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VOLTAGE PROFILE IMPROVEMENT WITH APPLICATION OF DIFFERENTLY OPTIMIZED FACTS CONTROLLERS

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Abstract*: This research 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 augments device parameters as it searches for the best FACTS location and sizes. Objective function was resolved Security Constrained Optimal Load Flow (SCOLF) with the integration FACTS power electronics controllers for TTC without violating active and reactive power generation confines, voltage boundaries, line flow limits, and FACTS devices operation restrictions and ratings. TCSC controller parameters have been effectively optimized for the research and the work has been successfully carried out on MATLAB platform using IEEE 30-bus test bus systems. Power system procedures and parameters can be augmented using artificial intelligence techniques like ANN, ANFIS, Fuzzy Logic, DEPSO and MGA together with power electronics built versatile and highly adaptable Flexible AC Transmission Systems controllers. 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.*

1. INTRODUCTION

Currently, electrical energy utilities run on constraints of complex interconnectivity and operation limits therefore forcing them to operate within their existing infrastructure at a higher effectiveness. There is an ever growing interest in better operation and usage of the prevailing electricity infrastructure to enable the effective control of load flow, advance network dynamics, and upsurge system dependability by use of these devices. In addition, the devices can also play a pivotal role in augmentation of power grid transmission capability [1]. Extensive variety of algorithms have been advanced for computing TTC, increasing voltage profiles, optimizing via minimization the generation costs and loss lessening. Optimization of network parameters can be executed by methods including but not limited to SQP, DEA, DEPSO, MGA, BGA, ABCA, PSO and transfer based TSCOPF techniques. These ways necessitate the formulation of an objective function for the 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 these optimized devices, the electrical energy can be transmitted over the selected paths with considerable increase in transmission line capability and additionally enhancement for the security of interconnected power network. UPFC, for example, is very adaptable and versatile amongst the FACTS controllers [4]. Augmentation of total transfer capability, optimization via minimization of power losses and enhancement of voltage profiles in strained and overloaded transmission network guarantees that the system is steady and effectual even under stressed circumstances. AI methods can be suitably applied to determine the optimum ratings and values of these devices for simultaneous resolution of diverse power grid problems.

2. CONTEXT

Placement of FACTS is achievable and optimization is critical in realization of the device ultimate capability. In early days, stabilization of electrical grids was realized via equipment like PSS, AVRs and approaches like breaking resistor, discounting of system transmission reactance, use of grouped or bundled conductors, SCC limiters and the most lately placement of FACTS devices. These devices have the capability to alter the three main control parameters, i.e. the bus voltage, reactance of the transmission line, and phase angle between two buses, either concurrently or autonomously. They achieve this via the regulatory control of the in-phase voltage, voltage of the quadrature axis and parallel compensation to better voltage stability, power transmission and shrink system losses of the composite interconnected power grid. To harness the several benefits of these devices, AI techniques can be used to augment the parameters. This way, FACTS devices optimization models for objective functions of more than parameter. This is critical since the devices are very expensive and comparative analysis is required for commercial reasons [4]. Heuristic search methods have been found to be robust and efficient to solve such complex problems and give fairly optimal results. The IGWO augmentation algorithm applied in this work, is susceptible to premature fall into the local optimum and its convergence speeds are quite low. Consequently, so as to increase the global convergence and equivalent speed, this research has utilized MGA to mitigate this phenomenon. IGWO's searching ability is based on two principles: survey and exploitation. Survey 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 IGWO 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, IGWO 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. Usually, there is no guarantee that IGWO 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 MGA technique is used, which adds randomness to the IGWO technique and allows it to escape out of the local optimum and look in a new direction for the global optimum. Since the MGA 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 Modified Genetic Algorithm (IGWO-MGA) is proposed in this thesis, which combines the IGWO algorithm with a better convergence factor and the MGA algorithm with a dynamic scaling factor with the help of a MGA crossover operator [5][7][11].

3. PREVIOUS RESULTS

From the previous literature studies, optimum placement various FACTS devices have been research with mainly singular heuristic methods. To realize the peak performances of these devices; the best location, hybrid AI methods need to be introduced and their performances assessed with single ones. The assessment has also deduced that the devices have been utilized jointly and separately to offer voltage over active and real power control and regulation via the voltage injection and absorption properties they possess. The controllers have used to enhance one or two parameters like voltage stability, loss reduction or transient stability and other system parameters. This research has gone a step further. It will further delve into the development of hybrid GA-IGWO FACTS-controlled model for optimization of total capability transfer and observation of voltage profile enhancement and loss reduction. The unique FACTS controlled AI optimization model for TTC enhancement crucial for comparative analysis, system performance and economic reasons. Performances of single AI models also need be compared with the hybrid ones for both optimization of the system parameter as well FACTS devices allocation. Hybrid evolutionary heuristics with different strengths are also presented in this work. This work will create a basis of evaluating their optimization capabilities with other techniques in the foreseeable future.

4. METHOD USED

4.1. 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 instantaneously subject to the numerous equality and inequality limitations. The objectives maximizing TTC and observation of profiles of bus voltages and power loss lessening characteristics. The formulation covered the TTC base case (without FACTS controllers), TTC with UPFC and TTC with TCSC. TTC is the utmost power transfer without any line thermal overload, within violation of voltage bounds voltage unsteadiness or transient probations. It's the central constituent of the ATC. Its dependent 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 Load Flow and Security Constrained Load Flow. The Security Constrained Power Flow has been utilized for this study [5]-[12].

4.2. Base case CPF (without FACTS controllers)

To find TTC, the objective is to optimize through maximization strategy the power transfer between two areas while operating within thermal, voltage and stability confines. A typical TTC problem formulation is presented as illustrated in the following equation:

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

The above is subject to: -

$$P_{Gi} - P_{Di} + V_i V_j V_{ij} \cos\left(\theta_{ij} + \delta_i - \delta_j\right) = 0 \tag{2}$$

$$Q_{Gi} - Q_{Di} + V_i V_j Y_{ij} \sin\left(\theta_{ij} - \delta_i + \delta_j\right) = 0 \tag{3}$$

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

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \tag{5}$$

$$S_{ij} \leq S_{ij.max} \tag{6}$$

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{7}$$

where: MB_{SNK} is the number of load buses in the receive end and P_{Di} is the real load at bus i.

The other equations are the power flow restraints and the following equations denote active and reactive power generation bounds, the second last equation stands for the thermal limitations and the last equation denotes the voltage level constraint.

4.3. CPF with TCSC FACTS Controller

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

$$P_r = \sum_{k=1}^{MB} P_{Di} \tag{8}$$

The equality constraints with TCSC controller are formulated as follows:

$$P_{Gi} - P_{Di} + \sum_{k=1}^{m} P_{Pi}\,(\alpha_{Pk}) + V_j Y_{ij}(X_S)\,cos\big(\theta_{ij}\,(X_s) - \delta_j + \delta_j\big) = 0 \tag{9}$$

$$Q_{Gi} - Q_{Di} + \sum_{k=1}^{m} P_{Pi}\,(\alpha_{Pk}) + V_j Y_{ij}(X_S)\,sin\big(\theta_{ij}\,(X_s) - \delta_j + \delta_j\big) = 0 \tag{10}$$

Given that:

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \tag{11}$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \tag{12}$$

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{13}$$

$$T_i^{min} \leq T_i \leq T_i^{max} \tag{14}$$

$$0 \leq X_{si} \leq X_{si}^{max} \tag{15}$$

$$\alpha_{Pi}^{min} \leq \alpha_{Pi} \leq \alpha_{Pi}^{max} \tag{16}$$

$$0 \leq V_{Ui} \leq V_{Ui}^{max} \tag{17}$$

$$-\pi \leq \alpha_{Ui} \leq \pi \tag{18}$$

$$Q_{vi}^{min} \leq Q_{vi} \leq Q_{vi}^{max} \tag{19}$$

where:
P_{Gi} and Q_{Gi} are active and reactive power generation at bus i
P_{Di} and Q_{Di} are active and reactive loads at bus i
$P_{Pi}(\alpha_{Pk})$ and $Q_{Pi}(\alpha_{Pk})$ are the injected real and reactive power of TCSC at bus i
V_i and V_j are voltage magnitude at buses $_i$ and j
$Y_{ij}(X_s)$ and $\theta_{ij}(X_s)$ are the magnitude and angle the ij^{th} component in admittance matrix with TCSC
δ_i and δ_j are the bus *i* and *j* voltage angles
P_{Gi}^{min} *and* P_{Gi}^{max} are minimum and maximum bounds of real power generated at bus i
V_i^{min} *and* V_i^{max} are minimum and maximum bounds of real voltage valueat 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
M is the sum of all buses
MG is the quantity of generator units
ML is the sum of all branches, and
MB_{SNK} is the total quantity r of load buses in sink/receive end area.

4.4. Proposed Optimization Techniques

i. Modified Genetic Algorithm

MGA is a stochastically biologically inspired technique presented 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, characters are abridged chromosomes which programs the control parameters of the problem. Strengths of an individual characters gives the objective function commonly denoted as fitness that must be augmented in the optimization process. An arbitrary function has the chance yield the primary population size. Soon after the commencement, successive populaces are produced using the MGA process of iteration. This incorporates three rudimentary functional operations: -reproduction, crossover and mutation procedures. Finally, the population steadies since no healthier individual can be created. As the algorithm converges, and majority of the individual characters in the population are nearly undistinguishable hence denotes a sub-optimal results. The outcomes are critical in the determination of the optimization characteristics of the augmentation procedure. For application of MGA in resolution of additional and particular problem, one has to outline the solution illustration and the coding of control parameters. The augmentation problem in question is solved by use of Security Constrained Power Flow (SCOPF) to find the Total Transfer Capability for specified MGA-tuned FACTS devices to define optimal positions and compensation dimensions [13]. The basic operation of MGA is stated as follows: -

a) Initialization operation

The procedure for initialization will choose the primary population while operating within the span of the control parameters with an arbitral number creator. Users can hypothesize the quantity of population in this process.

b) Selection operation

This is a key reproduction procedure where individual chromosomes are derived as per their respective objective function/fitness. This is a simulated procedure that imitates the version of the Darwinian natural selection phenomenon. Initially, the reproduction process begins with selection of chromosomes for pairing. The roulette wheel selection is best suited in this for application at this instance. It is observed that stochastic common samples exhibit superior convergence characteristics.

c) Crossover operation

It's one of the crucial physiognomies of MGA augmentation tenets dissimilar from other optimization algorithms. The operation focal objective is to reconstitute blocks on varied individuals to create a new block of generations as shown in the equations below:

$$x^1 = \mu_1 x + \ \mu_2\, y \tag{20}$$

$$y^1 = \mu_1 y + \mu_2 x \tag{21}$$

$$\mu_1 + \mu_2 = 1, \mu_1 \mu_2 > 0 \tag{22}$$

where *x*, *y* denotes two parents, *x'*, *y'* defines two descendants. μ_1 is gotten by an unchanging random number generator sandwiched between the range (0~l).

d) Mutation operation

This is vital in presentation of artificial divergence in the populace to shun untimely convergence to local optima. A computation operation demonstrated positive result in a numerous study is dynamic or non-even mutation is formulated for fine-tuning intended at attaining a highest degree of precision. For instance, provided with parent *x*, if gene x_k is designated for mutation operation, the resulting gene is chosen with equivalent likelihood from the two selections:

$$x_k^1 = x_k + r(b_k - x_k)\left(1 - \frac{t}{T}\right)^b \tag{23}$$

$$x_k^1 = x_k - r(x_k - a_k)(1 - \frac{t}{T})^{\mathrm{b}} \tag{24}$$

r denotes uniform random number selected between the span of (0,1), t is the prevailing generation number, T is the highest number of generations and b is a variable responsible for the degree of absence of constancy. The extent of mutation lessens as the number of generations upsurges.

e) Replacement of population

There are two population substitution approaches, non-overlapping generations and steady-state substitution. When utilizing non-overlapping generations, a generation was completely swapped by its progeny made via selection, crossover and mutation operation. It is conceivable for the offspring to be inferior than their parentages. Some of the fitter chromosomes may be vanished from the evolutionary process at this stage. The steady-state replacement or constant substitution is applied to go over and circumvent 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. [14] –[19]

ii. Improved Grey Wolf Optimization (IGWO) Algorithm

IGWO a newfangled swarm intelligence algorithm grounded on the firmly orderly scheme and hunting conduct of grey wolves, which comprises three parts: tracking prey, surrounding prey, attacking prey, and other optimization processes. It's abridged as shown in the diagram below:

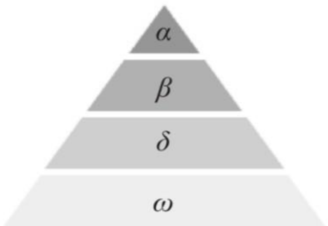

Figure 1: Grey wolf pack ranking

Wolf ranking Hierarchy

These wolves largely animate in clusters, and they follow a social pecking order, as shown in *figure 1*, displayed above. It can be realized from the figure that the α Wolf is the trailblazer of the social group and is mostly in authority for making choices and deciding about actions such as predation as the other wolves submit to the command of the α Wolf. Level 2: β Wolf, submitting and supplementary to the α Wolf, controls all the wolves excluding the α Wolf. Level 3: δ Wolf, submitting the authority of α and β Wolf at the same time, can rule the residual wolf pack. The ω wolves rank is the lowermost class in the pecking order. The universal predation conduct of grey wolves is controlled by α wolves, and the duty of other wolves is to confine the prey.

Surrounding prey

Grey wolves confine their prey as they hunt, hence stifling their movement. The computational model of enclosing the prey is outlined as follows: -

$$D = | C. Xp\,(t) - X\,(t) | \tag{25}$$

where $X(t)$ denotes the location of grey wolves, and Xp signifies the point vector of prey:

$$X\,(t+1) = X_{p\,-}\,A\cdot D \tag{26}$$

where A and C symbolize constant vectors, and the computational formula is shown below:

$$A = 2a\cdot(r_1\text{-}1) \tag{27}$$

$$C=2r\cdot t \tag{28}$$

where t denotes the existing sum of all iterations, and $a = 2\ (1\text{-}t/T_{max})$ denotes that the varying parameter decreases in a linear manner from 2 to 0, $r_1, r_2 \in [0,1]$ throughout the iteration course.

Hunting prey

These wolves also recognize prey and edge it. The hunt procedure is α Wolf commands and leads, β and δ sometimes, they will participate in hunting as well. Hypothesis α, β and δ. The wolf can have a profound comprehension of the probable site of prey, and consequently, during the algorithm process of iteration, keep the finest location of the three wolves in the existing population, and mark them as α, β and δ. Thereafter, in accordance with the position of the three parameters ϖ Wolf individuals are rationalized and updated. The computational model is thus advanced and established.

iii. Hybrid MGA and IGWO Algorithm

IGWO augmentation technique has been efficaciously applied in the areas of job planning, power system analysis, control and protection simulation, economic forecasting, among others. Yet, similar to other approaches, the algorithm is predisposed to falling prematurely into the local optimum and possess convergence speed of very low magnitudes. Hence, in order to increase the global convergence levels and better the convergence speeds, this research work has utilized MGA to mitigate this inadequacy. 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 “N_p” 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:

$$|X_i^t|=\left(x_{i,1}^t, x_{i,2}^t, x_{i,3}^t \dots\dots\dots x_{i,d}^t\right) \tag{29}$$

where $i \in \{1,2, 3\ldots N_p\}$, and t is the current value of iteration and each individual can be calculated as follows:

$$x_{i,j} = x_{l,b} + rand\ (0,1) * (x_{ub} - x_{lb}) \tag{30}$$

where x_{ub}, x_{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 ($X{\to}\alpha$), beta ($X{\to}\beta$), and delta ($X{\to}\delta$) solutions from the target vector. Succeeding the saving of the results, the target vector is exposed to a mutation in a manner resembling the MGA technique. In the proposed algorithm, donor vector $V{\to}it$ is created from the target vector $X{\to}it$ using a DE/best/1 mutation approach with a dynamic scaling factor F', which offers more arbitrariness in the initial stages, preventing the algorithm from dropping into a local optimum, while the value of F' decreases in the final stages, boosting the algorithm's convergence speed. So, the donor vector can be stated as follows:

$$|V_i^t| = \left|X_{alpha}^t\right| + F' * (|X_{R1}| - |X_{R2}|) \tag{31}$$

where X_{alpha}, t is the α solution or best solution as far and X_{R1}, X_{R2} are the randomly selected solution from the target vector and F' can be expressed as follows:

$$F' = \frac{2}{1+e^{(k*(\frac{t}{tmax})}} \tag{32}$$

IGWO's searching ability is primarily determined by the vectors A and C, where C is a randomly generated vector ranging from 0 to 2, the wolves favor exploration if $C \rightarrow > 1$ and exploitation if $C < 1$, and C plays no role in IGWO's convergence speed. Now, the only vector that is important in convergence is A, but the value of A is determined by the convergence factor or a, and the value of a 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:

$$F' = \frac{2}{1e^{(k*(\frac{t}{tmax}-\frac{1}{2})}} \tag{33}$$

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 i^th^ position vector of wolves in the t^th^ iteration as $W_i^t = \left[w_{i,2}^t, w_{i,2}^t \dots w_{i,d}^t\right]$ 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 [20-24]:

$$X_{i,j}^{t+1} = \begin{cases} V_{i,j}^t \ if\ rand(0,1) \leq CR\ OR\ j = \delta \\ X_{i,j}^t \ if\ rand(0,1) > CR\ AND\ j \neq \delta \end{cases} \tag{34}$$

4.5. Research procedure

The objectives of this will be realized as follows:

1. An objective function based (base case, without FACTS) for maximization total transfer capability as the optimization problem will be formulated and solution derived
2. 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
3. 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
4. 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

5. The results will be assessed and effects of individual FACTS devices compared to each other for the four system parameters under consideration.
6. The proposed test networks will be the standard IEEE 30 bus test system
7. Simulation will be carried out in MATLAB

5. RESULTS AND DISCUSSION

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

5.1.1. Voltage profile curve (Base case, without optimized FACTS)

Figure 2 below shows the voltage profile curve for the base case (Base case, without optimized FACTS). The maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995 p.u.).

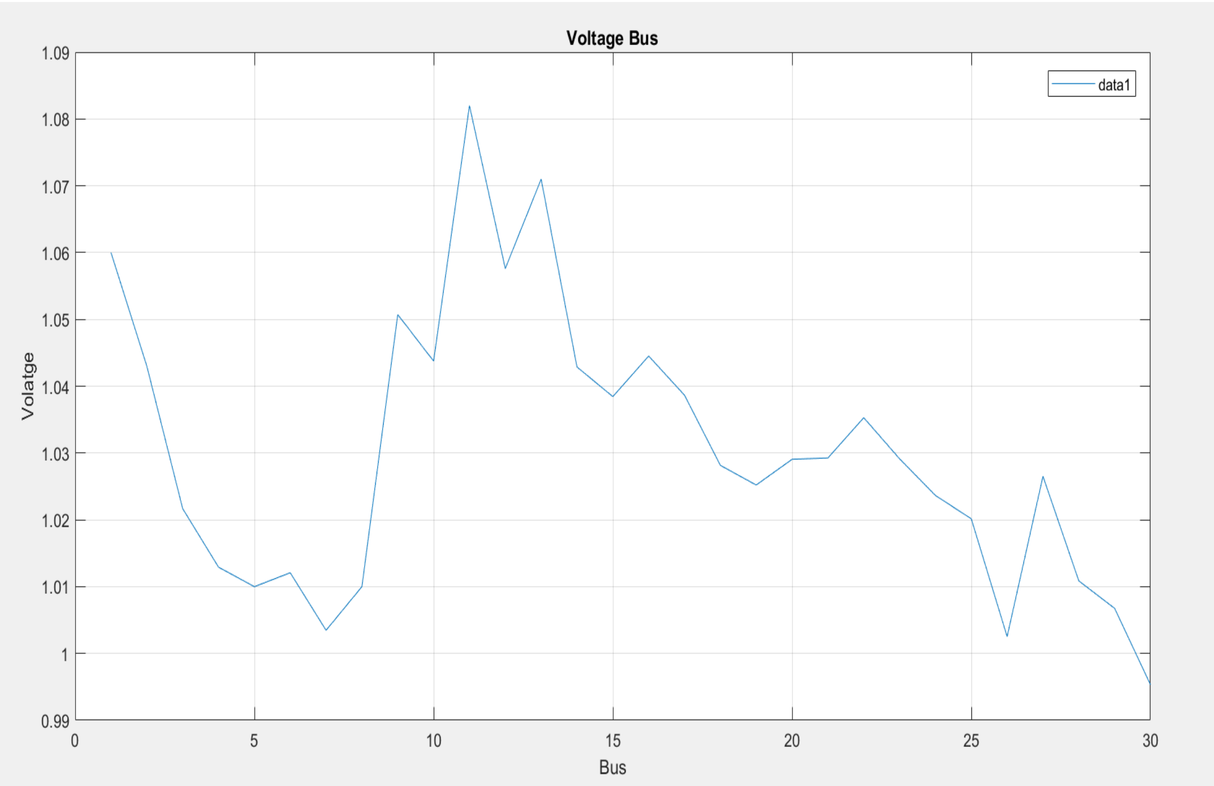

Figure 2: Voltage profile curve (Base case, without optimized FACTS

5.2. OPF with GA-tuned UPFC

5.2.1. Optimization results

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

Table 1. Optimization results

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

5.2.2. Voltage profile curve with GA-tuned UPFC

Figure 3 below shows the voltage profile curve for the with GA-optimized UPFC FACTS). The maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995 p.u.). There is no significant variation of the voltage profiles with application of GA-tuned UPFC FACTS controller as compared to the base case scenario.

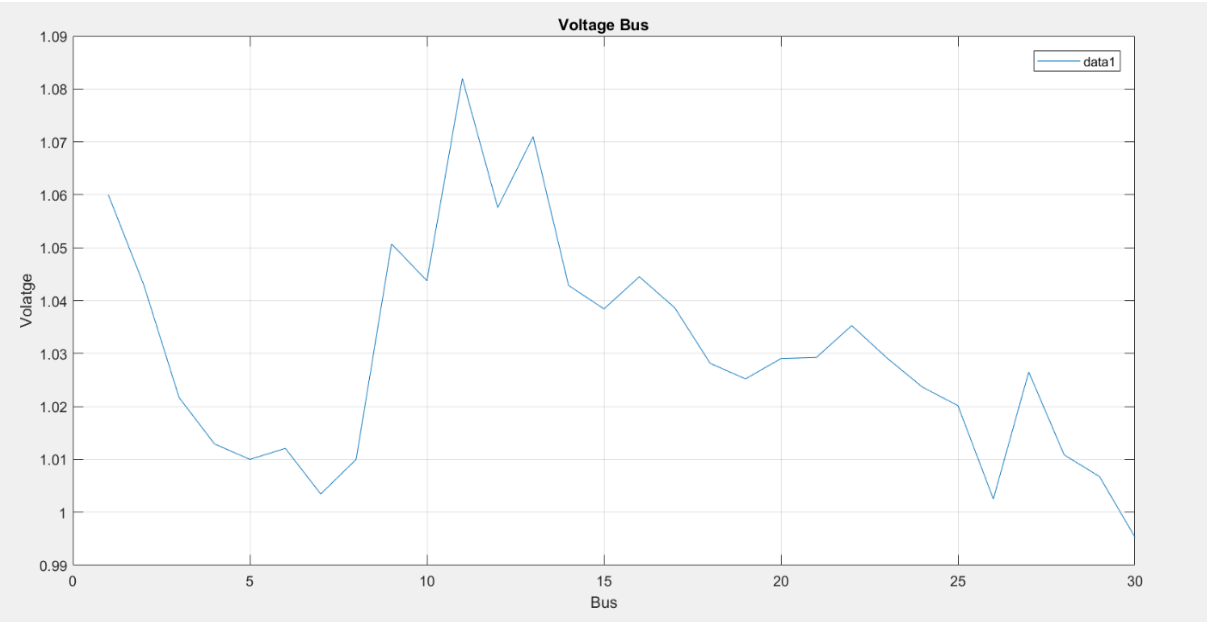

Figure 3: Voltage profile curve with GA-tuned UPFC

5.3. OPF with GA-tuned TCSC

5.3.1. Optimization Results

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

Table 2. Optimization Results

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

5.3.2. Voltage profile curve with GA-tuned TCSC

Figure 4 below shows the voltage profile curve for the with MGA-optimized TCSC FACTS controller. The maximum p.u. value is observed at bus 12 (1.081p.u.) and lowest value is observed at bus 30 (0.997 p.u.). There is no significant variation of the voltage profiles with application of GA-tuned UPFC FACTS controller as compared to the base case scenario.

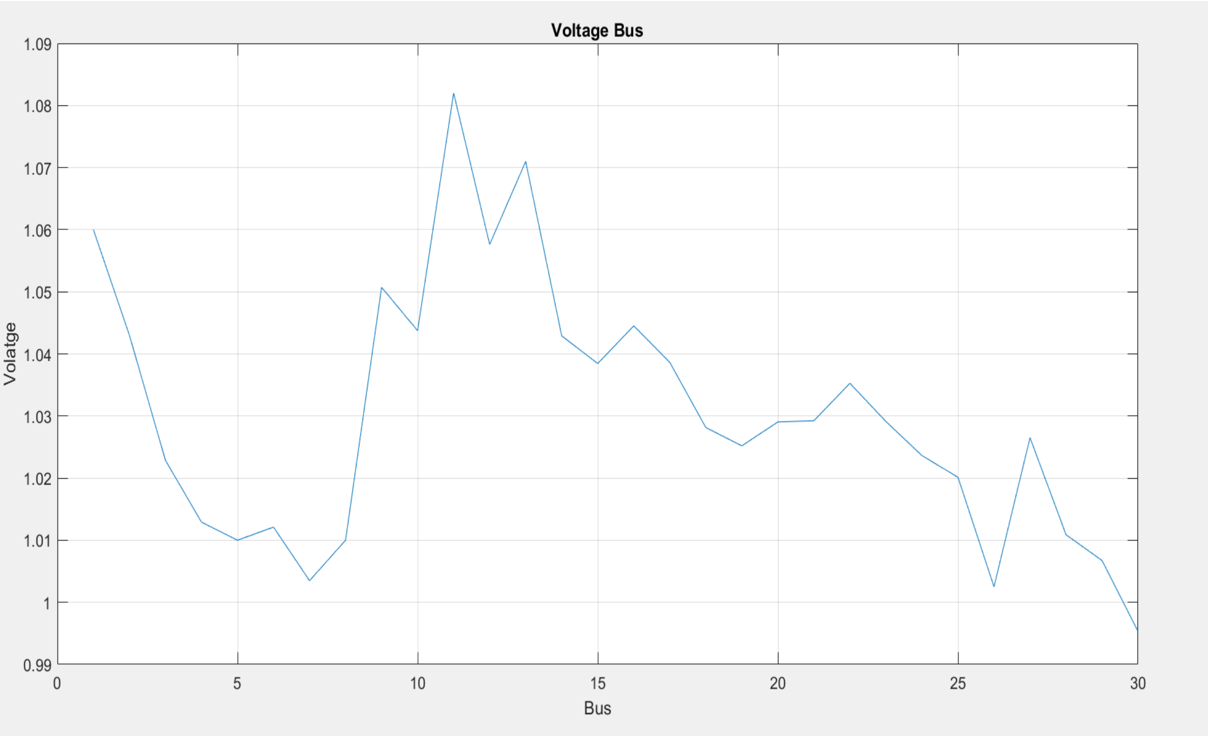

Figure 4: Voltage profile curve for the with GA-optimized TCSC FACTS Device

5.4. OPF with IGWO-tuned UPFC

5.4.1. Optimization results

Table 3 below shows the optimization results for IGWO-tuned UPFC:

Table 3: 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

5.4.2. Voltage profile curve with IGWO-tuned UPFC

Figure 5 below shows the voltage profile curve for the IGWO-optimized UPFC FACTS controller. The maximum p.u. value is observed at bus 12 (1.102p.u.) and lowest value is observed at bus 5 (1.03 p.u.). There is significant variation of the voltage profiles with application of IGWO-tuned UPFC FACTS controller as compared to the base case scenario and GA-tuned UPFC and GA-tuned TCSC FACTS controllers.

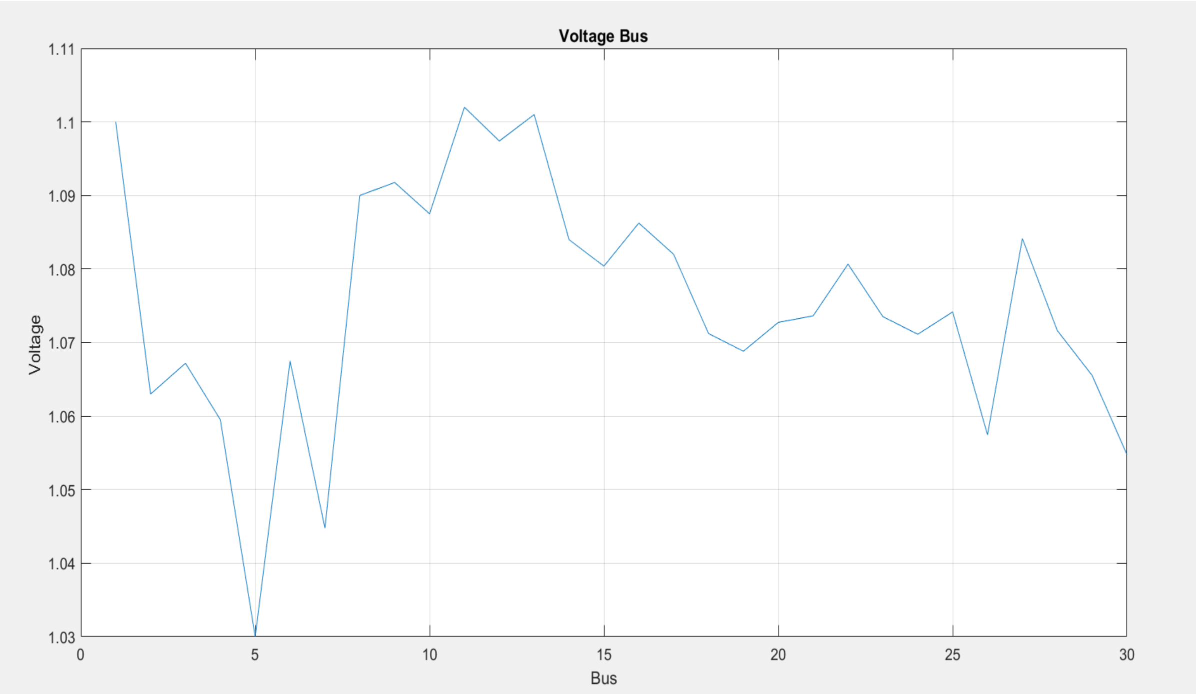

Figure 5: Voltage profile curve with IGWO-tuned UPFC

5.5. OPF with IGWO-tuned TCSC

5.5.1. Optimization results

Table 4 shows the optimization results for IGWO-tuned TCSC

Table 4. Optimization results

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

5.5.2. Voltage profile curve with IGWO-tuned TCSC

Figure 6 below shows the voltage profile curve for the with IGWO-optimized TCSC FACTS controller. The maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995p.u.). There is no significant variation of the voltage profiles with application of IGWO-tuned TCSC FACTS controller as compared to the base case scenario and GA-tuned TCSC FACTS controllers but there is significant variation of the voltage profiles with GA-tuned UPFC case.

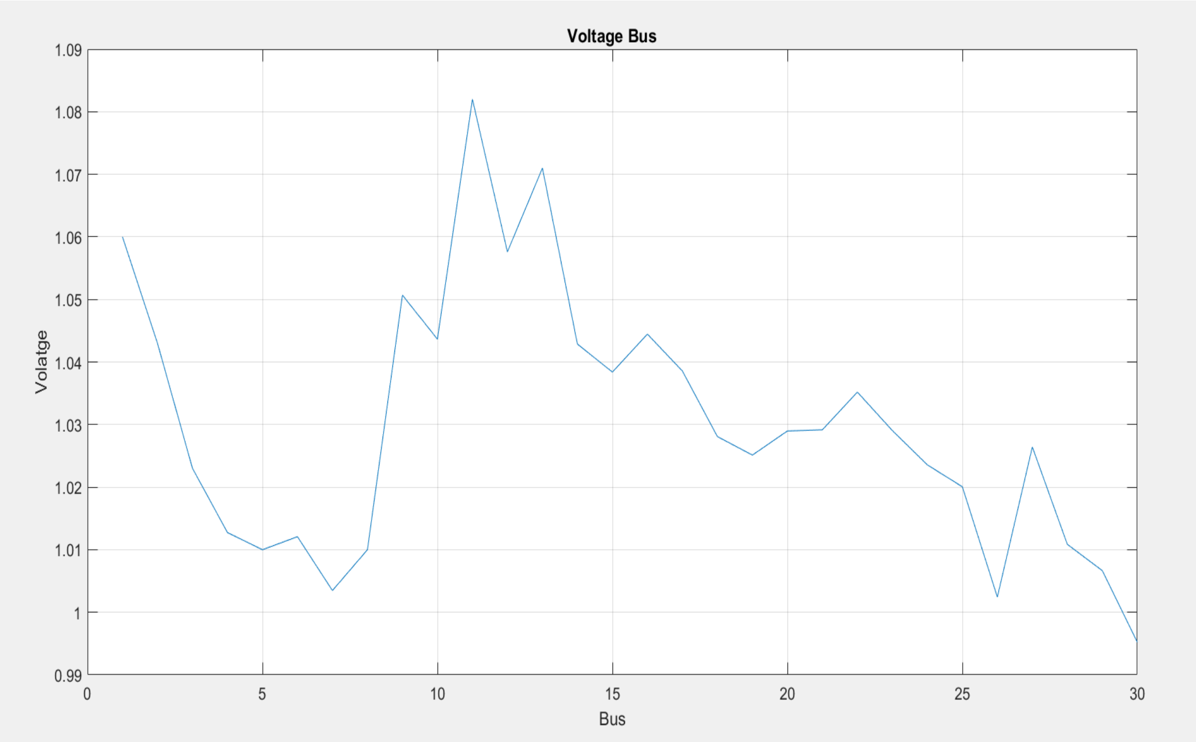

Figure 6: Voltage profile curve with IGWO-tuned TCSC

5.6. OPF with Hybrid MGA and IGWO-tuned UPFC

5.6.1. Optimization results

Table 5 below shows the optimization results for Hybrid MGA and IGWO-tuned UPFC

Table 5. Optimization results

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

5.6.2. Voltage profile curve with Hybrid M and IGWO-tuned UPFC

Figure 7 below shows the voltage profile curve for the with Hybrid MGA and IGWO-optimized UPFC FACTS controller. The maximum p.u. value is observed at bus 12 (1.1302p.u.) and lowest value is observed at bus 5 (1.04 p.u.). There is significant variation and enhancement of the voltage profiles with application of Hybrid GA and IGWO-tuned UPFC FACTS controller as compared to the base case scenario and also as compared MGA-tuned UPFC MGA-tuned TCSC FACTS and IGWO-tuned UPFC controllers.

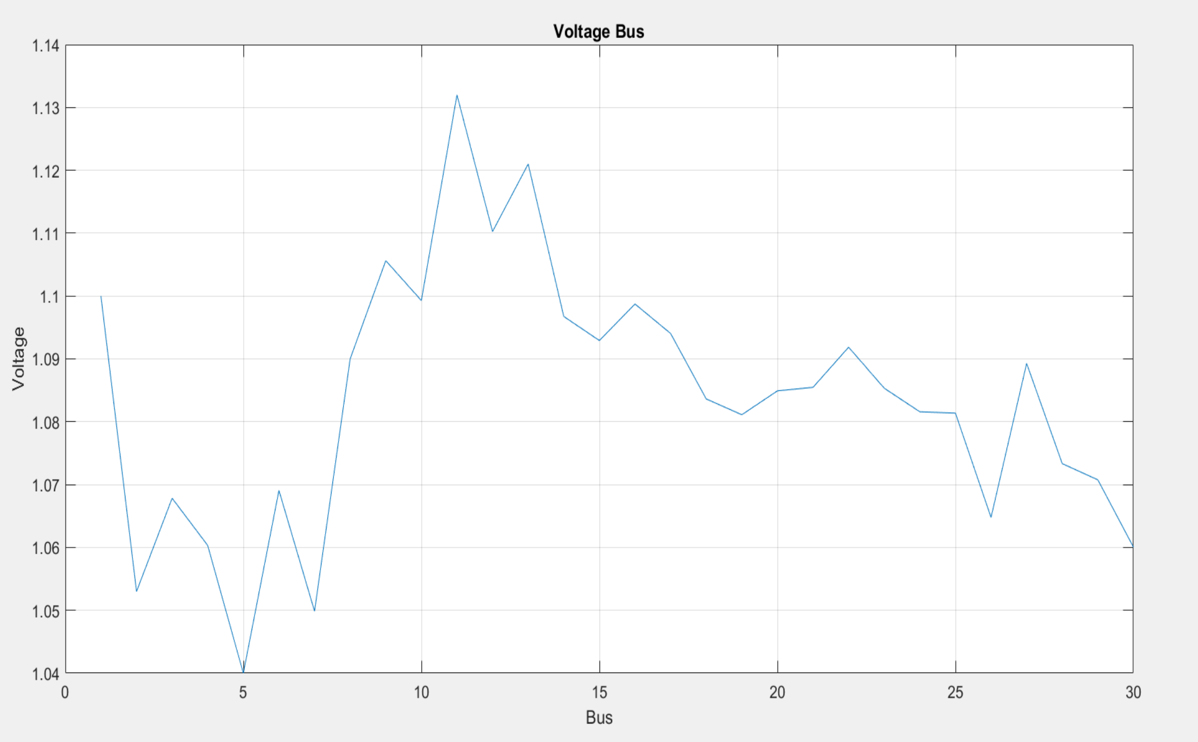

Figure 7: Voltage profile curve with Hybrid MGA and IGWO-tuned UPFC

5.7. OPF with Hybrid GA and IGWO-tuned TCSC

5.7.1. Optimization results

Table 6 below shows the optimization results for Hybrid MGA and IGWO-tuned TCSC

Table 6: Optimization results

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

5.7.2. Voltage profile curve with Hydrid MGA and IGWO-tuned TCSC

Figure 8 below shows the voltage profile curve for the Hybrid MGA and IGWO-tuned TCSC FACTS controller. The maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995 p.u.). There is no significant variation and enhancement of the voltage profiles with application of Hybrid MGA and IGWO-tuned TCSC FACTS controller as compared to the base case scenario and also as compared to MGA-tuned TCSC FACTS and IGWO-tuned TCSC. There is however significant variation and enhancement of the voltage profiles with MGA-tuned UPFC.

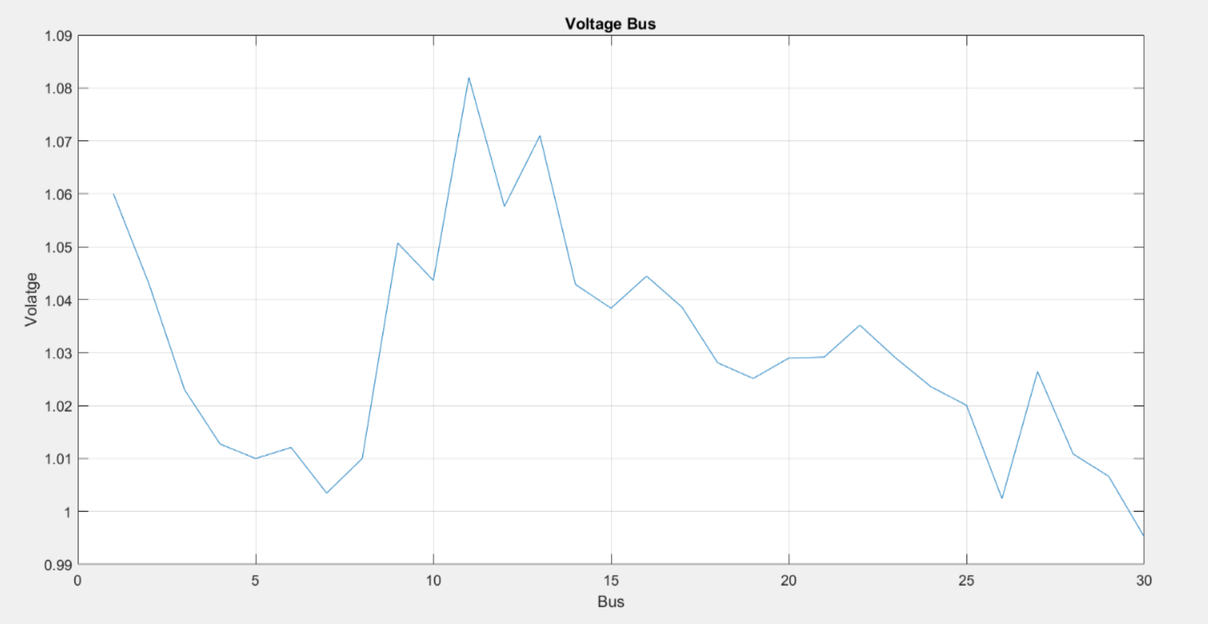

Figure 8: Voltage profile curve with Hybrid GA and IGWO-tuned TCSC

5.8. Bus voltage profiles for different optimization techniques

The voltage profile curve for the base case (Base case, without optimized FACTS). The maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995 p.u.). For the voltage profile curve for the with GA-optimized UPFC FACTS), the maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995 p.u.). There is no significant variation of the voltage profiles with application of GA-tuned UPFC FACTS controller as compared to the base case scenario. For the voltage profile curve for the with MGA-optimized UPFC FACTS), the maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995 p.u.). There is no significant variation of the voltage profiles with application of GA-tuned UPFC FACTS controller as compared to the base case scenario. For the voltage profile curve for the with MGA-optimized TCSC FACTS controller, the maximum p.u. value is observed at bus 12 (1.081p.u.) and lowest value is observed at bus 30 (0.997 p.u.). There is no significant variation of the voltage profiles with application of MGA-tuned UPFC FACTS controller as compared to the base case scenario. For the voltage profile curve for the with IGWO-optimized UPFC FACTS controller, the maximum p.u. value is observed at bus 12 (1.102p.u.) and lowest value is observed at bus 5 (1.03 p.u.). There is significant variation of the voltage profiles with application of IGWO-tuned UPFC FACTS controller as compared to the base case scenario and GA-tuned UPFC and GA-tuned TCSC FACTS controllers. For the voltage profile curve for the with IGWO-optimized TCSC FACTS controller, the maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995p.u.). There is no significant variation of the voltage profiles with application of IGWO-tuned TCSC FACTS controller as compared to the base case scenario and GA-tuned TCSC FACTS controllers but there is significant variation of the voltage profiles with MGA-tuned UPFC case. For the voltage profile curve for the with IGWO-optimized UPFC FACTS controller, the maximum p.u. value is observed at bus 12 (1.1302p.u.) and lowest value is observed at bus 5 (1.04 p.u.). There is significant variation and enhancements of the voltage profiles with application of Hydrid MGA and IGWO-tuned UPFC FACTS controller as compared to the base case scenario and also as compared MGA-tuned UPFC GA-tuned TCSC FACTS and IGWO-tuned UPFC controllers. For the voltage profile curve for the with Hydrid MGA and IGWO-tuned TCSC FACTS controller, the maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995 p.u.). There is no significant variation and enhancement of the voltage profiles with application of Hydrid MGA and IGWO-tuned TCSC FACTS controller as compared to the base case scenario and also as compared to MGA-tuned TCSC FACTS and IGWO-tuned TCSC. There is however significant variation and enhancements of the voltage profiles with MGA-tuned UPFC.

The figure below shows the bus voltage profiles for different optimization techniques**:**

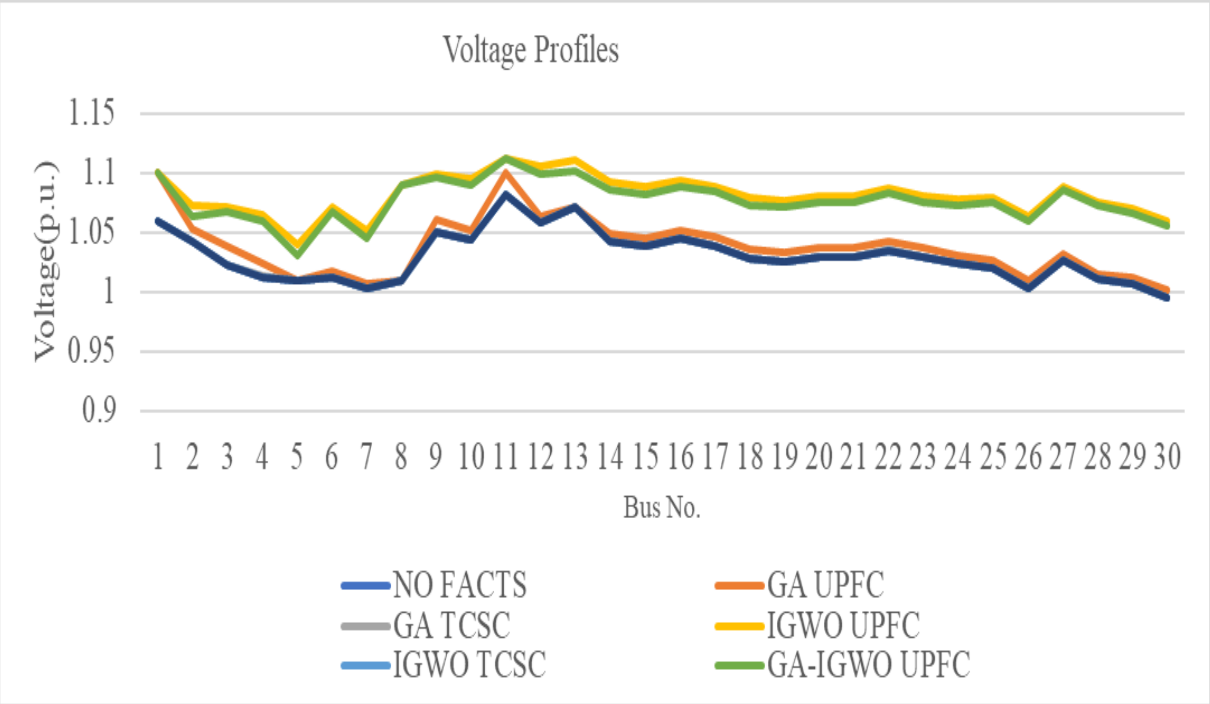

Figure 9: bus voltage profiles for different optimization techniques

6. CONCLUSION

There is no significant variation of the voltage profiles with application of GA-tuned UPFC FACTS controller as compared to the base case scenario. For the bus voltage profile curve for the GA-optimized TCSC FACTS controller, the maximum p.u. value is observed at bus 12 (1.081p.u.) and lowest value is observed at bus 30 (0.997 p.u.). There is no significant variation of the voltage profiles with application of GA-tuned UPFC FACTS controller as compared to the base case scenario. For the voltage profile curve for the with IGWO-optimized UPFC FACTS controller, the maximum p.u. value is observed at bus 12 (1.102p.u.) and lowest value is observed at bus 5 (1.03 p.u.). There is significant variation of the voltage profiles with application of IGWO-tuned UPFC FACTS controller as compared to the base case scenario and GA-tuned UPFC and GA-tuned TCSC FACTS controllers. For the voltage profile curve for the with IGWO-optimized TCSC FACTS controller, the maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995p.u.). There is no significant variation of the voltage profiles with application of IGWO-tuned TCSC FACTS controller as compared to the base case scenario and GA-tuned TCSC FACTS controllers but there is significant variation of the voltage profiles with GA-tuned UPFC case. For the voltage profile curve for the with IGWO-optimized UPFC FACTS controller, the maximum p.u. value is observed at bus 12 (1.1302p.u.) and lowest value is observed at bus 5 (1.04 p.u.). There is significant variation and enhancements of the voltage profiles with application of Hydrid GA and IGWO-tuned UPFC FACTS controller as compared to the base case scenario and also as compared MGA-tuned UPFC, GA-tuned TCSC FACTS and IGWO-tuned UPFC controllers. For the voltage profile curve for the with Hydrid GA and IGWO-tuned TCSC FACTS controller, the maximum p.u. value is observed at bus 12 (1.082p.u.) and lowest value is observed at bus 30 (0.995 p.u.). There is no significant variation and enhancements of the voltage profiles with application of Hydrid GA and IGWO-tuned TCSC FACTS controller as compared to the base case scenario and also as compared to GA-tuned TCSC FACTS and IGWO-tuned TCSC. There is however significant variation and enhancements of the voltage profiles with GA-tuned UPFC. From the bus voltage profiles, Hybrid MGA and IGWO with UPFC FACTS controller showed the most significant improvement of bus voltages. It imperative to note that the techniques have brought out the inherent strengths of the FACTS controllers applied. UPFC FACTS controller showed strong performance in voltage profile improvement compared to TCSC FACTS controller. Thus, for systems with voltage profile challenges, IGWO tuned UPFC FACTS controller is preferred to tuned TCSC FACTS controller.

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