H_p(Y_m)$ represents the response of the p^th^ neuron of the hidden layer which is evaluated. Here, C_p represents the centre value of the p^th^ neuron and R_p, the scalar factor.

Step 5: Then, the new weights of the all neurons of the network are updated by the following equation:

$$w_{new} = w_{previous} + \Delta w \tag{25}$$

Where, $\Delta w = \delta . Y_m . BP_{Error}^{m}$ represents the change in weight and δ, the learning rate (0.2 - 0.5).

Step 6: Repeat the above steps till the BP_{Error}^{m} gets minimized $(BP_{Error}^{m} < 0.1)$.

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.

4. Results and discussion

The numerical results of the proposed RBFNN based GSA technique is presented and discussed in this section. The proposed method is implemented in MATLAB platform and improved system performances are observed by comparing the results with traditional GSA method and Fuzzy based GSA method. RBFNN is used to evaluate the new agent velocity and their positions and thus accelerates and improvises the searching performance of GSA. Establishment of OPF with TCSC is done by optimally placing it and performance of proposed method was evaluated by overloading transmission line arbitrarily. 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 30 bus system. Thirty bus transmission system single line diagram is given in figure 4. In general, IEEE-30 bus network consists of 41 branches, six generators and 21 load buses. The bus data, line data and the limits of control variables are measured from [14]. The fuel cost coefficient of IEEE 30 bus system are referred from [15] and are given in Table 2. The Newton Raphson power flow method is used to calculate the power flow solution before and after setting TCSC.

By using proposed method, the performance is evaluated by increase the demand value of load buses and the secured power flow is calculated. The results of total generated power, power loss and generation cost are tabulated in Table 1 and 3.

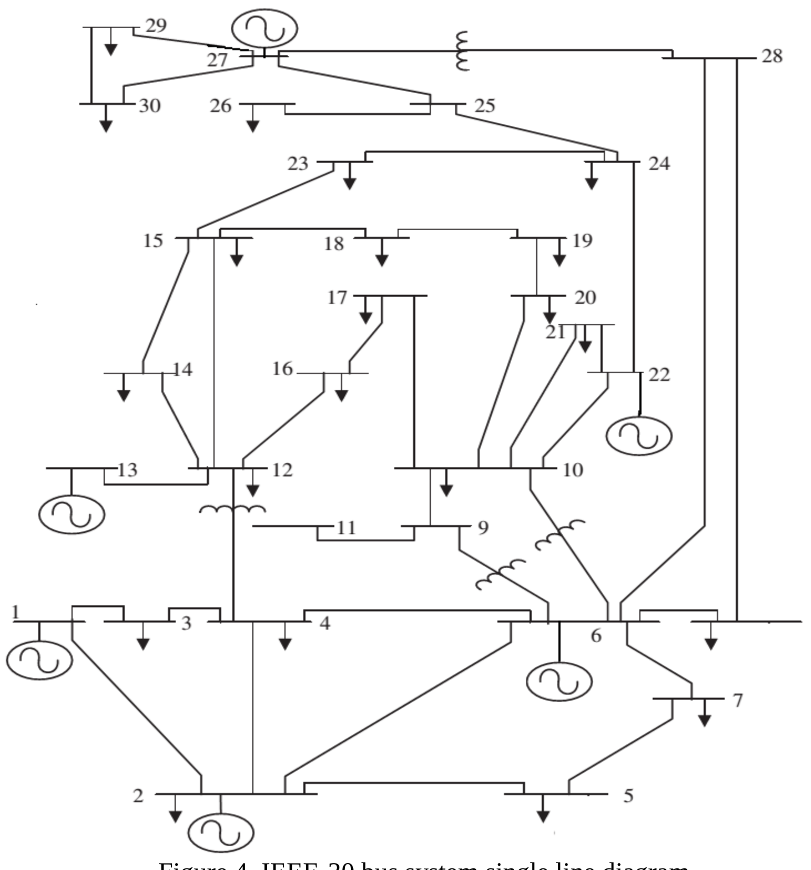

Figure 4. IEEE-30 bus system single line diagram.

The results obtained candidly presents the superior performance of proposed method to attain secured power flow with less power loss and reduced active power generation cost. The optimal location of TCSC as obtained by GSA algorithm is between 14 and 15 buses and as obtained by fuzzy based GSA and proposed RBFNN GSA is between 12 and 13 buses. During this overloading condition, the optimal placement of TCSC is established and the TCSC injection is obtained as 0.41288 with Fuzzy GSA and 0.33797 with proposed RBFNN GSA. The overload of the transmission line is reduced after placing TCSC on the precise location. In this paper, the total generation cost using RBFNNGSA is 800.317 \$/hr which is least as compared to GSA and Fuzzy GSA as shown in the work done and also less than the cost obtained in [16]. Also the total real power loss is 3.7917 MW which is less than the loss obtained in [16]

Table 1. Active power profile with respect to secured OPF

Methods	Prior to Loading	Subsequent to Loading without TCSC	Subsequent to Loading and TCSC installed with various methods		
			TCSC in line between 14 and 15 buses with GSA	TCSC in line between 12 and 13 buses with Fuzzy GSA	TCSC in line between 12 and 13 buses with proposed RBFNN GSA
Total active power generation (MW)	283.4	293.9	283.8684	282.5044	283.4
Total Real Power loss in MW	8.641	10.8095	8.2651	7.5797	3.7917
Total active power generation cost (\$/hr)	810.2864	828.3393	812.6234	809.2	800.317

Table 2. 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	50	200	0	2.0	0.0038
	2	20	80	0	1.75	0.0175
	6	15	50	0	1.00	0.0625
Synchronous Condenser	13	10	35	0	3.25	0.083
	22	10	30	0	3.00	0.0250
	27	12	40	0	3.00	0.0250

Table 3. Active power of IEEE-30 bus generators

CASES		Prior to Loading	Subsequent to Loading without TCSC	TCSC in line between 14 and 15 buses with GSA	TCSC in line between 12 and 13 buses with Fuzzy GSA	TCSC in line between 12 and 13 buses with RBFNN GSA
Active power in MW	G1	111.5234	169.4171	147.1743	142.1018	126.7369
	G2	58.41801	48.49221	46.1788	43.5944	75.06105
	G6	32.88061	23.47725	41.1762	30.3378	19.09552
	G13	25.46275	23.1801	11.6485	17.913	22.87083
	G22	20.9112	12.79994	14.656	12.921	21.09596
	G27	34.62022	16.4603	23.0344	33.6361	17.6868

To further substantiate the better performance of proposed RBFNNGSA method error calculation is done by individual relative error (%) and individual absolute error and the formulas for these statistical measurement are given below:

$$Individual\ relative\ error\,(\%) = \frac{(TCSC\,with other cases - TCSC\,with RBFNN\,GSA)}{TCSC\,with RBFNNGSA} \times 100 \tag{26}$$

$$Individual\ \ absolute\ error = TCSC other cases - TCSC\,with RBFNN\,GSA \tag{27}$$

Table 4 provides the results for Individual absolute error and figure 5 presents Individual relative error (%) comparing RBFNN GSA to cases of existing methods of GSA, Fuzzy GSA and without placing TCSC controller for IEEE 30 bus system. The individual relative error depicts that power loss and cost of power is significantly reduced with proposed method and OPF is enhanced after installing TCSC.

Table 4. Individual Absolute Error of proposed method with existing methods

Methods	Proposed method-Fuzzy based GSA	Proposed method-traditional GSA	Proposed method - without TCSC installed
power	0.8956	0.4684	10.5
power loss	3.788	4.4734	7.0178
cost of power	8.883	12.3064	28.0223

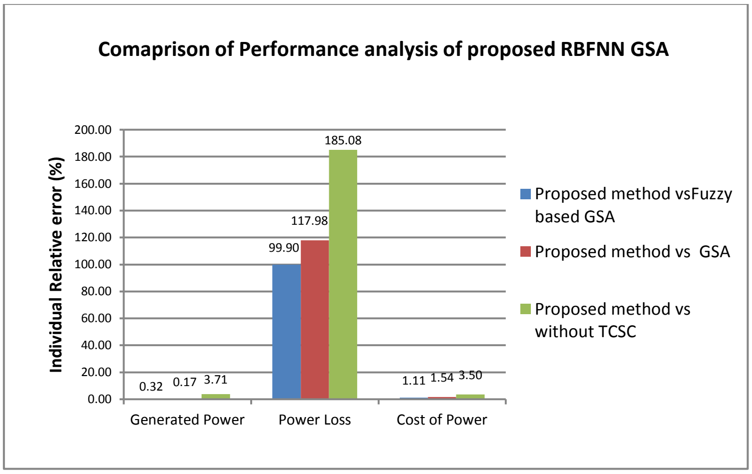

Figure 5. Performance analysis of proposed method with existing method in IEEE 30 bus system

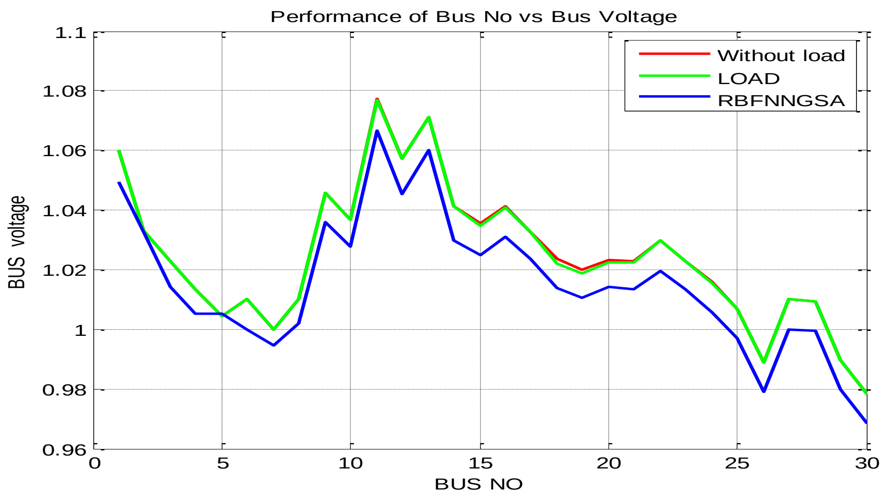

Figure 6. Performance analysis of proposed method for Bus Voltage deviation

The result for performance analysis of proposed method with regards to voltage deviation at the buses when system loading is changed is provided in figure 6. It is observed that voltage profile is improved under loaded condition implemented with RBFNNGSA.

The result for performance analysis of proposed method with respect to line loss at various transmission lines is depicted for normal loading, loaded condition and loaded case with RBFNN GSA in figure 7. It is evident that under loaded condition implemented with RBFNNGSA line loss are effectively minimized.

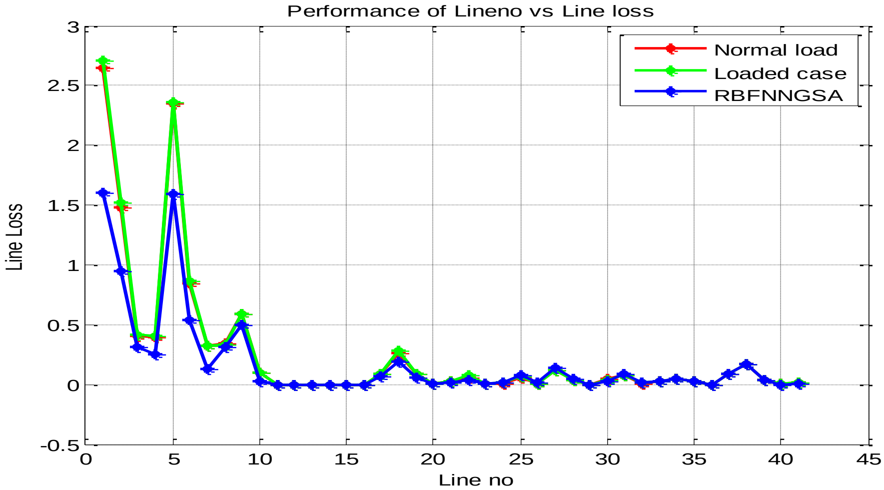

Figure 7. Performance analysis of proposed method for Line loss

5. Conclusion

In this paper, a hybrid technique of RBFNN based GSA was proposed for securing the optimal power flow problem with TCSC installation. The parameters of TCSC and its locations were optimized by using the proposed method. Then, the generation cost, generated power and power losses which depend on the load factor and the power flow index and changing loading state of the system were evaluated and compared with that of the existing method. Also, the power flow security of the proposed method is studied by line outage and the load power limits were reduced. From the analysis, it is observed that the results of line outage can ensure the power flow security by setting the installed TCSC. Therefore, secured power flow of transmission system is active by locating the TCSC optimally in normal and loading conditions and the error measurement confirms the effectiveness of proposed method.

6. References

[1]. David I. Sun, Bruce Ashley, Brain Brewer, Art Hughes and William f. Tinney, “Optimal Power Flow By Newton Approach”, *IEEE Transaction on Power Apparatus and Systems*, Vol.103, No.10, pp. 2864-2880, October 1984

[2]. H. Amhriz-PBrez, E. Acha and C. R. Fuerte-Esquivel, "Advanced SVC Models for Newton-Raphson Load Flow and Newton Optimal Power Flow Studies", *IEEE Transaction on Power Systems*, Vol.15, No.1, pp.129-131, February 2000

[3]. William. F. Tinney and Clifford E. Hart, "Power Flow Solution by Newton's Method", *IEEE Transaction on Power Apparatus and Systems*, Vol. 86, No.11, pp.1449-1450, November 1967

[4]. G. Baskar, and M.R. Mohan, "Contingency constrained economic load dispatch using improved particle swarm optimization for security enhancement", *Electric Power Systems Research*, Vol.79, pp.615–621, 2009

[5]. Tongxin Zheng, and Eugene Litvinov, "Ex Post Pricing in the Co-Optimized Energy and Reserve Market", *IEEE Transactions on Power Systems*, Vol.21, No.4, pp.1528-1538, November 2006

[6]. Dash, P.K., Mishra, S. and Panda, G., "Damping multimodal power system oscillation using a hybrid fuzzy controller for series connected FACTS devices", *IEEE Transactions on Power Systems*, Vol.15, No.4, pp.1360-1366, 2000

[7]. E.S. Ali, and S.M. Abd Elazim, "TCSC damping controller design based on bacteria foraging optimization algorithm for a multimachine power system", *International Journal of Electrical Power & Energy Systems* Vol.37, No.1, pp.23–30, 2012

[8]. S. Nagalakshmi and N. Kamaraj, "On-line evaluation of loadability limit for pool model with TCSC using back propagation neural network", *International Journal of Electrical Power & Energy Systems*, Vol. 47, pp. 52–60, May 2013

[9]. Prashant Kumar Tiwari, and Yog Raj Sood, "An Efficient Approach for Optimal Allocation and Parameters Determination of TCSC with Investment Cost Recovery under Competitive Power Market", *IEEE Transactions On Power Systems*, Vol.28, No.3, pp.2475-2484, 2013

[10]. Esmat Rashedi, Hossein Nezamabadi-pour, and Saeid Saryazdi, "GSA: A Gravitational Search Algorithm", *Information Sciences*, Vol.179, pp.2232–2248, 2009

[11]. A. Bhattacharya, and P.K. Roy, "Solution of multi-objective optimal power flow using gravitational search algorithm", *IET Generation, Transmission & Distribution*, Vol.6, No.8, pp.751-763, 2012

[12]. Esmat Rashedi, Hossein Nezamabadi-pour, and Saeid Saryazdi, "BGSA: binary gravitational search algorithm", *Natural Computing*, Vol.9, No.3, pp.727-745, September 2010

[13]. Iman Sadeghkhani, Abbas Ketabi and Rene Feuillet, "Radial Basis Function Neural Network Application to Power System Restoration Studies", *Computational Intelligence and Neuroscience*, Vol. 2012, 2012.

[14]. IEEE-30 bus transmission system data is refereed from: http://www.ee.washington.edu/research/pstca/pf30/ieee30cdf.txt

[15]. Naresh Acharya, and N. Mithulananthan, "Locating series FACTS devices for congestion management in deregulated electricity markets", *Electric Power Systems Research*, Vol.77, pp.352–360, 2007

[16]. Ben Attous, D; Labbi, Y, "Particle swarm optimization based optimal power flow for units with non-smooth fuel cost functions, ELECO 2009, I-377-I381, *IEEE Xplore*

[17]. M.A Abido, "Optimal power flow using PSO", *Electrical Power and Energy Systems", Elsevier*, 2002; 563-571

[18]. Lai LL, Ma J.T, "Improved Genetic Algorithm Search for Optimal Power flow under both normal and Contingent Operation States, *International Journal of Electrical Power and Energy Systems*, 1997, 19(5), 287-292

[19]. Zhang J, Sanderson AC. JADE: adaptive differential evolution with optional external archive. *IEEE Trans Evol Compt* 2009;13 (5):945–58.

[20]. K.Shanmukha Sundar, H.M Ravikumar, " Selection of TCSC location for secured optimal power flow under normal and network contingencies, *Electrical Power and Energy Systems*, Elsevier, 34(2012) 29-37

[21]. S. Nagalakshmi, and N. Kamaraj, "On-line evaluation of loadability limit for pool model with TCSC using back propagation neural network", *Electrical Power and Energy Systems*, Vol.47, pp.52–60, 2013

[22]. Berizzi, A., Delfanti, M., Marannino, P., Pasquadibisceglie, M.S., and Silvestri, Andrea, "Enhanced Security-Constrained OPF With FACTS Devices", *IEEE Transactions on Power Systems*, Vol.20, No.3, pp.1597-1605, 2005

[23]. Rashedi E, Rashedi E, Nezamabadi-pour H, Saryazdi. GSA: a gravitational search algorithm. Inform Sci 2009; 179:2232–48.

Sheila Mahapatra has completed her B.Tech in Electrical Engineering from Utkal University and M.Tech in Power Systems from Andhra University. She has a total experience of 9 years in academics and her areas of interest include Power Systems, Power Electronics, Control Systems and Electrical Machines. She has guided several B-Tech and M-Tech projects and attended several IEEE workshops in areas like Smart Grid, FACTS Technology, Computational Intelligence, Renewable Energy, Power Electronics converters. She joined NC University (formerly ITM university), Gurgaon in July 2008 and is still serving the university. She is currently pursuing PhD from NC University, Gurgaon. She is a lifetime member of ISTE and a student member of IEEE.

A. N. Jha obtained his PhD degree in Electrical Engineering in the year 1977 from Indian Institute of Technology, Delhi. He joined I.I.T Delhi as a lecturer in Electrical Engineering Department in the year 1981.He is Professor in the same department since February 1994. He is working in areas of Estimation, Identification and Control of Systems. He has published more than 110 research papers in National and International journals and conferences. He is a senior member of I.E.E.E USA, fellow of the Institution of Electronics and Telecommunication Engineers, India and life member of system society of India. His interests are in soft computing applications to power system control, power quality, distributed generation and renewable energy.

B.K. Panigrahi obtained his PhD degree from Sambalpur University and is currently working in Electrical Engineering Department, IIT, Delhi. His areas of interest include Power Quality, FACTS Devices, Power System Protection, application to Power Systems.