Minimization of Reactive Power Losses with FACTS with the application various optimization techniques

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Abstract— **This paper work presents a novel individual and Hybrid MGA and IGWO was utilized to develop FACTS-controlled optimization model for improvement of bus voltage profiles. The algorithm simultaneously solved the objective problem and tunes as it searches for FACTS location and sizes. Objective function constrained optimal power flow (CPF) with FACTS devices for TTC within real and reactive power generation limits, voltage limits, line flow limits, and FACTS devices operation limits. Thyristor-Controlled Series Capacitor (TCSC) parameters has been optimized for the research and the work has been successfully carried on MATLAB platform using IEEE 30-bus test bus systems. Power system processes and parameters can be optimized using artificial intelligence techniques like artificial neural networks and genetic algorithm alongside power electronics based Flexible AC Transmission Systems (FACTS) devices. FACTS normalize voltage or control the power that is either added into or absorbed from the system. They enhance the overall grid capacity and performance. They also increase the dependability and efficiency of power systems. Apart from alleviating power transients, FACTS provide greater system real and reactive control augmentation.**

Index Terms— **Augmentation, Artificial intelligence, Bus, Normalize, Genetic algorithm grid capacity reactive control.**

I. Introduction

Currently, electrical energy utilities run on constraints of complex interconnectivity and operation limits therefore forcing them to operate their existing infrastructure at a higher effectiveness. There is an interest in better utilization of the existing power systems to control power flow, improve system dynamics, and increase system reliability by using Flexible AC Transmission Systems (FACTS). Besides, FACTS devices can be used to increase power system transfer capability [1]. Wide variety of algorithms have been developed for calculating TTC, boosting voltage profiles, minimizing generation costs and loss reduction. Optimization of system parameters can be implemented by techniques such as sequential quadratic programming (SQP), Genetic Algorithm, Artificial Bee Colony Algorithm, Particle Swarm optimization and transfer based security constrained optimal power flow (TSCOPF) method. These methods require an objective function to get the optimal solution. [2]. Under constantly increased electricity demands, it is becoming more critical to boost the system capability such that more power transfers, maintenance of voltage stability margins and losses are minimized with less network expansion investment. In the place of building new supply substations or lines, proper installation and optimization, with Artificial Intelligence (AI), of transmission as well as generation units can make power networks billet more from source end to load [3]. With application of optimized FACTS devices, the power can be flown through the chosen routes with consideration on an increase in transmission line capability and improvement for the security of power system. UPFC, for instance, is very versatile FACTS controllers [4]. Enhancement of total transfer capability, minimization of power losses and improvement of voltage profiles in overloaded transmission network ensures that the system is stable and efficient even under stressed conditions. AI methods like genetic algorithm, fuzzy-logic, artificial bee colony algorithm and particle swarm optimization are applied to determine the optimum ratings of FACTS devices for simultaneous minimization of power loss and voltage profile enhancement, improved line flows and loss therefore boosting of available power transfers.

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1. METHODOLOGY

1.1 Problem formulation

The problem will be formulated to form the maximization the viable TTC while making observation on voltage profiles and system loss reduction. The optimization problem can be augmented simultaneously subject to the various equality and inequality constraints. The objectives minimization of voltage stability index, generation cost, real power loss and maximization the power that can be transferred from a generators source area to loads in a sink area. The formulation will cover the TTC base case (without FACTS controllers), TTC with UPFC and TTC with TCSC. TTC is the maximum power transfer without any line thermal overload, violation of voltage limits voltage instability or transient instability; the core constituent of the ATC. It reliant on system base case operating conditions, system operating limits, configuration of the system network, network contingencies among other constraints. TTC can be accomplished using Repeated Power Flow, Continuation Power Flow and Security Constrained Power Flow. The Security Constrained Power Flow has been utilized for this study.

1.2 Base case CPF (without FACTS controllers)

To determine TTC, the objective is to maximize the power transfer between two areas without any violation of thermal, voltage and stability limits. A standard TTC problem formulation can be written as shown in the following equation: -

$$P_r = \sum_{k=1}^{ND_{SNK}} P_{Di} \tag{1}$$

The above is subject to: -

$$P_{Gi} - P_{Di} + V_i V_j V_{ij} \cos(\theta_{ij} + \delta_i - \delta_j) = 0 \quad (2)$$
$$Q_{Gi} - Q_{Di} + V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (3)$$
$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}$$
$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \quad (4)$$
$$S_{ij} \le S_{ij.max} \quad (5)$$
$$V_i^{min} \le V_i \le V_i^{max} \quad (6)$$

Where: ND_SNK: Number of load buses in the sink area and PDi is the real load at bus i. The other equations are the power flow constraints and the following equations represent real and reactive power generation bounds, the second last equation stands for the thermal limitations and the last equation denotes the voltage level constraint.

1.3 CPF with TCSC FACTS Controller

The modified TTC function with TCSC FACTS controller, Pr for maximizing the TTC [44] of power transactions between source and sink areas in power system is given as:

$$P_r = \sum_{k=1}^{ND_{SNK}} P_{Di} \quad (7)$$

Where: ND_SNK: Number of load buses in the sink area and PDi: Real load at bus i

This is subject to the constraints below which are simply the real and reactive power balance equations with TCS FACTS controller at all the bus bars. The equality constraints with TCSC controller are formulated as follows: -

$$P_{Gi} - P_{Di} + \sum_{k=1}^{m} P_{Pi}(\alpha_{Pk}) + V_j Y_{ij}(X_S) \cos(\theta_{ij}(X_s) - \delta_j + \delta_j) = 0 \quad (8)$$
$$Q_{Gi} - Q_{Di} + \sum_{k=1}^{m} P_{Pi}(\alpha_{Pk}) + V_j Y_{ij}(X_S) \sin(\theta_{ij}(X_s) - \delta_j + \delta_j) = 0 \quad (9)$$
$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \quad (10)$$
$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \quad (11)$$
$$V_i^{min} \le V_i \le V_i^{max} \quad (12)$$
$$T_i^{min} \le T_i \le T_i^{max} \quad (13)$$
$$0 \le X_{si} \le X_{si}^{max} \quad (14)$$
$$\alpha_{Pi}^{min} \le \alpha_{Pi} \le \alpha_{Pi}^{max} \quad (15)$$
$$0 \le V_{Ui} \le V_{Ui}^{max} \quad (16)$$
$$-\pi \le \alpha_{Ui} \le \pi \quad (17)$$
$$Q_{vi}^{min} \le Q_{vi} \le Q_{vi}^{max} \quad (18)$$

Where:
PGi and QGi are real and reactive power generation at bus i
PDi and QDi are real and reactive loads at bus i
PPi(αPk) and QPi(αPk) are the injected real and reactive power of TCSC at bus i
Vi and Vj are voltage magnitude at buses i and j
Yij(Xs) and θij(Xs) are the magnitude and angle the ijth element in admittance matrix with TCSC
δi and δj are the voltage angles at bus i and j
P_{Gi}^{min} *and* P_{Gi}^{max} are lower and upper limits of real power generated at bus i
V_i^{min} *and* V_i^{max} are lower and upper limits of real voltage magnitude at bus i
T_i^{min} *and* T_i^{max} are the minimum and maximum range of tap changing transformer
X_S is the vector reactance of TCSC
N is the total number of buses
NG is the number of generators.
NL is the number of branches, and
ND _ SNK is the number of load buses in sink area.

1.4 Proposed Optimization Techniques

a. Modified Genetic Algorithm

The Modified GA is a stochastically population-based technique introduced by Storm and Price in 1997. MGA belongs to the family of genetic algorithms (GA). MGA performs just like a GA and it has the following operation: initialization, mutation, crossover, and selection. In MGA, individuals are abridged to a chromosome that programs the control variables of the problem. The strength of an individual is the objective function (fitness) that must be optimized. A random s function might produce the initial population size. After the start, consecutive populations are generated using the GA iteration process, which encompasses three basic functional operators: reproduction, crossover and mutation. Lastly, the population stabilizes, because no better individual can be found. When algorithm converges, and most of the individuals in the population are almost identical, it represents a sub-optimal solution. These parameters are vital to determine the optimization properties of the algorithm. To apply MGA to solve a specific problem, one has to define the solution representation and the coding of control variables. The optimization problem here is to use Constrained Power Flow (CPF) to find the Total Transfer Capability for various MGA-tuned FACTS devices to determine optimal locations and compensation sizes. The basic operation of MGA is stated as follows: -

- **Initialization**

The initialization procedure will select the initial population within the range of the control variables with a random number generator. The user can postulate the population number in this procedure.

- **Selection**

This is a key reproduction process in which individual chromosomes are derived according to their objective function (fitness); it is an artificial operation that mimics the version of the Darwinian procedure of natural selection. The first stage of the reproduction process is to select chromosomes for coupling. The roulette wheel selection is applied here. It is seen that stochastic universal sampling exhibits better convergence.

Crossover

Crossover is one of the key characteristics of GA that make them dissimilar from other algorithms. Its focal objective is to recombine blocks on diverse individuals to make a new block of generations as shown in the equations below: -

$$x^1 = \mu_1 x + \mu_2 y \quad (19)$$
$$y^1 = \mu_1 y + \mu_2 x \quad (20)$$
$$\mu_1 + \mu_2 = 1, \mu_1 \mu_2 > 0 \quad (21)$$

where x, y are the two parents, x', y' are their two descendants. µ1 is obtained by a uniform arbitrary number generator between the range (0~l).

- **Mutation**

Mutation is used to present some sort of artificial divergence in the population to avoid untimely convergence to local optimum. An arithmetic mutation operation that has demonstrated positive result in a number of studies is dynamic or non-uniform mutation is designed for fine-tuning aimed at achieving a high degree of accuracy. For a given parent x, if the gene xk is selected for mutation, then the resulting gene is selected with equal probability from the two selections: -

$$x_k^1 = x_k + r(b_k - x_k)\left(1 - \frac{t}{T}\right)b \quad (22)$$

$$x_k^1 = x_k - r(x_k - a_k)(1 - \frac{t}{T})b \quad (23)$$

Where r is a uniform arbitrary number selected between the range (0,1), t is the existing generation number, T is the maximum number of generations and b is a parameter determining the degree of lack of consistency. The amount of mutation reduces as the number of generations increases.

- **Replacement of population**

Two population replacement methods, non-overlapping generations and steady-state replacement. When using non-overlapping generations, a generation was entirely replaced by its progeny created through selection, crossover and mutation. It is conceivable for the offspring to be worse than their parents and some fitter chromosomes may be lost from the evolutionary process. Steady-state replacement is used to go over this problem. In this course, a number of offspring are created and these replace the same number of the least fit individuals in the population hence providing better convergence.

b. Improved Grey Wolf Optimization (IGWO) Algorithm

IGWO a new swarm intelligence algorithm based on the firmly organized scheme and hunting behavior of grey wolves, which includes three parts: tracking prey, surrounding prey, attacking prey, and other optimization processes. Its summarized as follows: -

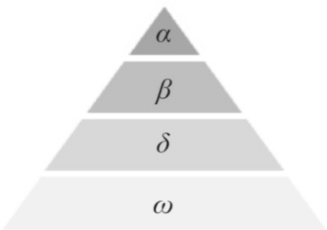


Figure 1: Grey wolf pack ranking

- **Wolf ranking Hierarchy**

Grey wolves mainly animate in groups, and the cluster follows the social pecking order, as shown in figure shown above. It can be seen from the figure that the α Wolf is the leader of the social group and is mainly accountable for making decisions about actions such as predation, while the rest of the wolves obey the command of the α Wolf. Level 2: β Wolf, submitting and supplementary to the α Wolf, can control all the wolves except for α Wolf. Level 3: δ Wolf, obeying the arrangement of α and β Wolf at the same time, can rule the rest of the residual wolf pack, and rank ω is the lowermost level. The general predation behavior of grey wolves is led by α wolves, and the task of other wolves is to surround the prey.

- **Surrounding prey**

Grey wolves surround their prey as they hunt. The mathematical model of encircling prey is as follows: -

$$D = | C. Xp(t) - X(t) | \quad (24)$$

where X(t) represents the position of grey wolves, and Xp represents the position vector of prey:

$$X(t+1) = Xp - A \cdot D \quad (25)$$

where A and C represent coefficient vectors, and the calculation formula is as follows:

$$A = 2a \cdot (r1-1) \quad (26)$$

$$C = 2r \cdot t \quad (27)$$

where t denotes the current number of iterations, and a = 2 (1-t/Tmax) denotes that the variable reduces linearly from 2 to 0, r1, r2 [0,1] during the iteration process.

- **Hunting prey**

Grey wolves can identify prey and surround it. The search process is α Wolf commands and leads, β and δ sometimes, they will take part in hunting. Hypothesis α, β and δ. The wolf can have a deeper understanding of the potential location of prey, and accordingly, during the algorithm iteration process, save the best location of the three wolves in the current population, and mark them as α, β and δ. Then, according to the position of the three parameters ϖ Wolf individuals are updated, and the mathematical model is thus developed.

1.5 Hybrid MGA and IGWO Algorithm

The IGWO algorithm has been successfully applied in the fields of job shop scheduling, power system analysis, economic forecasting, etc. Yet, like other algorithms, the IGWO is prone to fall into the local optimum and has a very slow convergence speed. Therefore, in order to improve the global convergence and convergence speed, this research has utilized MGA. GWO's searching ability is based on two principles: exploration and exploitation. Exploration refers to the process of exploring new areas or mathematically, the process of looking for a solution as much as possible in a search space to prevent local optimum stagnation. On the other hand, exploitation refers to looking in the same direction in greater depth or mathematically, searching for a solution with high precision. Using the GWO algorithm to find the global optimum with high efficiency necessitates achieving the proper balance between exploration and exploitation. As compared to other swarm intelligent techniques, GWO algorithms perform well in finding the global optimum for the high-dimensional problem, but not so well in finding the global optimum for low-dimensional problems. Normal there is no guarantee that GWO will identify global minima, it is conceivable that it will stick with local minima and calculate corresponding angles that do not eliminate the third harmonic. To mitigate this issue, a donor vector from a MGA like the differential evolution technique is used, which adds randomness to the GWO technique and allows it to escape out of the local optimum and look in a new direction for the global optimum. Since the DE technique is based on accomplish random initialization, it outdoes finding the global optima, but it has a limitation in that it lacks a parameter that is directly related to algorithm convergence, so the speed of convergence is very slow and provides power oscillation around the global optima. As a result, the flaw in one approach is offset by another method. Therefore, a new algorithm called improved gray wolf optimization and differential evolution (IGWO-MGA) is proposed in this thesis, which combines the IGWO algorithm with a better convergence factor and the DE algorithm with a dynamic scaling factor with the help of a DE crossover operator. The initialization of a arbitrary vector of population size “Np” with dimension “d” under boundary conditions is the first step in the

IGWO-MGA method. Where 'd' denotes the problem dimension or the number of variables in the problem, and this random vector is referred to as the target vector, which can be described as shown below:-

$$|X_i^t| = \left(x_{i,1}^t, x_{i,2}^t, x_{i,3}^t \dots \dots \dots x_{i,d}^t\right) \quad (28)$$

where {1,2, 3…Np}, and is the current value of iteration and each individual can be calculated as follows:

$$x_{i,j} = x_{l,b} + \text{rand}\,(0,1)*(x_{ub} - x_{lb}) \quad (29)$$

where ub, lb are the upper bound and lower bound vectors with d individuals respectively. The same way as in IGWO, the three best results in IGWO-MGA are kept as alpha solutions from the target vector. Succeeding the saving of the results, the target vector is exposed to a mutation in a manner like the MGA technique. In the suggested algorithm, the donor vector is generated from the target vector using a DE/best/1 mutation approach with a dynamic scaling factor ′, which offers more arbitrariness in the initial stages, preventing the algorithm from dropping into a local optimum, while the value of ′ decreases in the final stages, boosting the algorithm's convergence speed. So, the donor vector can be stated as follows: -

$$|V_i^t| = |X_{alpha}^t| + F' * (|X_{R1}| - |X_{R2}|) \quad (30)$$

where alpha, is the α solution or best solution as far and are the randomly selected solution from the target vector and F' can be expressed as follows:

$$F' = \frac{2}{1+e^{(k*(\frac{t}{tmax})}}; \text{k} \quad (31)$$

IGWO's searching ability is primarily determined by the vectors A and , where is a randomly generated vector ranging from 0 to 2, the wolves favor exploration if exploitation and plays no role in IGWO's convergence speed. Now, the only vector that is important in convergence, but the value of is determined by the convergence factor, and the value decreases linearly from 2 to 0 over the course of iteration. We need to adjust the convergence factor to enhance the speed of the algorithm as shown in the equation below: -

$$F' = \frac{2}{1e^{(k*(\frac{t}{tmax} - \frac{1}{2})}}; \text{k} \quad (32)$$

Using this better convergence factor, the improved placement of the wolves can be calculated on the foundation of the position of the greatest wolves. Let us consider the ith position vector of wolves in the tth iteration as $W_i^t = [w_{i,2}^t, w_{i,2}^t \dots w_{i,d}^t]$ which can be calculated using equation. The two vectors are combined using a binomial crossover operator to generate a position vector for the next iteration. The new location vector can be defined as follows:

$$X_{i,j}^{t+1} = \begin{cases} V_{i,j}^t \; if \; rand(0,1) \le CR \; OR \; j = \delta \\ X_{i,j}^t \; if \; rand(0,1) > CR \; AND \; j \ne \delta \end{cases} \quad (33)$$

Research procedure

1.6 Research procedure

a. The objectives of this will be realized as follows:
b. An objective function based (base case, without FACTS) for maximization total transfer capability as the optimization problem will be formulated and solution derived
c. Singular Modified Genetic Algorithm and Improved Grey Wolf Optimization to solve the objective function, separately, via optimal location and sizing of FACTS devices will be developed
d. Hybrid Genetic Algorithm and Improved Grey Wolf Optimizer Algorithm will be developed and used to solve the function for maximizing power transfer capability while observing the voltage profiles and loos reduction
e. Hybrid Improved Grey Wolf Optimizer Algorithm and Genetic Algorithm with FACTS model above will be utilized to carry out simulations and evaluate effectiveness of model on improvement of power transfer capability
f. The results will be assessed and effects of individual FACTS devices compared to each other for the four system parameters under consideration
g. The proposed test networks will be the standard IEEE 30 bus test system
h. Simulation will be carried out in MATLAB

2. RESULTS AND DISCUSSION

2.1 Results from the optimal power flow (Base case, without optimized FACTS)

Table 1 shows the optimal load flow result, the total real power loss is 17.53MW, reactive power losses (20.92MVAR), TTC (240.26MW) and total system load of 283.4MW for the power flow without optimized FACTS. The power flows from send end bus to receiving buses are generally with limits apart from power flow from bus 1 to bus 2.

Table 1

Optimal Power flow Solution by Newton Raphson	
Power-Loss (MW)	17.53
Reactive-Loss (MVAR)	20.92
Total System Load (MW)	283.4
Total Transfer Capability (MW)	240.26

2.2 OPF with GA-tuned UPFC

Optimization results

The optimized values for GA-tuned UPFC are indicated in the table 2 below: -

Table 2

Parameter	Values
Voltage UPFC (PU) :	1.01 and 1.03
Angle UPFC (R) :	-0.01 and 0.54
Location UPFC (Bus) :	Bus 1 and Bus 8

Optimal NR Load flow Solution with GA-tuned UPFC

Table 3 shows the optimal load flow result; the reactive power losses are 15.29MVAR. The power flows from send end bus to receiving buses are generally with limits apart from power flow from bus 1 to bus 2 where the loss load has reduced to 41.735MW from 43.143MW (a difference of 1.408MW).

Table 3: Newton Raphson Load flow Solution

Newton Raphson Load flow Solution

Newton Raphson Load flow Solution	
Power-Loss (MW)	16.75
Reactive-Loss (MVAR)	15.29
Total System Load (MW) :	283.4

Total Transfer Capability (MW)	241.66

2.3 OPF with GA-tuned TCSC

Optimization Results

The optimized values for MGA-tuned TCSC are indicated in the table below: -

Table 4

Parameter	Values
Reactance TCSC (p.u.)	0 and 0.02
Location TCSC (Line)	40 and 4

Optimal NR Load Flow Solution for GA-tuned TCSC

Table 5 shows the optimal load flow result; the total reactive power losses are 19.53MVAR. The power flows from send end bus to receiving buses are generally with limits apart from power flow from bus 1 to bus 2 where the loss load has reduced to 38.182 MW from base value of 43.143MW (a difference of 4.961MW).

Table 5

Newton Raphson Load flow Solution for GA-tuned TCSC	
Power-Loss (MW)	17.5
Reactive-Loss (MVAR)	19.53
Total System Load (MW)	283.4
Total Transfer Capability (MW)	245.22

2.4 OPF with IGWO-tuned UPFC

Optimization results

Table 6 below show the optimization results for IGWO-tuned UPFC

Table 6: Optimization results

Parameter	Values
Voltage UPFC ()	1.04 1.05
Angle UPFC (R)	-1.08 -0.71
Location UPFC (Bus)	Bus 1 and Bus 8

Optimal NR Load flow Solution for IGWO-tuned UPFC

Table 7 shows the optimal load flow result; the reactive power losses are 15.14MVAR. The power flows from send end bus to receiving buses are generally with limits apart from power flow from bus 1 to bus 2 where the loss load has reduced to 41.353MW from base value of 43.143MW (a difference of 1.790MW).

Table 7: Newton Raphson Load flow Solution

Newton Raphson Load flow Solution	
Parameter	Values
Power-Loss (MW)	17.36
Reactive-Loss (MVAR)	15.14
Total System Load (MW)	283.4
Total Transfer Capability (MW)	242.05

OPF with IGWO-tuned TCSC

Optimization results

Table 8 below show the optimization results for IGWO-tuned TCSC

Table 8: Optimization results

Parameter	Values
Reactance TCSC (PU) (p.u.)	0.015 and 0.0015
Location TCSC (Line)	Line 2 and Line 4

Optimal NR Load Flow Solution for IGWO-tuned TCSC

Table 9 shows the optimal load flow result, the total real power loss is 17.32MW, reactive power losses (17.62MVAR), TTC (246.11MW) and total system load remained unchanged at 283.4MW for the power flow with the application of IGWO-tuned TCSC FACTS controller. The power flows from send end bus to receiving buses are generally with limits apart from power flow from bus 1 to bus 2 where the loss load has reduced to 41.353MW from base value of 43.143MW (a difference of 1.7.743MW).

Table 9: Newton Raphson Load flow Solution

Newton Raphson Load flow Solution	
Parameter	Values
Power-Loss (MW)	17.32
Reactive-Loss (MVAR)	17.62
Total System Load (MW)	283.4
Total Transfer Capability (MW)	246.11

2.5 OPF with Hybrid MGA and IGWO-tuned UPFC

Optimization results

Table 10 below show the optimization results for Hybrid MGA and IGWO-tuned UPFC

Table 10: Optimization results

Optimization Results	
Voltage UPFC (p.u.) :	1.03 and 1
Angle UPFC (R) :	-0.51 and -0.65
Location UPFC (Bus) :	Bus 30 and Bus 1

Optimal NR Load flow Solution for Hybrid GA and IGWO-tuned UPFC

Table 11 shows the optimal load flow result, the total real power loss is 16.54 MW, reactive power losses (14.53MVAR), TTC (243.91MW) and total system load remained unchanged at 283.4MW for the power flow with the application of Hybrid MGA and IGWO-tuned UPFC FACTS controller. The power flows from send end bus to receiving buses are generally with limits apart from power flow from bus 1 to bus 2 where the loss load has reduced to 41.281MW from base value of 43.143MW (a difference of 1.6506MW).

Table 11: Newton Raphson Load flow Solution

Newton Raphson Load flow Solution	
Power-Loss (MW)	16.54

Reactive-Loss (MVAR)	14.53
Total System Load (MW)	283.4
Total Transfer Capability (MW)	243.91

2.6 OPF with Hybrid GA and IGWO-tuned TCSC

Optimization results

Table 12 below show the optimization results for Hybrid MGA and IGWO-tuned TCSC

Table 12: Optimization results

Parameter	Values
Reactance TCSC (p.u.):	0.02 0.02
Location TCSC (Line):	Line 4 and Line 2

Optimal NR Load flow Solution for Hybrid GA and IGWO-tuned TCSC

Table 13 below shows the optimal load flow result, the total real power loss is 17.52MW, reactive power losses (17.92 MVAR), TTC (250.8 MW) and total system load remained unchanged at 283.4MW for the power flow with the application of Hybrid GA and IGWO-tuned TCSC FACTS controller. The power flows from send end bus to receiving buses are generally with limits apart from power flow from bus 1 to bus 2 where the loss load has reduced to 32.6 MW from base value of 43.143MW (a difference of 10.543MW).

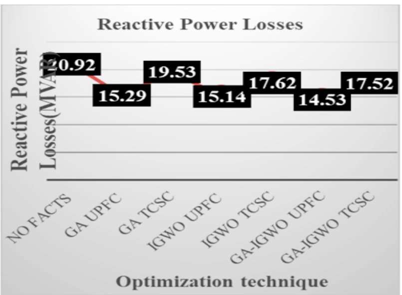
Table 13: Newton Raphson Load flow Solution

Newton Raphson Load flow Solution	
Power-Loss (MW)	17.52
Reactive-Loss (MVAR)	!7.92
Total System Load (MW)	283.4
Total Transfer Capability (MW)	250.8

2.7 Assessment of the comparative effects of the hybrid optimization technique using UPFC and TCSC FACTS for Reactive Power Losses

The figure 14 below shows the reactive power for different optimization techniques: -

Figure 14: Reactive power for different optimization techniques



CONCLUSION

For the base case solution without FACTS devices, the reactive power losses were 20.92MVAR, for solution with MGA-tuned FACTS controller the reactive power losses were 15.29MVAR, for MGA-tuned TCSC the reactive power losses were 19.53MVAR, for IGWO-tuned UPFC the reactive power losses were 15.14MVAR, for IGWO-tuned TCSC the reactive power losses were 17.62MVAR, for the solution with hybrid MGA and IGWO-tuned UPFC controller the reactive power losses were 14.53MVAR and for the solution with hybrid MGA and IGWO-tuned TCSC the reactive power losses were 17.52 MW. The novel Hybrid MGA and IGWO-tuned TCSC FACTS controller CPF solution for reduction of reactive power losses solution was 17.52MVAR, a reduction of 3.4MVAR from the base case solution of 20.92MVAR. There was reduction of 6.39MVAR for the solution with Hydrid MGA and IGWO-tuned UPFC FACTS controller from the reactive power losses' base solution, a reduction of 3.3MVAR from IGWO-tuned TCSC FACTS controller from the reactive power losses' base case solution, a reduction of 5,78MVAR from IGWO-tuned UPFC FACTS controller from the reactive power losses' base solution and a reduction of 1.39MVAR from MGA-tuned TCSC FACTS controller from the reactive power losses' base case solution of 20.92MVAR. The reduction of reactive power loss with MGA-tuned UPFC FACTS controller from the base reactive power losses' solution was 5.63MVAR. This makes the reactive power losses' solution with Hybrid MGA and IGWO with UPFC tuned FACTS controllers the most superior solution to all solution accomplished and tested in this research. It imperative to note that the hybrid technique has brought out the inherent strengths of the FACTS controllers applied. For reduction of reactive power losses, similar to the performance for real power losses, UPFC is more superior to TCSC for all scenarios. Hence for power system networks with reactive power losses' problems, UPFC is more recommended for application than TCSC. In addition, the performance of MGA with tuned UPFC FACTS controller (reduction of 0.78MW) optimization techniques has proven to be better than the IGWO with tuned UPFC FACTS controller (reduction of 0.78MW) for reduction of reactive power losses. Finally, there significant reduction of reactive power losses for all optimization techniques applied compared to the values observed for reduction of real power losses.

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