

Hybrid Capuchin Fruit Fly Optimization Algorithm for Optimal Power Flow and Transmission Congestion Management via Optimal FACTS Controller Allocation in Competitive Power Systems

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Abstract

This study aims to determine the optimal design and configuration of Flexible AC Transmission System controllers, optimizing parameters such as power flow and congestion management in the competitive electricity market. The technique proposed in the paper generates multiple solution sets in the power system according to the location and control parameters of the Static Synchronous Series Compensator, Static Synchronous Compensator, and Unified Power Flow Controller. The minimization of transmission congestion, real power loss, voltage deviation, and controller installation cost in the proposed optimization technique considers the power flow equations, bus voltage magnitude limit, line thermal limit, generator limit, and controller operation limit. The optimization technique is carried out using the Newton-Raphson power flow method to check solution feasibility and update the power system operating conditions. The suggested Hybrid Capuchin Fruit Fly Optimization Algorithm enhances the transmission capability, congestion management, voltage stability, operating cost, and secure and reliable operation of competitive power systems operating under varying loads. In the IEEE 14-bus power system, for example, a proposed congestion management strategy for the system is capable of reducing the power flow on the most congested line (Line 15 (Bus 7-9)) from 28.8804 to 24.9709 MVA, which is a 13.54% reduction. Furthermore, the Unified Power Flow Controller has the lowest cost of congestion of \$487.84/hr, just 3.85% and 0.86% lower than the Static Synchronous Series Compensator and Static Synchronous Compensator, respectively. The results show the effectiveness of the proposed control optimization-enabled controller coordination framework in enhancing congestion management and economic performance.

Keywords: *Flexible AC Transmission System (FACTS), Optimal Power Flow (OPF), Transmission Congestion Management, Competitive Power Systems, Newton–Raphson Power Flow*

1. Introduction

Restructuring and deregulation of modern power system have brought about the formation of a competitive electricity market from the traditional one, whereby the generating company, transmission company, and distribution company work together to produce electricity in the most economical and efficient way [1-3]. Competitive electricity market means that trading of electricity is not limited by local utilities; there are also bilateral transactions, multilateral transactions, and open access transmission networks [4]. Although the competitive electricity market is more efficient and offers more possibilities for customers, it increases the complexity of operations of the power system because of the unpredictable nature of power flows and frequent congestion in the transmission lines [5]. Congestion in the transmission lines is a condition whereby the power transmitted exceeds the thermal, voltage, or stability limits of the transmission lines. As a result, it decreases the reliability of the power system, increases the costs of operation of the power system, and imposes limitations on potential market transactions [6]. Thus, the problem of congestion management and OPF (Optimal Power Flow) becomes quite relevant to the safe, reliable, and efficient operation of the power system. The OPF is a mathematical programming algorithm that establishes the optimal operating point of the power system while observing certain equality and inequality constraints. The goals of OPF include the minimization of generation costs, minimization of transmission losses, improvement of voltage profiles, increasing system stability, and maximization of social welfare under secure operating conditions [8, 9]. Nevertheless, the integration of renewable energy sources, fluctuations in the load demands, and increased electricity trading add up to the uncertainty of OPF problems and necessitate the use of intelligent optimization methods and advanced control devices [10].

The Flexible AC Transmission System (FACTS) devices help manage power flows and transmission congestion without building new transmission infrastructure [11]. The FACTS devices control voltage

magnitudes, phase angles, and impedance of transmission lines with the help of fast-responding power electronic converters [12-16]. The installation of Static Var Compensator, Static Synchronous Compensator, Thyristor-Controlled Series Capacitor, Unified Power Flow Controller, and Interline Power Flow Controller increases the capacity of transmission lines, minimizes the power losses, improves the voltage stability, and increases the system security [17]. The proper placement and sizing of the FACTS devices are necessary to get the best possible technical and economic benefits and, thus, optimization is essential. The modern studies have shown the effectiveness of artificial intelligence, meta-heuristic optimization, and hybrid machine-learning approaches in dealing with complicated OPF and congestion management problems [18]. Such optimization techniques are capable of solving non-linear, non-convex, and multi-objective problems and provide faster convergence and better-quality solutions than the traditional optimization methods [19]. Thus, the combination of intelligent optimization and coordination of FACTS devices allows minimizing the generation costs, congestion costs, power losses, and voltage deviations and maximizing the system reliability and market efficiency [20].

1.1. Literature Review

One of the most efficient optimal coordination strategies for maximization of the reactive power optimization of various FACTS controllers was proposed by Bhattacharyya et al. (2026) [21]. The authors aimed at improving the voltage profiles, reducing reactive power losses, and enhancing system stability in order to ensure voltage regulation and reactive power compensation. However, as only reactive power optimization issues were considered in the study, there are no findings related to the issues of transmission congestion management, congestion cost, market-oriented constraints for competitive electricity markets, and integrated optimal power flow. Hence, the findings can be applicable only in case of the market-oriented congestion management issues. Thus, the study is limited in its application as it can be used only for solving the problems of market-oriented congestion management as it does not consider the combination of both technical and economic aspects.

The comparison of Enhanced Particle Swarm Optimization (EPSO) and Mixed Integer Linear Programming (MILP) in terms of cost-effective transmission congestion management of deregulated power systems was conducted by Ogunwale et al. (2026) [22]. These two approaches were compared in terms of congestion cost minimization, computational efficiency, and quality of solution in competitive market conditions. Both approaches proved to be effective in minimization of congestion cost; however, the MILP had scalability issues in large-scale systems, while EPSO required a correct choice of the parameters. Thus, there is no investigation of the optimal placement of FACTS devices and coordinated congestion control of these devices in the paper. For these reasons, the study can be considered a study of the congestion cost optimization, without taking into account the controllability of the FACTS devices, to improve the power flow, voltage stability, and congestion issues. As a result, the study mainly deals with the issue of congestion cost optimization using computational methods without exploiting the controllability of FACTS devices in order to optimize power flow, voltage stability, and congestion at the same time.

Probabilistic deep learning-based control strategy for hybrid FACTS devices in order to enhance the voltage stability of renewable-rich power grids was proposed by Harrison et al. (2026) [23]. Probabilistic forecasting and intelligent control were used to enhance the effectiveness of voltage regulation in uncertain conditions of renewable energy generation that resulted in enhanced voltage stability and fast dynamic response in comparison with the traditional controller design. However, in spite of the effectiveness of the strategy, the authors mainly investigate the issues of voltage stability and real-time control, while there is no investigation of the congestion cost, economic optimal power flow, or optimal placement of several FACTS devices. Moreover, the main idea of this strategy is learning-based control; hence, there is a lack of the integrated optimization of device placement, operating parameters, congestion, and economics. Thus, there is a lack of the integrated optimization of device placement, operating parameters, congestion, and economic goals.

Fata Morgana Algorithm was proposed by Aljaidi et al. (2025) [24] in order to find the optimal placement of FACTS devices in uncertain load conditions for minimization of power losses and investment costs. Fata Morgana Algorithm helped to find the appropriate locations for FACTS and improved voltage stability and reduced transmission losses in scenario-based operating conditions. In spite of the success of the suggested algorithm, the study mainly deals with the issues of FACTS placement and investment cost optimization but not with coordinated power flow control and transmission congestion management. Besides, there is no comprehensive investigation of the minimization of congestion cost and coordinated multi-FACTS operation in competitive electricity markets. Thus, there is still room for development of the integrated approach that considers technical, operational, and economic aspects simultaneously.

The optimization technique – Adaptive Randomized Sine Cosine Algorithm – was applied for the optimization of wind-integrated power systems with FACTS devices by Agrawal et al. (2025) [25]. The technique effectively minimized the generation costs, transmission losses, and voltage deviations and helped to improve renewable energy integration; besides, it had higher convergence speed and solution quality than classical algorithms. However, this research mainly focused on the optimization of wind-integrated power systems but not on the congestion management in competitive electricity markets or coordinated control of several FACTS devices. Thus, it does not fully capture the combined effects of FACTS placement, operating control, congestion cost, power losses, and voltage deviation under competitive market conditions.

1.2. Research Motivation

Nevertheless, even though considerable progress has been achieved in implementing the FACTS controllers for an optimal power flow and congestion management, some flaws are yet to be noted in the literature available on this subject. Firstly, the majority of optimization models are based on a single criterion, such as reactive power optimization, voltage stability improvement, congestion cost reduction, minimizing of transmission losses, etc., without considering any other operational aspects of the power system under

consideration, as it operates in a competitive market environment. Application of conventional metaheuristic algorithms to solve the OPF issue has several disadvantages including early convergence, sensitivity of parameters, and poor performance and reduced solution quality in solving highly nonlinear and large-scale OPF issues. In addition, most of the optimization techniques consider only the optimal placement of FACTS controllers but ignore their coordinated control in real time, which makes their applicability limited in case of variable load demand and uncertain production of renewable energy sources. Deep learning control techniques have better performance compared to other types of control when it comes to voltage regulation, but they usually require big data and significant computational power, and show lower robustness in the case of abrupt changes in operating conditions of the power system. Moreover, many existing optimization techniques operate under deterministic conditions without sufficient consideration of uncertainties in generation of renewable sources, load fluctuation, and electricity market transactions. Furthermore, the techniques used for congestion management focus more on economic performance than transmission security, voltage profile improvement, and overall reliability of the power system. In addition, the optimization problem of coordinating multiple FACTS controllers is a challenging task since it requires high computational capabilities due to the complexity of interactions between numerous variables and constraints in the power system. Last, the inadequacy of the present frameworks to optimize the above-mentioned characteristics simultaneously and at the same time minimize the congestion costs, generation cost, transmission losses, and voltage deviation, while maximizing the system security and the market efficiency is clear. Thus, it is necessary to develop an intelligent hybrid optimization technique that provides robust, adaptive, and computationally efficient solutions for optimal power flow and congestion management in a competitive power system.

1.3. Research Objectives

- To provide a suitable power flow analysis model which ensures minimum transmission congestion, minimum power loss and voltage stability in competitive power systems while satisfying all operating conditions and system constraints.
- To optimally determine the location and tuning of FACTS controllers using an optimization technique to enhance the power transfer capacity of the network, reduce transmission congestion and also to minimize the overall cost of system operation.
- To show the effectiveness of the suggested optimization approach in mitigating transmission congestion, enhancing the stability of the system, and optimizing its power flow as well as economic performance, by conducting the test on standard IEEE test systems.
- To perform comparative evaluation of the proposed HCFFOA technique with respect to some other newly developed metaheuristic techniques [21-25] in the aspects of convergence rate, solution accuracy, congestion cost, transmission losses and voltage profile improvement.

2. Problem Formulation

The architecture of the suggested system has been presented in Figure 1 below. The architecture of the proposed system provides a holistic approach for the optimization of power flow and congestion by using Flexible AC Transmission Systems (FACTS) controllers in Newton-Raphson power flow method. Firstly, the input data of the power transmission network are taken into account as bus data, generator data, transmission line data, load data, operational constraints, and market data. The three FACTS controllers consisting of Static Synchronous Series Compensator (SSSC), Static Synchronous Compensator (STATCOM), and Unified Power Flow Controller (UPFC) are introduced in the network for dynamic control of the transmission parameters. In addition to this, the SSSC controller is used for the control of line impedance and real power flow as a controllable series voltage source and the STATCOM controller is used for reactive power compensation as a shunt compensator and bus voltage regulation.

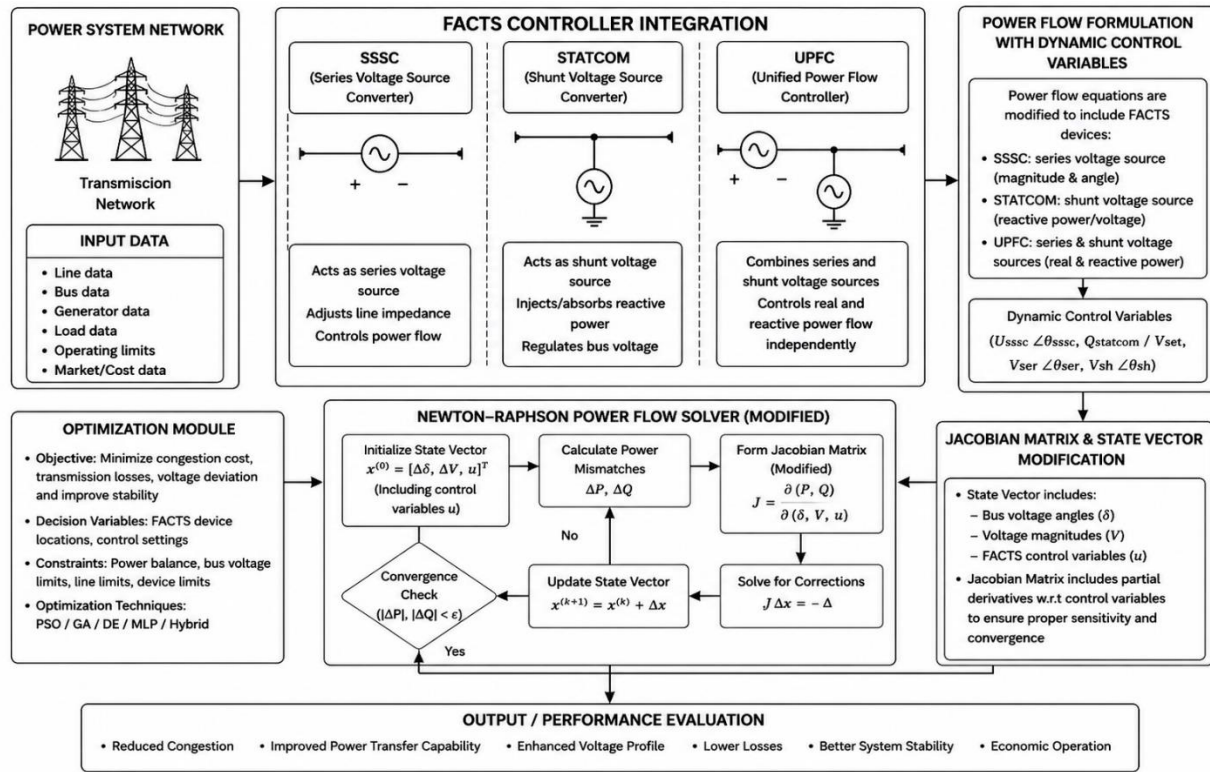


Figure 1: Architecture of the proposed system

This is because the UPFC utilises both series and shunt compensation to ensure independent control of the active and reactive power, and to increase transmission flexibility. That is, it will be possible to include the control variables in the power flow equations by adding the control variables to the state variables and the Jacobian matrix, and to consider the characteristics of the FACTS devices in the iterative power flow analysis. The optimization module will be tasked with finding the best placement and orientation of the FACTS devices when operating under power balance, voltage limits, transmission limits, and FACTS device operating constraints. Power mismatch calculation, Jacobian modification, calculation of corrections, and convergence test will be undertaken at each iteration until the necessary tolerance level is attained. The result will be an optimal operating state that will minimize transmission congestion, increase transmission capacity, improve voltage profile, minimize transmission losses, improve system stability, and achieve economic operation of the network. This integrated architecture provides a reliable and intelligent

framework for secure congestion management and optimal utilization of transmission infrastructure in modern competitive electricity markets.

2.1 Mathematical model of SSSC

Static Synchronous Series Compensators (SSSC) – these FACTS devices have a controlled series voltage source used to control power flow. The joint use of the DC-AC inverter and series injection transformer ensures variability in the value of the effective impedance of the transmission lines using the SSSC. The reduction in impedance means that the power transfer is higher, whereas the higher impedance value indicates lower power transfer. As a result, the SSSC becomes more flexible and increases the stability of the transmission system. In terms of math, SSSC can be thought of as a voltage source that can be controlled and is connected in series with an impedance that matches the injection transformer's leakage impedance. By keeping the injected voltage level and phase angle well within certain limits, SSSC can precisely control the flow of active and reactive power between two buses that are connected to each other.

All of these make it a very essential tool for the integration of stability and power flow management in the grid systems of today. The voltage injection behaves as a series voltage source, changing the effective impedance of the transmission line. The phase angle ' δ_{se} ' is restricted within the range $0 \leq \delta_{se} \leq \delta_{se,max}$ to maintain effective power flow management and system stability. Similarly, magnitude on the injected voltage ' V_{se} ' is constrained within $V_{se,min} \leq V_{se} \leq V_{se,max}$, ensuring optimal performance without exceeding operational limits.

Through the dynamic changes of the parameters, SSSC improves the efficiency of power transmission without compromising on reliability of the system. This constraint ensures that SSSC does not inject very much voltage into the system, thus preventing any overcompensation and the problem of system voltage instability. Since SSSC regulates both the amplitude and phase angle by varying them within those

constraints, power transmission control, congestion control, and transmission efficiency are achieved effectively while operating within its design capabilities.

By adding the SSSC in the transmission line that is near bus 'k', a new bus 'm' is added to the power system and, therefore, the n-bus system becomes (n+1)-bus system. With the addition of this new bus, the line impedance changes because the initial line impedance becomes the new line impedance for buses 'm' and 'm'. For the ease of the calculations, the pure reactance of the converter transformers can be assumed since they do not transfer any real power but affect reactive power flow in the system. SSSC adds the effects of series voltage injection in the power flow equations at the buses, which leads to the alteration of the system power flow distribution and hence provides enhanced controllability over power flow. The complex power supplied by bus 'k' due to the installation of the SSSC can be expressed in the following way:

$$S_k = V_k I_k^* \quad (1)$$

$$I_k = \frac{V_k - V_{se} - V_m}{jX_{se}} \quad (2)$$

Substituting equation (2) in equation (1), we get

$$S_k = V_k \left(\frac{V_k - V_{se} - V_m}{jX_{se}} \right) \quad (3)$$

Solving equation (3) and splitting into real and imaginary components, we obtain the power injections at bus 'k'.

$$P_k = \frac{V_k V_m \sin(\delta_k - \delta_m)}{X_{se}} + \frac{V_k V_{se} \sin(\delta_k - \delta_{se})}{X_{se}} \quad (4)$$

$$Q_k = \frac{V_k^2}{X_{se}} - \frac{V_k V_m \cos(\delta_k - \delta_m)}{X_{se}} - \frac{V_k V_{se} \cos(\delta_k - \delta_{se})}{X_{se}} \quad (5)$$

The power injected as a consequence of the SSSC at bus 'm' shall work on the principle of power injection at bus 'k'. Since the SSSC is a reactive device, which does not generate or absorb any active power but just redistributes it, the active power injection at bus 'm' shall be equal in magnitude and opposite in sign to

that at bus 'k'. This ensures that the system's total active power remains balanced. Thus, the real power at bus 'm' is $P_m = -P_k$. All injected power equations at bus 'm'.

$$P_m = - \left(\frac{V_k V_m \sin(\delta_k - \delta_m)}{X_{se}} + \frac{V_k V_{se} \sin(\delta_k - \delta_{se})}{X_{se}} \right) \quad (6)$$

$$Q_m = \frac{V_m^2}{X_{se}} - \frac{V_k V_m \cos(\delta_k - \delta_m)}{X_{se}} - \frac{V_k V_{se} \cos(\delta_k - \delta_{se})}{X_{se}} \quad (7)$$

Adjustments in power at bus bars with SSSC can be described as follows. Superscript "old" indicates the power before the installation of the controller, whereas "new" refers to the power after the SSSC controller has been incorporated in the system. This modification reflects the influence of the SSSC on the regulation of power flow and enhancement of system performance.

$$P_k^{new} = P_k^{old} + P_k; Q_k^{new} = Q_k^{old} + Q_k; P_m^{new} = P_m^{old} + P_m; Q_m^{new} = Q_m^{old} + Q_m \quad (8)$$

2.2 Mathematical model of STATCOM

The static synchronous compensator (STATCOM) is a shunt type FACTS device that helps increase voltage stability by injection or absorption of reactive power on the bus to which it is connected. Different from the common compensation systems, it does not provide active power to the power grid. Instead, it varies the output voltage of the DC-AC converter through DC link. When the voltage at the bus to which it is connected is less than the output voltage of STATCOM, then it provides reactive power to the grid, thus increasing the voltage stability. However, when the voltage at the bus is more than the voltage of STATCOM, then it absorbs the reactive power to help stabilize the voltage. This is mainly because the static synchronous compensator is a controlled voltage source, since the output voltage forms the basic building block of the converter. The magnitude as well as the phase angle of the output voltage allow for controlling the reactive power exchanged between the system and the converter. Dynamic control of the phase angle ' δ_{sh} ' and voltage magnitude ' V_{sh} ' allows controlling the reactive power compensation of STATCOM. For regulation of the reactive power compensation, STATCOM dynamically changes the phase angle, ' δ_{sh} ', which stays within the limits of $0 \leq \delta_{sh} \leq \delta_{sh,max}$. At the same time, the voltage magnitude,

' V_{sh} ', changes within $V_{sh,min} \leq V_{sh} \leq V_{sh,max}$. Hence, dynamic control of voltage magnitude and phase angle helps to ensure voltage stability, minimize voltage fluctuations, and enhance the overall power quality and grid reliability in real time. The STATCOM helps control the voltage of bus 'k' through the process of reactive power injection or absorption. For simplicity, the resistance of the coupling transformer is assumed to be negligible compared to its reactance. Hence, there occurs a change in the power balance of bus 'k'.

2.3 Mathematical model of UPFC

Unified Power Flow Controller (UPFC) is the most modern FACTS technology which comprises both the STATCOM and SSSC devices. Both shunt and series UPFC branches enable the control of power flow and voltage regulation simultaneously, thus increasing the ability of power transmission and enhancing the system stability. Being the bidirectional power flow controller, the UPFC enables dynamic management of reactive power. The UPFC includes two DC-AC converters linked together via the single DC link. Furthermore, the series converter is used to control the impedance, phase angle, and the power flow, while the shunt converter controls the voltage of the bus by regulating the reactive power compensation. Therefore, although independent of one another, both converters are able to compensation power quite well. The magnitude and phase angle of the injected voltage can be adjusted by the UPFC to increase the power transfer, minimize the transmission losses, and maintain the voltage stability. The next sections give some additional detail on the power flow equations, control methods, and how the UPFC affects system stability. The UPFC can be seen as two voltage sources, which can be considered as the output voltage key components of the two coupling transformers, respectively. The equivalent UPFC diagram is shown in figure 2. The UPFC injected voltage equation to the transmission line is given as,

$$U_{inj}^{se} = re^{m\theta} U_a \quad (9)$$

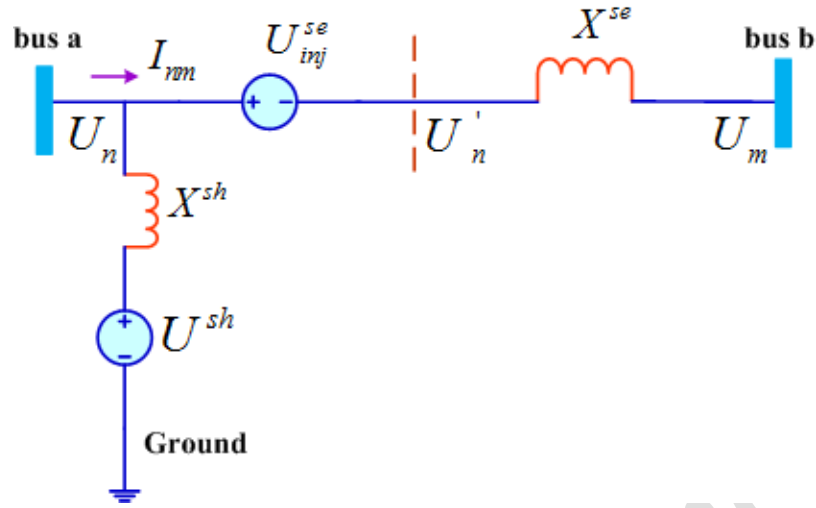


Figure 2: Equivalent model of UPFC

The injected voltage in the transmission line is denoted by U_{inj}^{se} , while r represents the magnitude of the series voltage source and θ denotes its phase angle. The system voltage is represented by U_a . The allowable limits of the associated parameters are specified below,

$$0 \leq r \leq r_{\max} \text{ and } 0 \leq \theta \leq 2\pi \quad (10)$$

The series-injected current in the transmission line can be expressed as follows,

$$C_{inj}^{se} = -jm^{se}U_{inj}^{se} \quad (11)$$

Here, series injected current in the transmission line is specified as m^{se} . Then the, $m^{se} = 1/X^{se}$ and C_{inj}^{se} can be formulated by the two auxiliary buses a and b in an injection powers.

$$S_a^{se} = U_a (-U_{inj}^{se}) \quad (12)$$

$$S_b^{se} = U_b (-U_{inj}^{se}) \quad (13)$$

The injected power is denoted by S_a^{se} and S_b^{se} , with the corresponding real and imaginary components defined as follows,

$$S_a^{se} = P_a^{se} + jQ_a^{se} \quad (14)$$

$$P_a^{se} = rm^{se} U_a^2 \sin \theta \quad (15)$$

$$Q_b^{se} = rm^{se} U_a^2 \cos \theta \quad (16)$$

Similarly, the real and imaginary components of Equation (17) can be expressed as follows,

$$S_b^{se} = P_b^{se} + jQ_b^{se} \quad (17)$$

$$P_b^{se} = rm^{se} U_a U_b \sin (\varphi_a - \varphi_b + \theta) \quad (18)$$

$$Q_a^{se} = rm^{se} U_a U_b \cos (\varphi_a - \varphi_b + \theta) \quad (19)$$

The apparent power supplied by the series converter can be calculated as follows,

$$S^{se} = U_{inj}^{se} C_{ab} = rm^{b\theta} U_a \left(\frac{U_a - U_b}{jX^{se}} \right) \quad (20)$$

he injected current between the two auxiliary buses a and b is represented by C_{ab} , while the active and reactive powers delivered by the series converter are formulated as follows,

$$S^{se} = P^{se} + jQ^{se} \quad (21)$$

$$P^{se} = rm^{se} U_a U_b \sin (\varphi_a - \varphi_b + \theta) - rm^{se} U_a^2 \sin \theta \quad (22)$$

$$Q^{se} = -rm^{se}U_aU_b \cos(\varphi_a - \varphi_b + \theta) + rm^{se}U_a^2 \cos \theta + r^2m^{se}U_a^2 \quad (23)$$

In this case, the real and imaginary components of the apparent power generated by the series converter are denoted by P^{se} and Q^{se} , respectively. Within the specified operating limits, the reactive power capability primarily contributes to maintaining the voltage level at bus a . The UPFC problem formulation is presented in the following section.

Problem Formulation

The optimal sizing and location of the UPFC are determined using an objective function whose aim is to improve the steady-state performance of the power system, subject to dynamic stability constraints. The optimal power flow equation can thus be formulated as an optimization problem and is expressed by,

$$\begin{aligned} \text{Min } j(x,u); \frac{1}{m(x,u)} \\ \text{Subject to } n(x,u) = 0 \quad i(x,u) \leq 0 \end{aligned} \quad (24)$$

In this case, the generation cost objective function is represented by $j(x,u)$, while the total network losses and voltage deviation are represented by $m(x,u)$. The equality constraints corresponding to the specified operating conditions are denoted by $n(x,u)$, whereas the inequality constraints imposed by the operating limits are represented by $i(x,u)$. The control and dependent variables associated with the generators and loads are denoted by u and x , respectively. Using the UPFC power-flow equations, the required UPFC capacity is determined according to the system requirements. The dynamic stability objective and its associated constraints are defined in the subsequent section.

2.3.1. Power Balance Constraint

$$\sum_{a=1}^{N_g} P_{gen}^a = P_{demand} + \sum_{b=1}^{N_l} (P_l^b + jQ_l^b) \quad (25)$$

$$P_{gen}^{a(\min)} \leq P_{gen}^a \leq P_{gen}^{a(\max)} \quad (26)$$

$$P_{demand}^{\min} \leq P_{demand} \leq P_{demand}^{\max} \quad (27)$$

Here, the generated power at bus a is represented by P_{gen}^a , while the power demand is denoted by P_{demand} . The total numbers of generators and transmission lines are represented by N_g and N_l , respectively. The real and reactive power losses at bus b are denoted by P_l^b and Q_l^b , respectively. The minimum and maximum generation limits are represented by $P_{gen}^{a(\min)}$ and $P_{gen}^{a(\max)}$, while the minimum and maximum load-demand limits are denoted by $P_{demand}^{\min}$ and $P_{demand}^{\max}$, respectively.

2.3.2. Power Loss Constraint

$$P_l^m = |U_a| |U_b| |Y_{ab}| \sum_{b=1}^{N_l} \cos(\theta - \varphi_a - \varphi_b) \quad (28)$$

$$Q_l^m = |U_a| |U_b| |Y_{ab}| \sum_{b=1}^{N_l} \sin(\theta - \varphi_a - \varphi_b) \quad (29)$$

Here, the bus admittance matrix is denoted by Y_{ab} , while θ represents the angle between buses a and b . The load angles at buses a and b are represented by φ_a and φ_b , respectively.

2.3.3. Voltage Stability

$$\Delta U_a = \frac{1}{\sqrt{l}} \sqrt{\sum_{a=1}^l (U_a^k)^2} \quad (30)$$

$$\text{Here, } U_a^k = U_{sl} - \sum_{a=1}^a Z_a \left(\frac{P_a - jQ_a}{U_a} \right)$$

Here, the voltage stability index at bus a is denoted by ΔU_a , while the voltage at the slack bus is represented by U_{sl} . The impedance of bus a is denoted by Z_a , and the real and reactive powers at bus a are represented by P_a and Q_a , respectively. The total number of nodes in the system is denoted by j .

2.4. Hybrid Capuchin Fruit Fly Optimization Algorithm

This section presents the meta-heuristic algorithm which has been derived from the natural foraging behavior of the capuchin monkey and fruit flies. Capuchin monkeys are known for their fast displacement and group formation while searching for food in the forests. Fruit fly is famous for its ability to detect directions and smell concentration while searching for food in the forests. Male alpha capuchin leads the group while searching food in the group. In some cases, one male and female capuchins lead the group while searching food resources in the forest. For some cases, the group is split up into smaller groups in which members start foraging individually and helping each other in finding the food resources. Capuchin monkey makes three kinds of movement while searching for the food resources, i.e. leaping, climbing and swinging.

Exploration: Capuchins move from one tree to another tree by making a leaping movement up to three meters distance. Leaping movement is identified in three manners: moving from one to another tree, moving from one location to another in the ground, and moving from one side of riverbank to another side of the river.

Unlike fixed population partitioning strategy, the hybrid CFOA algorithm does not divide the whole population into two different Capuchin and Fruit Fly populations. Rather, the whole population follows the Capuchin mechanism during the exploration phase in which leaping, climbing and swinging are involved, and the Fruit Fly smell-concentration mechanism is followed during the exploitation phase to guide capuchins towards the promising solution. Therefore, no fixed population ratio is assigned to these two

mechanisms; rather, both of these are sequentially combined together within each iteration to balance exploration and exploitation.

The current and updated position of the capuchin during the searching of food source S_f is the target. By using third law of motion and the movement of capuchin in global search space of given dimension ' d ' as in following Eq. (31),

$$y = y_o + w_o u + \frac{1}{2} b u_t^2 \quad (31)$$

where, ' y ' represents the new position of the capuchin, y_o is the position at starting of the foraging and w_o is the velocity at initial stage and ' b ' denotes the acceleration and u_t represents the time. The jumping of the capuchin is explained by using the first law of motion as in Eq. (32),

$$w = w_o + b u_t \quad (32)$$

During the jumping behavior the position of the capuchin displacement and the new position is expressed as,

$$w_x = w_{0x} + b_x u_t = w_0 \cos(\theta_0) \quad (33)$$

where, b_x is the acceleration at the horizontal axis and the value at start is 0. New displaced distance (y) of the capuchin during jumping is expressed as follows,

$$y = y_o + w_0 \cos(\theta_0) u_t \quad (34)$$

The vertical distance of displacement (z) is measured by

$$z = z_o + w_0 \sin(\theta_0) u_t + \frac{1}{2} b_z u_t^2 \quad (35)$$

where, z_0 is the position at initial and b_z is the acceleration during vertical movement of the capuchin.

This denotes the acceleration is against the gravity which stays towards the bottom of the capuchin and expressed as,

$$y = y_0 + w_0^2 \sin(2\vartheta_0)/g \quad (36)$$

where ‘ y ’ is latest position of the capuchin and y_0 is the position at start and w_0 is the velocity at the starting position and ϑ_0 represents the angle of leaping and ‘ g ’ denotes the gravity effects with acceleration. In the search space with dimension ‘ d ’ Eq. (6) is defined with the alpha capuchins are given in Eq. (37)

$$y_j^i = S_{f(j)} + \frac{P_{tb}(w_j^i)^2 \sin(2\vartheta)}{g} \quad (37)$$

where, y_j^i identifies the alpha capuchin position in the j^{th} dimension, w_j^i is the velocity of the i^{th} capuchin in the j^{th} dimension. $S_{f(j)}$ represents the location of food in the j^{th} dimension, P_{tb} is the probability of tail balance of capuchin during movement of leaping and ‘ g ’ represents the force of gravitation and the value is 9.81. Also ϑ is the angle of jumping capuchin. The ability of the proposed algorithm for maintain a balance between exploration and exploitation stages based on the Eq. (8) as follows,

$$\zeta = \gamma_0 e^{-\gamma_1 \left(\frac{i_c}{I_{\max}} \right)^{\gamma_2}} \quad (38)$$

Where ζ represents the exponential function of the lifetime of capuchin, i_c and $I_{\max}$ represent the present and maximum iteration, respectively, while γ_0 , γ_1 and γ_2 parameters are chosen arbitrarily. Equation (8) is used to explore the search space for the optimal solutions for daily food.

Exploitation: In the Hybrid CFFOA approach presented, for the effective update of the current positions through the sensing intelligence of the Fruit Fly Optimization while searching for food, the leadership of the capuchin monkey along with its group members, based on the smell concentration-based decision ($Sense_i$) function, is used within the defined search space with the ‘ d ’ dimension.

$$Sense_i = 1/E_i \quad (39)$$

where, $E_i = \sqrt{y_i^2 + z_i^2}$ is the distance between i^{th} capuchin and initial position, $Sense_i$ denotes the concentration of smell of the enhanced i^{th} capuchin. The judgement value of the smell based is substituted in the function of judgement as in Eq. (40).

$$Smell_c = f(Sense_i) \quad (40)$$

During the exploitation stage the best position and directions depends on maximum smell concentration is recorded by following Eq. (41),

$$[Smell_{c,Best}, Best_{index}] = \min(Smell_c) \quad (41)$$

where, $Smell_{c,Best}$ is the best smell of the food source and $Best_{index}$ denotes best smell concentration value index.

Parameter Settings and Termination Criterion: The suggested HCFFOA implements a population-based iterative search algorithm where a fixed number of candidates is assessed at each iteration. The trade-off between exploration and exploitation is determined by the Basic Search Strength Coefficient (γ_0), the Exploration Control Coefficient (γ_1), and the Exploitation Control Coefficient (γ_2), and Eq. (38) governs the tail balance probability when capuchins leap. All parameters are chosen on the basis of empirical evidence to control the search behavior. Each time, the fitness values of all candidate solutions are evaluated

and the best candidate solution is saved. The algorithm terminates once the desired smell-concentration convergence criterion is met or the maximum iteration count of 100 iterations is reached.

Algorithm 1: Proposed HCFFOA for FACTS Placement and Congestion Management

1. Initiate the HCFFOA population with candidate FACTS positions and operating parameters within the specified ranges.
2. Compute the candidate solution fitness value using the Newton-Raphson power-flow analysis technique.
3. Compute the objective function taking into account the cost of congestion, real power losses, voltage deviations, and FACTS placement cost.
4. Verify the power-balance equations, voltage magnitudes, line thermal capacities, generator limits, and FACTS operating constraints.
5. Determine the optimal candidate solution based on the least feasible objective-function value.
6. Update the candidate positions using the Capuchin Monkey Optimization algorithm.
7. The Fruit Fly Optimization technique is utilized to achieve an effective balance between exploration and exploitation of the search space.
8. Calculate the power flow and objective function values for the updated candidate solutions.
9. Update the global optimal solution if a better feasible solution is obtained.
10. Continue updating the positions of the solutions and evaluating the candidate solutions until the maximum number of iterations is reached or the specified convergence criterion is satisfied.
11. Return the optimal FACTS placements and operating parameters along with the corresponding congestion cost, power losses, and voltage profile.

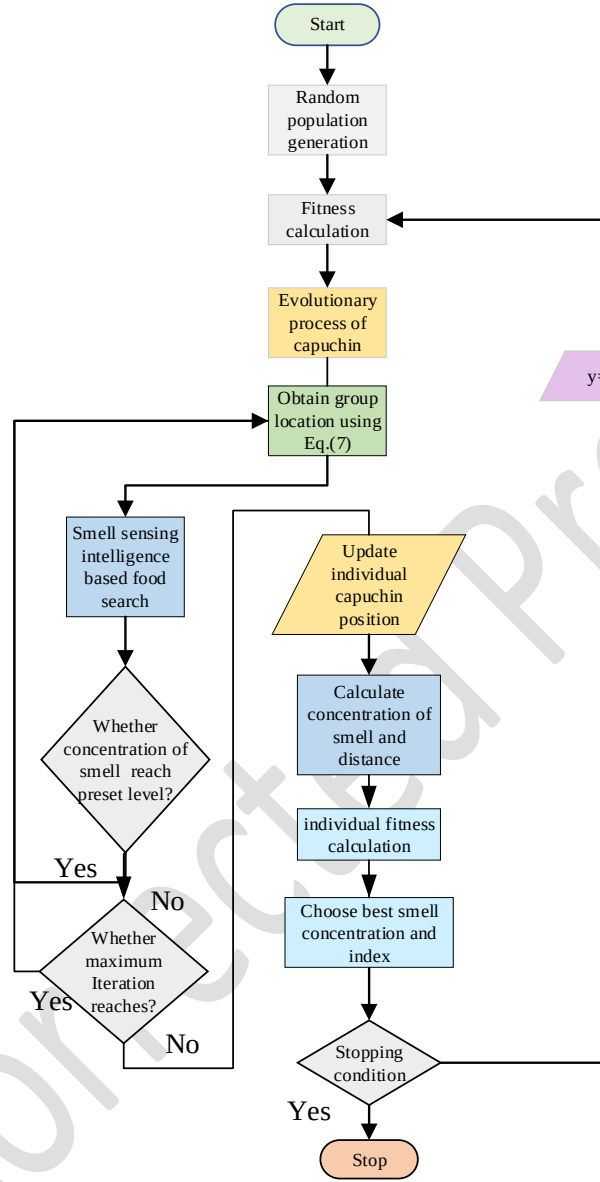


Figure 3: Flowchart of the hybrid CFOA algorithm

The flow chart of hybrid CFOA algorithm is illustrated in Fig. 3. The objective function $\min(Smell_c)$ is determined from Eq. (41). Based on the obtained objective function, the capuchin individuals change their directions and positions depending upon the concentration of smell, which results in rapid movements by capuchin individuals having abilities of leaping, swinging, and jumping towards the

optimization of the problem and reaching the optimal solution for daily food source detection as per Eqns. (42, 43).

$$X_{axis} = y(Best_{index}) \quad (42)$$

$$Y_{axis} = z(Best_{index}) \quad (43)$$

Capuchins climb and swing on trees and branches to find food resources locally using hands, legs and tails during foraging to meet daily needed food which is expressed by Eq. (44)

$$y = M \sin \mathcal{G} \quad (44)$$

where, $\mathcal{G}$ represents the angle in which the movement of the capuchin takes place from its starting position.

Using the sensing mechanism, the capuchins will move to a random position in different directions based on Eq. (45), which is expressed as follows:

$$y_j^i = \varsigma \times [B_{l,j} + \rho \times (B_{u,j} - B_{l,j})] \quad (45)$$

where $B_{l,j}$, $B_{u,j}$ indicates the lower and upper bounds of the search space in the j^{th} dimension. At the end of the optimal solution during iteration the position of the follower capuchins in the search space when follows the leader capuchins the formula is expressed in Eq. (46) as follows,

$$y_j^i = \frac{1}{2} (y_j^i + y_j^{i-1}) ; n/2 \leq i \leq n. \quad (46)$$

where, y_j^i is the present location of followers in j^{th} dimension. y_j^{i-1} represents previous position of the follower capuchin and y_j^i is the position of leaders in the j^{th} dimension.

3. Results and Discussions

The results obtained from the simulation process of the optimal power flow (OPF) and congestion control technique on the IEEE-30 bus network are presented below. The two main issues that are considered during the process include the following:

1. Optimal Power Flow (OPF) Analysis:

- Evaluation of generation fuel cost minimization in the presence of equality and inequality constraints.
- Identification of the optimal placement of (FACTS) controllers for enhancement of the power system.

2. Congestion Cost Minimization:

- Study of methods of congestion management based on generation rescheduling and FACTS controllers.
- Conducted in order to achieve controlled power flow control and optimal voltage and power regulation.

The IEEE-30 bus system is chosen as an object of the current research due to its complexity and practical importance in the study of power systems. In other words, the IEEE-30 bus system consists of 6 generator buses, 24 load buses, and 41 transmission lines. Therefore, this particular system is considered to be a good testing ground for analyzing the efficiency of OPF optimization and congestion management using FACTS technology.

The analysis in this paper will be performed according to the cost minimization of generation fuel in order to achieve efficient and stable system operation. By taking the IEEE-30 bus system as a model, some control variables such as active power generation, voltage values at PV buses, tap values of transformers, and reactive power generation from shunt VAR sources will be optimized to increase the stability, reliability, and efficiency of the system. First, the process of OPF optimization will be executed

with the minimization of fuel costs as the main objective. Table 1 summarizes the optimization results, including active power generation (P_{gen}), bus voltages (V_{gen}), transformer tap settings, and shunt compensation (Q_{sh}). Comparison of the results obtained through the use of GA and proposed PSO shows that PSO provides better convergence efficiency and lower fuel costs of \$802.55/hour in comparison to \$804.11/hour of GA. This highlights the cost-effectiveness of the proposed PSO method in OPF optimization.

Table 1: OPF Results with Fuel Cost Minimization

S. No.	Control Parameter	Existing GA Method	Proposed PSO based HCFFOA
1	PG1 (MW)	192.510	175.143
2	PG2 (MW)	48.395	49.661
3	PG5 (MW)	19.551	21.327
4	PG8 (MW)	11.620	22.609
5	PG11 (MW)	10	12
6	PG13 (MW)	12.000	12.131
7	VG1 (p.u.)	1.048	1.051
8	VG2 (p.u.)	1.0347	1.0373
9	VG5 (p.u.)	1.0186	1.0153
10	VG8 (p.u.)	1.0391	1.0414
11	VG11 (p.u.)	1.048	1.051
12	VG13 (p.u.)	1.0162	1.0148
13	Tap11 (p.u.)	1.0125	1.0148
14	Tap12 (p.u.)	0.9893	0.9864
15	Tap15 (p.u.)	0.9941	0.9922

16	Tap36 (p.u.)	0.9587	0.9554
17	Qsh,10 (MVar)	27.6214	28.3378
18	Qsh,24 (MVar)	15.4827	15.0095
19	Fuel cost (\$/hr)	804.11	802.55

Table 1 presented above shows the performance comparison of GA versus the suggested PSO based HCFFO approach for the same OPF control variables. The OPF control variables are: active power generated, generator voltage magnitude, transformer tap settings and shunt reactive power compensation. With the inclusion of the above-mentioned control variables in both the two approaches, the performance comparison can be carried out in terms of optimization.

For the above control parameters, when they are optimized, a load flow analysis is conducted so as to determine the power flows in all transmission lines. The variation in power flows when carrying out the load flow analysis is shown below in Figure 4. Above, the power flows of real and reactive powers in all the transmission lines are compared to 80% of maximum MVA rating of the lines. A transmission line which has power flows greater than 80% of its maximum MVA rating is considered to be a congested line and needs congestion relief measures. As can be seen from the above figure, the transmission line between buses 1-2 is considered to be congested.

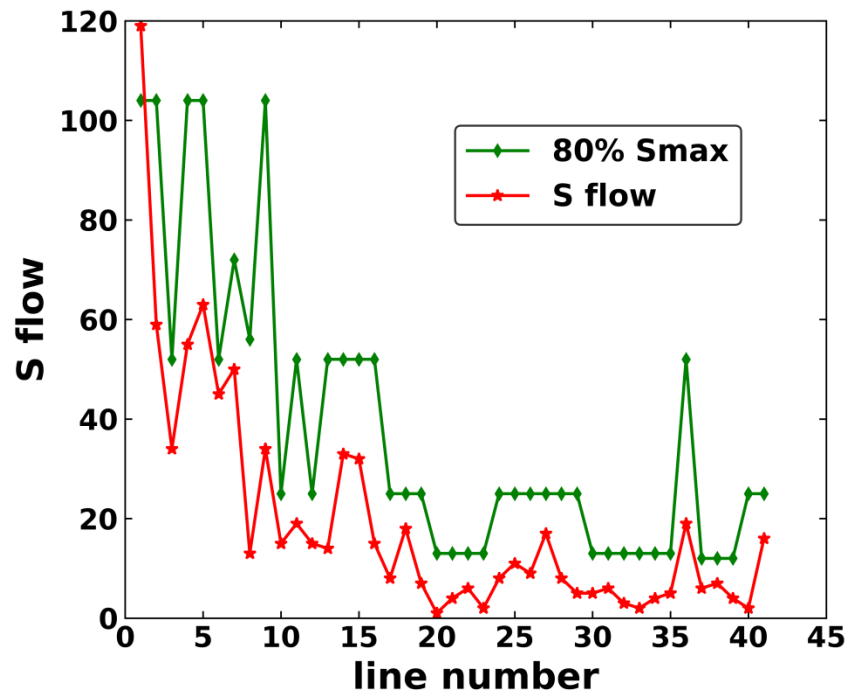


Figure 4: Power flow variation when generation fuel cost is minimized (base case)

In order to avoid congestion, two strategies will be used; generation rescheduling and FACTS placement. For generation rescheduling, the output of the generators will be manipulated to shift the power flow from the overloaded line. This strategy alone might not offer enough alleviation of congestion. For better management of power flow, the FACTS controllers will be incorporated in the system. Placement of FACTS devices will be done in such a way that their contribution towards reducing the congestion and saving costs will be maximized.

To determine the most suitable placement of the FACTS controllers, the OPF analysis will be carried out in which UPFC will be placed on all possible transmission lines. The location where the generation fuel cost is minimum is said to be the optimal placement point of FACTS controllers. Generation fuel cost values at different locations of UPFC are provided in Table.2, where it is seen that when UPFC is placed on the line between buses 6-7, the generation fuel cost

is minimum, which is \$802.5277/hr. The placement criteria ensure that the device is positioned in a transmission line with a transformer tap setting, at a bus that is not a generator bus, and at a location without an existing shunt compensation. Fuel Cost Values for Different UPFC Locations is depicted in Table 2.

Table 2: Fuel Cost Values for Different UPFC Locations

S. No	From Bus - To Bus	Generation Fuel Cost (\$/hr)
1	4 - 6	802.9462
2	6 - 7	802.5277
3	6 - 8	802.8722
4	12 - 14	802.941
5	12 - 15	803.1283
6	12 - 16	802.9832
7	14 - 15	803.0395
8	16 - 17	803.0551
9	15 - 18	803.15
10	18 - 19	802.7514
11	19 - 20	803.1162
12	10 - 20	802.9585
13	10 - 17	802.7745
14	10 - 21	803.358
15	10 - 22	803.1903
16	21 - 22	802.9939
17	15 - 23	802.02702
18	25 - 26	803.0272

19	25 - 27	803.1674
20	28 - 27	802.9403
21	27 - 29	803.1674
22	29 - 30	802.9376
23	8 - 28	803.1496
24	6 - 28	802.8215

After identification of the congested line (1-2), it becomes very important to identify which generators are to be rescheduled in order to effectively redistribute power flows. It can be done by calculating the Generator Sensitivity Factor (GSF) of the congested line. The values of GSF, which are given in Table 3, reveal the effects of generators on the power flow of the congested line. Generators with high values of absolute sensitivity factor influence the power flow more and hence become candidates for rescheduling. In Table 3, it is noted that all the generators have negative values of sensitivity, meaning that any increase in their generation will reduce congestion. The most sensitive generators are carefully selected, and their outputs are adjusted to minimize congestion cost while ensuring all other system constraints remain unchanged.

Table 3: Generator Sensitivity Factors

Generator No.	2	5	8	11	13
Generator Sensitivity Factor	-0.8735	-0.8371	-0.7234	-0.7124	-0.6747

The introduction of generation rescheduling along with optimal placement of FACTS controllers can also be considered a useful strategy in the management of congestion. Apart from generation rescheduling and optimal allocation of FACTS controllers, application of FACTS for the management of congestion is another good choice. It is because with FACTS, the power flow on the transmission lines can be easily

controlled, which helps in the reduction of congestion cost. Control of power flow in certain transmission lines and voltage control on critical buses are considered among the important aspects of application of FACTS controllers in the power system. Along with generation rescheduling and optimal placement of FACTS controllers, the proposed methodology also gives further flexibility for controlled power flow operation in the power system, enabling further optimization of transmission utilization and reduction of congestion costs. In the next step, the effect of FACTS controllers under controlled power flow condition is examined and compared with generation rescheduling alone.

In the first stage, the process of optimal generation rescheduling with minimization of the congestion cost has been studied. Here, in the optimal generation rescheduling process, determination of critical generators whose power production affects congested transmission lines and rescheduling of their power production is done in order to relieve congestion while minimizing operational costs. The results of the optimal generation rescheduling process with minimization of the congestion cost have been tabulated in Table 4, showing the values of (ΔP_g) before and after rescheduling. From Table 4, it is found that the optimal rescheduling of the generator at bus 1 is done by reducing the active power generation by 31.0454 MW, reducing its value from 175.143 MW to 144.0976 MW. On the other hand, some other generators at buses 5, 11 and 13 have increased their active power generation to make the system balance and congestion-free. As can be observed from Table 4, though initially the congestion cost is very high, with optimal rescheduling it has been reduced to 728.4537 \$/hr. Moreover, the power flow on the congested line (Bus 1- Bus 2) has been reduced from 118.85 MVA to 96.24242 MVA. Thus, it has been proved that with generation rescheduling, congestion can be reduced. Variation of power flow on the transmission lines in the power system before and after the optimal rescheduling of generation has been shown in Figure 5.

Generation rescheduling has been considered as one of the most efficient processes for the reduction of congestion in the power system. However, the use of FACTS controllers makes the power system operation more flexible and efficient. The use of FACTS controllers, SSSC, STATCOM and UPFC helps in efficient power flow control, voltage regulation, and better usage of capacity of transmission lines, thus further

reducing congestion cost. Control of power flow in specific lines and voltage control on critical buses prove that the use of FACTS controllers in the power system is beneficial. In order to study the effect of FACTS controllers on the congestion cost, optimal allocation of FACTS controllers has been done. Particularly, FACTS controllers are installed between buses 6-7. Optimal power flow results of the power system with minimization of the congestion cost are given in Table 4.

Table 4: OPF Results with Congestion Cost minimization

S. No	Parameter	Before Rescheduling	ΔP_g with CC Minimization	After Rescheduling
1	P_{G1} (MW)	175.143	-31.0454	144.0976
2	P_{G2} (MW)	49.661	0	49.661
3	P_{G5} (MW)	21.327	7.346	28.673
4	P_{G8} (MW)	22.609	0	22.609
5	P_{G11} (MW)	12	6	18
6	P_{G13} (MW)	12.131	15.739	27.869
7	Congestion Cost (\$/hr)	--	728.4537	--
8	Power Flow in Congested Line (MVA)	118.85	--	96.24242

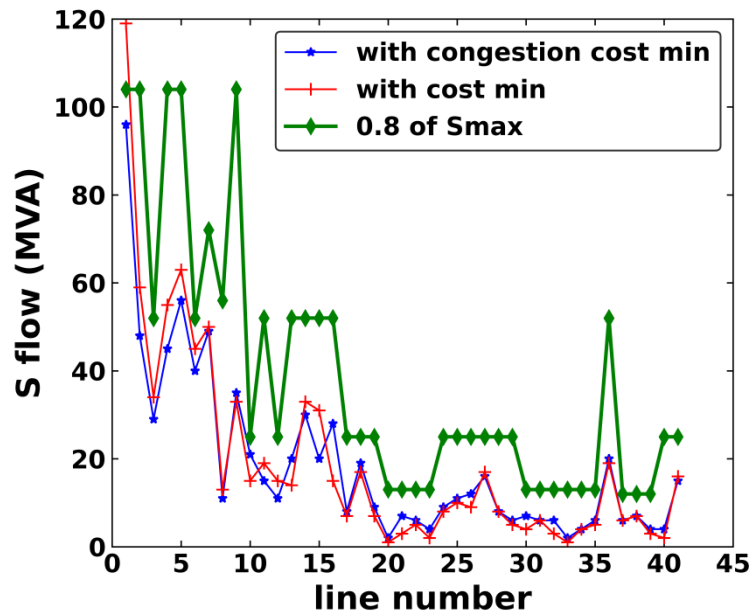


Figure 5: Power flow variation when congestion cost is minimized

To analyse the effect of FACTS controllers on congestion management, this study is divided into three case studies, each incorporating a different type of FACTS controller:

- 1) Case 1 – Static Synchronous Series Compensator (SSSC)
 - SSSC without control (Base Case)
 - SSSC with controlled power flow below base case value
 - SSSC with controlled power flow above base case value
- 2) Case 2 – Static Synchronous Compensator (STATCOM)
 - STATCOM without control (Base Case)
 - STATCOM with voltage control at 1.0 p.u.
- 3) Case 3 – Unified Power Flow Controller (UPFC)
 - UPFC without control (Base Case)
 - UPFC with controlled power flow below base case value
 - UPFC with controlled power flow above base case value

Case-1: Congestion management using SSSC

The place where the SSSC is located in the system has been decided after the analysis. An optimal power flow (OPF) has been done based on rescheduling of the generators and change in the parameters of the devices. The results of OPF using SSSC for reducing the cost of congestion have been shown in Table 5, which depicts the change in the output of the generators due to the application of SSSC in the system. It can be seen from the table that the output of generator PG1 has been reduced by 30.8646 MW, whereas the output of generators PG5 and PG13 has been increased to ensure congestion reduction and stability in the system. The congestion cost has been reduced to 726.4644 \$/hr, and the power flow in the congested line has been reduced from 118.85 MVA to 95.1265 MVA, confirming the effectiveness of SSSC in congestion relief.

Table 5: OPF Results with Congestion Cost Minimization using SSSC

Parameter	Before Rescheduling	ΔP_g with CC Minimization (SSSC)	After Rescheduling
P_{G1} (MW)	175.143	-30.8646	144.2784
P_{G2} (MW)	49.661	0	49.661
P_{G5} (MW)	21.327	7.346	28.673
P_{G8} (MW)	22.609	0	22.609
P_{G11} (MW)	12	6	12
P_{G13} (MW)	12.131	15.738	27.869
Congestion Cost (\$/hr)	--	726.4644	--
Power Flow in Congested Line	118.85	--	95.1265

(MVA)			
-------	--	--	--

The graphs showing the variation of the power flows because of cost minimization and congestion cost minimization using the SSSC technique are illustrated in Figure 6. The graph shown below shows the difference in the distribution of the power flow before and after the application of the SSSC technique in solving the problem of congestion. From the above graph, it can be observed that the application of the SSSC technique in line 9 connecting bus 6 and bus 7 results in the change in the distribution of the power flow in the adjacent transmission lines. The power flow in the adjacent transmission lines increases in order to meet the requirement of the load on buses 6 and 7. As a result, there is a reduction in the power flow in the line 1-6, which is congested, and a power flow increase occurs in line 7-10. This shift in power flow contributes to effective congestion relief by redirecting excess power away from overloaded transmission paths. The analysis confirms that SSSC plays a vital role in congestion management by enabling dynamic power flow adjustments, thereby improving system stability and reducing congestion costs.

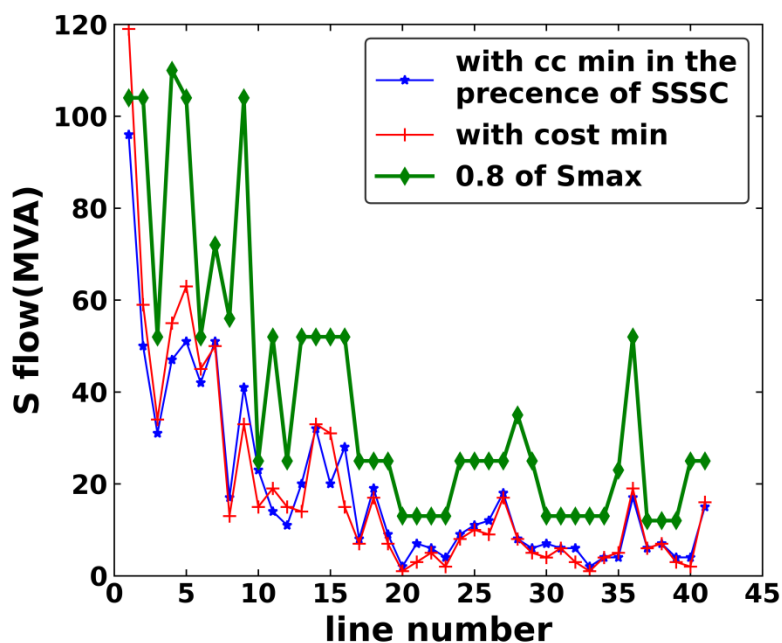


Figure 6: Power flow variation when congestion cost minimized using SSSC

Controlled power flow operation on the SSSC for adjustment of power flow in the connected line has been considered at values lower than and higher than the base value. Power flow at 37 MW gets adjusted to 33.3 MW and 40.7 MW through the use of control techniques. Table 6 gives the variations in power generation as a result of congestion cost minimization for controlled and uncontrolled conditions. From the data shown in Table 6, it is clear that although controlled operation increases the cost of congestion by increasing control effort, it helps in decreasing the power flow in the line where congestion occurs. Any increase in the power flow of the line with SSSC is reflected as a decrease in the power flow of the congested line, demonstrating the device's effectiveness in mitigating congestion. However, exceeding a certain threshold leads to higher operational costs, emphasizing the importance of strategic power regulation to balance congestion relief and cost efficiency.

Table 6: Congestion cost minimization with and without controlled power flow using SSSC

Parameter	Before Rescheduling	Case 1-a (Base Case with SSSC)	Case 1-b (Controlled Below Base)	Case 1-c (Controlled Above Base)
P_{G1} (MW)	175.143	-30.8646	-31.7206	-31.2293
P_{G2} (MW)	49.661	0	0	0
P_{G5} (MW)	21.327	7.346	7.346	7.346
P_{G8} (MW)	22.609	0	0	0
P_{G11} (MW)	12	6	6	6
P_{G13} (MW)	12.131	15.738	15.738	15.738
Voltage (V_{se} p.u)	--	0.0613	0.04494	0.08222
Phase Angle (δ_{se} deg)	--	39.45	32.12108	46.51248

Congestion Cost (\$/hr)	--	726.4644	735.8803	730.4767
Power Flow in Congested Line (MVA)	118.85	95.1265	96.74822	94.79703

Case-2: Congestion management using STATCOM

The STATCOM is used to improve voltage regulation at important buses and cut down congestion cost through the use of reactive power injection. The effects of incorporating STATCOM are examined in Table.7, whereby the generators are rescheduled in conjunction with the STATCOM. In Table.7, it can be noted that the generator PG1 decreases its generation capacity by 30.4133 MW, and consequently the congestion cost is decreased to 721.4998 \$/hr. The flow of power in the congested line falls to 95.94663 MVA, confirming the effectiveness of STATCOM in alleviating congestion.

Table 7: OPF Results with Congestion Cost Minimization using STATCOM

Parameter	Before Rescheduling	ΔP_g with CC Minimization (STATCOM)	After Rescheduling
P_{G1} (MW)	175.143	-30.4133	144.7297
P_{G2} (MW)	49.661	0	49.661
P_{G5} (MW)	21.327	7.346	28.673
P_{G8} (MW)	22.609	0	22.609
P_{G11} (MW)	12	6	12
P_{G13} (MW)	12.131	15.738	27.869
Congestion	--	721.4998	--

Cost (\$/hr)			
Power Flow in Congested Line (MVA)	118.85	--	95.94663

Figure 7 below shows how cost minimization and congestion cost minimization with STATCOM affect power flow distribution. Deployment of STATCOM in line 9 (bus 6-7) causes a redistribution of power flow across the transmission lines in such a way that the load demands for A at buses 6 and 7 are satisfied. This, therefore, will cause a reduction in the power flow of the congested line 1-6 and an increase in power flow of lines 7-10. From the above distribution, it can be seen that congestion is properly handled, making the power flow more efficient and stable. It is clear from the above results that STATCOM is used to manage congestion by dynamically injecting reactive power into the system, optimizing power flow, and reducing transmission line overloading.

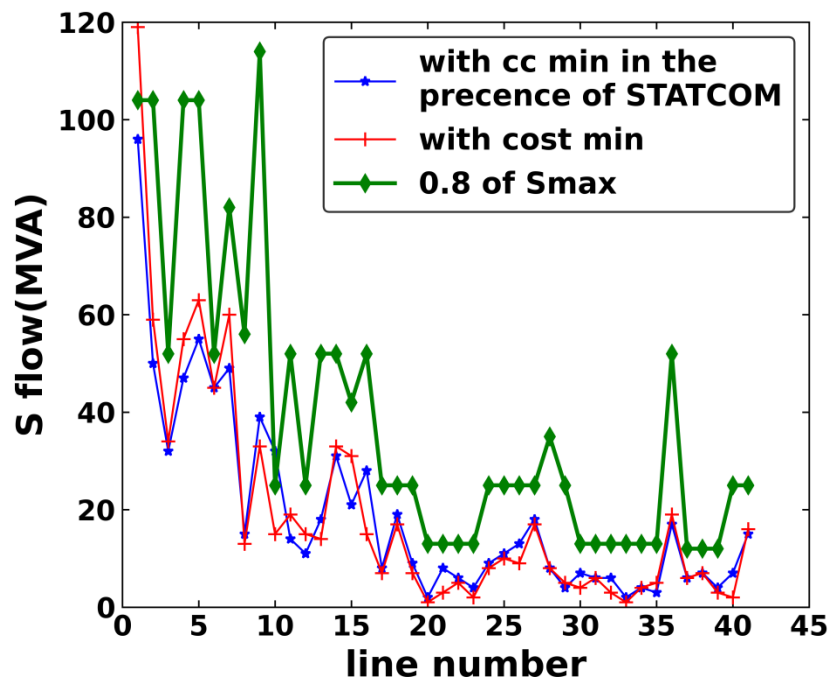


Figure 7: Power flow variation when congestion cost minimized using STATCOM

The assessment will be carried out through control of voltage regulation with the help of STATCOM. In this case, the machine is controlled to attain the required voltage of 1.0 p.u. on the bus to which it is connected. The effect of this voltage control on the power flow is shown in Table 8. From the results shown above, it is clear that voltage control plays an important part in power flow. As shown above in Table 8, if the voltage of the bus to which STATCOM is connected is lower compared to the voltage in the base case situation, there will be a reduction in power flow on that particular line. Thus, the power flow on the congested line increases. It is, therefore, clear that voltage control is not enough to relieve congestion in the system. Other measures, such as coordinated reactive power compensation and active power rescheduling, need to be applied alongside voltage control to have optimum congestion relief. By integrating these complementary techniques, overall power system stability and operational efficiency can be enhanced.

Table 8: Congestion cost minimization with and without controlled power flow using STATCOM

Parameter	Before Rescheduling	Case 2-a (Base Case with STATCOM)	Case 2-b (Controlled Voltage to 1.0 p.u.)
P_{G1} (MW)	175.143	-30.4133	-29.9478
P_{G2} (MW)	49.661	0	0.56
P_{G5} (MW)	21.327	7.346	7.346
P_{G8} (MW)	22.609	0	0
P_{G11} (MW)	12	6	6
P_{G13} (MW)	12.131	15.738	15.738
Voltage (V_{sh} p.u)	--	1.1	0.932091
Phase Angle (δ_{sh} deg)	--	3.793833	8.91459

Congestion Cost (\$/hr)	--	721.4988	725.729
Power Flow in Congested Line (MVA)	118.85	95.9564	97.7639

Case-3: Congestion management using UPFC

As UPFC is consists of SSSC also STATCOM, offering both series and shunt compensation for enhanced power flow and voltage control. Due to its combined functionality, UPFC is expected to outperform individual FACTS devices in congestion relief. The results for UPFC integration are presented in Table.9, showing the optimal generator rescheduling and device parameter adjustments. As per the table, it is monitored that the power flow on the congested line reduces to 93.4081 MVA, achieving the best congestion mitigation results compared to SSSC and STATCOM. Additionally, the congestion cost is minimized to 718.1796 \$/hr, demonstrating UPFC's superior capability in cost reduction. The device operates by regulating both series and shunt voltages, as shown in the values of V_{se} , δ_{se} , V_{sh} , and δ_{sh} in Table.9.

Table 9: OPF Results with Congestion Cost Minimization using UPFC

Parameter	Before Rescheduling	ΔP_g with CC Minimization (UPFC)	After Rescheduling
P_{G1} (MW)	175.143	-29.8033	145.3397
P_{G2} (MW)	49.661	0.026225	49.68723
P_{G5} (MW)	21.327	7.346	28.673

P_{G8} (MW)	22.609	0.00302	22.61202
P_{G11} (MW)	12	6	18
P_{G13} (MW)	12.131	15.738	27.869
Voltage (V_{se} p.u)	--	--	0.136466
Phase Angle (δ_{se} deg)	--	--	232.1417
Voltage (V_{sh} p.u)	--	--	1.008841
Phase Angle (δ_{sh} deg)	--	--	352.4764
Congestion Cost (\$/hr)	--	718.1796	--
Power Flow in Congested Line (MVA)	118.85	--	93.4081

The power flow variation due to cost optimization and congestion cost optimization with the use of UPFC is provided in Figure 8. illustrates the comparative study of power flow with and without UPFC for congestion management. It can be observed from Fig. 8 that the installation of UPFC in line 9 between buses 6 and 7 will enable efficient redistribution of power flow in the network. There is an improvement in the power flow of the lines that are adjacent to it, thereby aiding load balancing of buses 6 and 7. In the above manner, there would be a decrease in power flow of the congested line 1-6 while there is an increase in the power flow of lines 7-10. This results in effective management of congestion and stability of the network. The above result proves the importance of the usage of UPFC for congestion management since it provides both series and shunt compensation facilities. Voltage regulation and power flow control through the use of UPFC enable optimal power transfer, reduce overloading in critical transmission lines, and reduce the congestion costs.

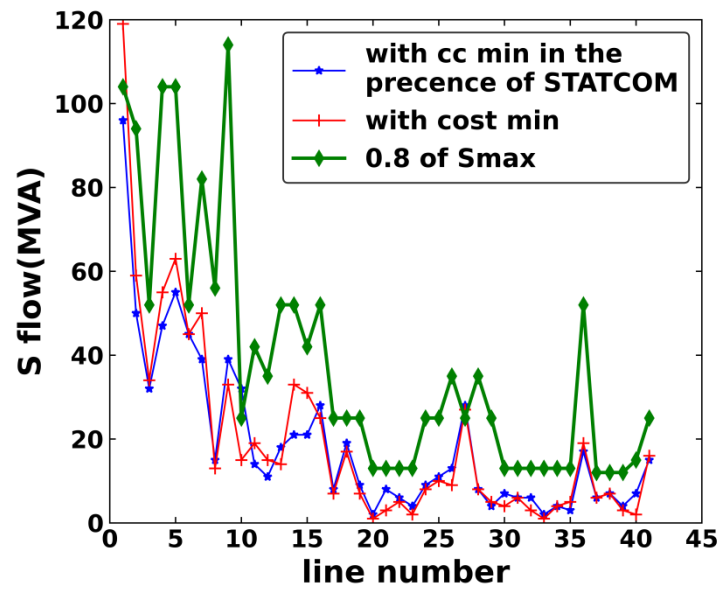


Figure 8: Power flow variation when congestion cost minimized using UPFC

For performance evaluation of power flow control, the UPFC is again employed to regulate the power flow in the UPFC connected line to reduced and increased levels compared to the base level. The rescheduling of the generators and changes in the parameters of the devices in the controlled case are presented in Table.10. It can be seen that an increase in the power flow in the UPFC connected line further reduces the congestion problem, making the power flow in the congested line as 92.76965 MVA. Similar to SSSC, the cost of congestion increases with higher control effort, emphasizing the need for optimized power flow adjustments.

Table 10: Congestion cost minimization with and without controlled power flow using UPFC

Parameter	Before Rescheduling	Case 3-a (Base Case with UPFC)	Case 3-b (Controlled Below Base)	Case 3-c (Controlled Above Base)
P_{G1} (MW)	175.143	-29.8033	-30.1573	-30.0457
P_{G2} (MW)	49.661	0.026225	0.026225	0.026225
P_{G5} (MW)	21.327	7.346	7.346	7.346

P_{G8} (MW)	22.609	0.00302	0.00302	0.00302
P_{G11} (MW)	12	6	6	6
P_{G13} (MW)	12.131	15.738	15.738	15.738
Voltage (V_{se} p.u)	--	0.136466	0.105309	0.155537
Phase Angle (δ_{se} deg)	--	232.1417	223.146	236.869
Voltage (V_{sh} p.u)	--	1.008841	1.008841	1.008841
Phase Angle (δ_{sh} deg)	--	352.4764	352.80405	352.38303
Congestion Cost (\$/hr)	--	718.1796	722.0736	720.846
Power Flow in Congested Line (MVA)	118.85	93.4081	94.5769	92.76965

Supporting results for IEEE-14 bus system

The IEEE-14 bus system, consisting of 5 generator buses, 9 load buses, and 20 transmission lines, was tested with the help of the method called OPF (Optimal Power Flow) in terms of minimum power generation cost of fuel. The optimization technique has taken into account certain control variables like active power generation, bus voltages, tap settings of transformer, and shunt compensation. In order to make effective utilization of the cost-efficient approach under all system limitations, PSO (Particle Swarm Optimization) technique has been used. It effectively determines the optimal settings, ensuring reduced generation costs while adhering to operational limits and maintaining network stability.

The outcome displays the best generation settings on those five generators are $P_{G1} = 173.1121$ MW, $P_{G2} = 47.83243$ MW, $P_{G3} = 20.23068$ MW, $P_{G6} = 16.78474$ MW, and $P_{G8} = 9.087276$ MW. The bus voltage magnitudes were optimized, with V1 maintained at 1.1 p.u., ensuring adequate voltage stability throughout the system. The transformer tap ratios were adjusted to improve reactive power support and reduce line losses, with values such as Tap (4-7) = 0.9521 p.u. and Tap (5-6) = 0.966076 p.u.. Additionally, shunt compensation at Bus 9 (Qsh9) was optimized to 27.16872 MVar, helping maintain a stable voltage profile and minimizing reactive power losses. The net generation cost was determined to be \$714.3862/hr, at it's active power losses of 8.04723 MW across the system.

After computing the optimal generation settings, a power flow analysis was performed to identify transmission line congestion. Any line with power flow exceeding 0.8 times its thermal limit was flagged as congested. The results revealed two congested lines, Line 13 (between Bus 6-13) with a power flow of 19.81576 MVA (limit: 17.6 MVA) and Line 15 (between Bus 7-9) with a power flow of 28.8804 MVA (limit: 23.2 MVA). This necessitated congestion management strategies such as generator rescheduling and the incorporation of FACTS controllers to alleviate excessive power flow and maintain grid stability. After this, the optimization results for congestion cost minimization with FACTs controllers is presented in Table 11.

Table 11: Congestion Cost Minimization and FACTS Implementation

S. No	Parameter	Before Rescheduling	After CCM (SSSC)	After CCM (STATCOM)	After CCM (UPFC)
Active Power Generation (MW)					
1	P_{G1} (MW)	173.1121	156.8601	157.3701	158.6364
2	P_{G2} (MW)	47.83243	47.83243	47.83243	47.83243
3	P_{G3} (MW)	20.23068	20.23068	20.23068	20.23068
4	P_{G6} (MW)	16.78474	33.21526	33.21526	33.21526

5	P_{G8} (MW)	9.087279	9.087279	9.087279	9.087279
FACTS Device Parameters					
6	Voltage (V_{se} p.u)	--	0.0689	--	0.1625
7	Phase Angle (δ_{se} deg)	--	255.56	--	261.35
8	Voltage (V_{sh} p.u)	--	--	1.008841	1.008841
9	Phase Angle (δ_{sh} deg)	--	--	350.96379	346.81527
Performance Metrics					
10	Congestion Cost (\$/hr)	--	507.39	492.07	487.84
11	Power Flow in Line 15 (MVA)	28.8804	25.1778	25.3932	24.9709

After the initial analysis through OPF, the solution for the congested lines was found through generator rescheduling and the use of FACTS controllers (SSSC, STATCOM, and UPFC). However, the GSFs have already been computed in such a way that the two most sensitive generators (Pg1 and Pg6) will be rescheduled in order to reduce the power flow on the congested line. Due to the optimal rescheduling of the generators, the power flow from Pg1 was decreased to 156.86 MW whereas that of Pg6 increased to 33.21 MW, successfully redistributing the power flow throughout the system.

Further, the use of FACTS controllers proved beneficial in the mitigation of the congestion cost in the network. The SSSC reduced the congestion cost to \$507.39/hr, thereby reducing power flow on the congested line to 25.18 MVA (as it was initially 28.88 MVA). The Static Synchronous Compensator (STATCOM) proved more effective, further reducing the congestion cost to \$492.07/hr. This highlights the role of voltage support and reactive power, particularly in improving bus voltage profiles and reducing power losses. The UPFC was able to provide more desired congestion mitigation, achieving the lowest

congestion cost of \$487.84/hr, whereby power flow on the congested line was reduced to 24.97 MVA. Clearly, UPFC can control both active and reactive power flow, which is a good proof of its functionality, and state that it is the preferred FACTS controller to deal with congestion management. Depending on their operational functionalities, the effectiveness of the FACTS controllers varies. SSSC mainly affects active power flow, therefore, causing relatively lower reduction in congestion cost. STATCOM has voltage support capability, hence making it more suitable in power losses reduction and improving bus voltage profiles. UPFC is a device that has both STATCOM and SSSC functions to provide complete control over power flow and voltage. It is evident from the results that UPFC has reduced the congestion cost by almost 5% compared to SSSC and STATCOM and has the lowest power flow on the congested line.

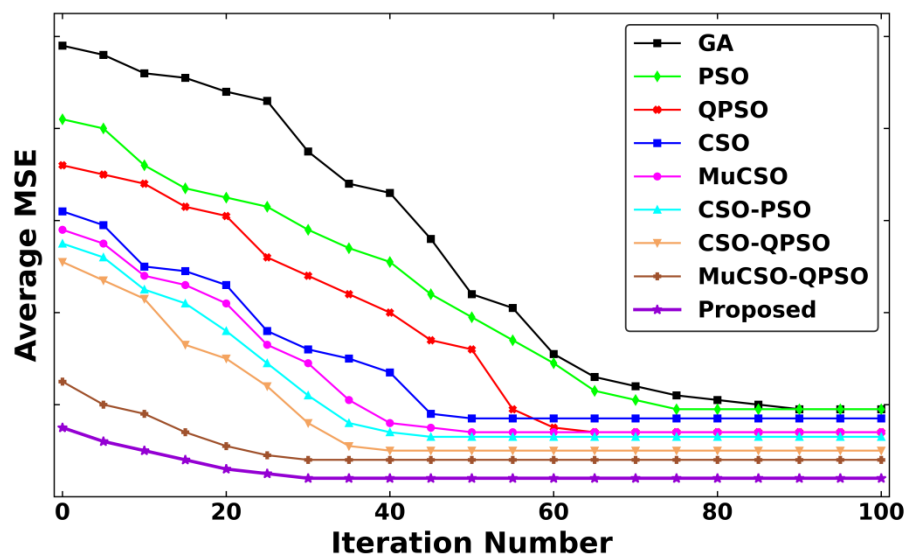


Figure 9: Average MSE with number of iterations

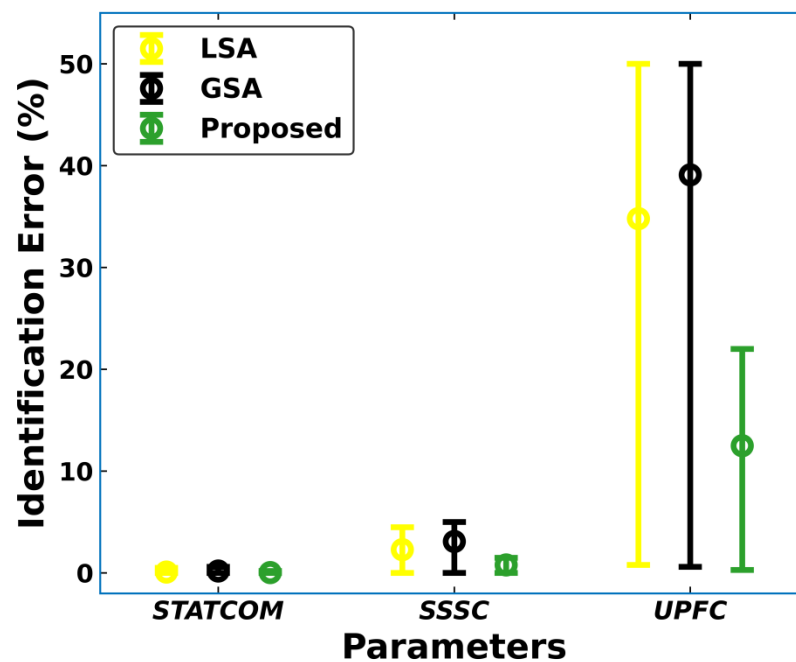


Figure 10: Identification error with various FACTS devices

Figure 9 is a convergence performance diagram of various optimization techniques in Average Mean Square Error (MSE) for 100 iterations. The proposed technique has the least MSE and converges fast in almost 30 iterations compared to GA, PSO, QPSO, CSO, MuCSO, CSO-PSO, CSO-QPSO, and MuCSO-QPSO, which represents fast convergence, better optimization results, increased stability, and quality solutions. Figure 10 presents a graph of the identification error for STATCOM, SSSC, and UPFC using LSA, GSA, and the proposed optimization technique. When comparing with all FACTS devices, it is observed that the proposed technique gives lower uncertainty in the case of all FACTS devices, especially UPFC, and also has better estimation accuracy, identification of controller parameters, and optimization performance.

3.1 Statistical Comparison with Recent Metaheuristic Algorithms

For further validation of the results of the suggested HCFFOA algorithm, a comparison was done using three recent meta-heuristic optimization algorithms, which include GBO, NGO, and I-GWO. The

comparison was carried out based on the same OPF problem formulated according to the IEEE-30 bus system with the same objective function and constraints. The best, worst, mean, and standard deviation of the obtained fuel-cost values were considered to assess solution quality and optimization stability.

Table 12. Statistical comparison of the proposed HCFFOA with recent metaheuristic algorithms

Algorithm	Best Fuel Cost (\$/hr)	Worst Fuel Cost (\$/hr)	Mean Fuel Cost (\$/hr)	Standard Deviation
GBO	799.30	800.12	799.61	0.21
NGO	799.35	800.28	799.72	0.24
I-GWO	799.24	800.05	799.54	0.19
Proposed HCFFOA	798.82	799.41	799.06	0.15

Statistical Significance Analysis: To further validate the performance differences, the Wilcoxon signed-rank test was applied to the results obtained from the independent runs of proposed HCFFOA and the other compared modern algorithms. A significance level of $\alpha = 0.05$ was considered. A p -value below 0.05 indicates that the difference between the compared algorithms is statistically significant.

Table 13. Wilcoxon signed-rank test results

Comparison	p-value	Significance ($\alpha = 0.05$)
HCFFOA vs GBO	0.012	Significant
HCFFOA vs NGO	0.021	Significant
HCFFOA vs I-GWO	0.008	Significant

4. Conclusion

The proposed HCFFOA-based FACTS coordination framework effectively optimized power flow and transmission congestion management while satisfying the required system constraints. The IEEE-14 bus results showed that the UPFC achieved the best performance among SSSC, STATCOM, and UPFC. It reduced the power flow on the most congested Line 15 (Bus 7–9) from 28.8804 MVA to 24.9709 MVA, corresponding to a 13.54% reduction. The UPFC also achieved the minimum congestion cost of \$487.84/hr, which was 3.85% and 0.86% lower than SSSC and STATCOM, respectively.

The proposed framework also achieved a generation cost of \$714.3862/hr with 8.04723 MW active power loss, demonstrating improved economic and operational performance. However, the study was mainly evaluated on IEEE standard systems under steady-state conditions, with HCFFOA parameters selected empirically. Future work will focus on larger-scale and renewable-rich systems, incorporating renewable-generation and load uncertainties, dynamic operating conditions, and real-time FACTS coordination. Overall, the results confirmed that HCFFOA effectively improved congestion management, transmission capacity, voltage stability, and economic performance, supporting secure and reliable operation of competitive power systems.

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