Intelligent Congestion Management for Power Transmission Systems: Integration of Machine Learning and FACTS Devices

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***Abstract*—It has become more challenging to manage congestion in power transmission lines due to the increasing usage of renewable energy sources and increased electricity consumption. To address issues with congestion management, this study examines the usage of an Advanced Interline Power Flow Controller (IPFC) in conjunction with AI and ML methods. The objective is to keep the electricity system running reliably and efficiently while keeping the cost of congestion management to a minimum. Models for congestion prediction and control are created using AI/ML techniques. Optimization methods are employed to determine the optimal strategies for IPFC operation and congestion control. To evaluate the proposed approach, the IEEE 30 bus system is utilized as a test case. The proposed AI/ML-based approach is compared to more traditional approaches to congestion management, and the results are analyzed side by side. Incorporating an IPFC and AI/ML methods results in less congestion on the power transmission lines of the IEEE 30 bus system. Significantly lower congestion levels, improved power flow optimization, and cost savings are shown in compared to earlier techniques.**

***Index Terms*—Congestion management, Interline Power Flow Controller, Artificial Intelligence, Machine Learning**

I. Introduction

THE development of reliable electrical energy sources has been a crucial factor in the expansion of industrial and technological societies, and the modern power system is largely responsible for this. Modern infrastructure would not be complete without the power system, which has grown in significance due to the ever-increasing need for electrical energy and is always being improved in both design and operation to suit societal demands. Power transmission lines are an essential part of any contemporary power system's electrical infrastructure, since they are responsible for the safe and efficient distribution of electricity to homes and businesses. In order to keep up with the increasing demand for electricity and make sure their power systems are stable, several countries are focusing on developing and maintaining transmission lines [1]. Maintaining a steady flow of electricity from generators to homes and businesses is the job of the power transmission system. Congestion problems in power transmission lines have resulted from rising electricity consumption, shifting patterns of power generation, and a lack of funding for transmission infrastructure growth. When power consumption outstrips transmission line capacity, congestion happens because of bottlenecks, voltage instability, and possible equipment overload [2]. If the electrical system is to function reliably and efficiently, congestion control is an essential component. To lessen the impact of power transmission line congestion, numerous methods and approaches have been created and put into use. To address specific congestion conditions and obtain best results, it is common to apply a combination of congestion management approaches. System features, market structure, regulatory frameworks, and the specific issues of congestion in a given electricity system are some of the elements that determine the approaches to be used [3]. New transmission lines can be built as an expansion of the existing transmission system to alleviate congestion. Congestion in heavily populated corridors is reduced and transmission capacity is increased. An additional tactic is to enhance the capacity of already-existing transmission lines. This can involve using high-tech materials like High Temperature Low Sag (HTLS) conductors, upgrading transformers, or reconductoring [4]. Power generator output levels can be adjusted by system operators to relieve congestion and redistribute power flows. Loads on overloaded lines can be decreased by relocating generation to less populated regions [5]. In order to decrease overall demand and alleviate congestion, it is recommended that users modify their electricity usage patterns during peak periods. Customer electricity usage during off-peak hours can be incentivized through demand response schemes and time-of-use pricing. The optimum generation dispatch and device control to reduce system costs while satisfying operational limits is determined by OPF by considering network constraints and system economics [6]. With the use of con-

Manuscript received March 27, 2024; revised July 25, 2025

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gestion limitations, OPF is able to optimize power flow patterns while simultaneously reducing congestion. Limitations on Safety Congestion management goals and system security limitations like voltage limits and contingency analyses are both considered by OPF. It safeguards the power flow solutions against many possible system failures [7]. Static synchronous compensators (STATCOMs), interline power flow controllers (IPFCs), and static voltage compensators (SVCs) are all examples of FACTS devices that allow for the dynamic regulation of reactive power flow and voltage. By actively controlling power flows, regulating voltages, and improving grid stability, these devices can optimize power flow patterns, reduce congestion, and increase reliability [8].

Research into the use of AI and ML in electrical grids is a dynamic and ever-changing area. More complex algorithms, real-time data integration, computing efficiency enhancement, and cyber security problem solving are all areas of active research. Smarter, more efficient, and more sustainably managed power systems are possible with the incorporation of AI/ML technology [9]. To anticipate how a system will behave in the future, Model Predictive Control (MPC) uses optimization algorithms and mathematical models to determine the best course of control action. In order to reduce congestion and keep the system stable, MPC can optimize control strategies, such as generation dispatch and device settings [10].

One of the most useful technologies for power transmission networks is the Interline Power Flow Controller (IPFC). Optimizing power system operation and guaranteeing a stable and efficient supply of electricity are made easier with its capabilities in power flow control, voltage stability enhancement, grid stability improvement, congestion management, adaptability, and scalability [11]. By incorporating AI and ML approaches, the IPFC is able to manage congestion and maintain grid stability even more efficiently, while also increasing its performance and agility. An optimized and resilient power grid can be achieved by developing and applying effective methods and technologies, such as the Interline Power Flow Controller (IPFC) combined with AI/ML, which can minimize congestion issues [12].

II. Interline Power Flow Controller (IPFC)

A brand new IPFC advanced model for analyzing power flows is suggested in this study. Both the line charging susceptance and the impedance of the series converter transformer are taken into consideration in this model. The original structure and symmetry of the admittance matrix can be shown to be preserved in this situation; hence, the block-diagonal properties of the Jacobian matrix may be kept and the sparsity method can be applied. Power transmission networks use the adaptable and dynamic Interline Power Flow Controller (IPFC) to regulate power flow and improve grid stability. Two or more transmission lines are connected at either end of the IPFC by voltage source converters (VSCs). The injected voltage can be independently controlled by these VSCs, which are usually built on insulated-gate bipolar transistor (IGBT) technology. Accurate regulation of reactive and active power flow is made possible by connecting the IPFC's VSCs in series with the transmission lines. By connecting in series, you can manage the flow of power effectively because the injected voltage is directly proportional to the line current [13].

A. *Operation of IPFC*

The IPFC is able to function by introducing a voltage into the transmission lines that can be controlled. Both the active and reactive power flows can be controlled by adjusting the amplitude and phase angle of the injected voltage. The phase angle of the injected voltage is controlled by the IPFC to adjust the power flow distribution between the transmission lines. By rerouting power from overloaded lines to less crowded ones, it can improve power flow and reduce congestion. Injecting or absorbing reactive power into the transmission lines is another way the IPFC can control reactive power flow. Because of this, the voltage may be regulated and the system's voltage stability can be improved. Line currents, voltages, and system conditions are monitored as part of the IPFC control method. This data is used by control algorithms to determine the needed injection voltage and change the converter parameters appropriately. Through the optimization of transmission capacity utilization, the dynamic redistribution of power flows, and the elimination of bottlenecks, the IPFC enables efficient congestion control [14]. An useful instrument for congestion management in power transmission networks, the IPFC offers multi-line control, high precision, fast response, and dynamic power flow control. System dependability, power flow optimization, and renewable energy integration can all benefit greatly from its capacity to reduce congestion, balance loads, manage voltage, and increase grid stability. The IPFC's capacity to handle congestion is further improved by its adaptability, modularity, and compatibility with AI/ML approaches.

B. *Modeling and Control Strategies for IPFC*

To keep the IPFC running smoothly, modeling and control strategies are essential. For optimal control of power flow and management of congestion, accurate modeling of the IPFC system and the application of suitable control algorithms are crucial [15]. Including control variables such injected voltage magnitude and phase angle, the IPFC model should reflect the current and voltage relationships between the IPFC and the transmission lines. System dynamics, such as converter response time and related control loops, should be accounted for in the models [16]. Any IPFC with an arbitrary number of series converters can benefit from the mathematical derivation. The IPFC circuit with two series converters is depicted in Figure 1.

From Figure 1:

$$V_{i_n} = V_{se_n} + I_{i_n} + Z_{se_n} + V_{ti_n} \quad (1)$$

$$I_{i_n} = I_1 + I_{10} = \frac{(V_{tn} - V_{rn})}{Z_{l_n}} + V_{t_n}\left(j\frac{B_{10}}{2}\right) \quad (2)$$

$V_{i_n} = V_{i_n}\angle\theta_{i_n}$ and $V_{j_n} = V_{j_n}\angle\theta_{j_n}$:The complex bus voltages at buses i_n and j_n

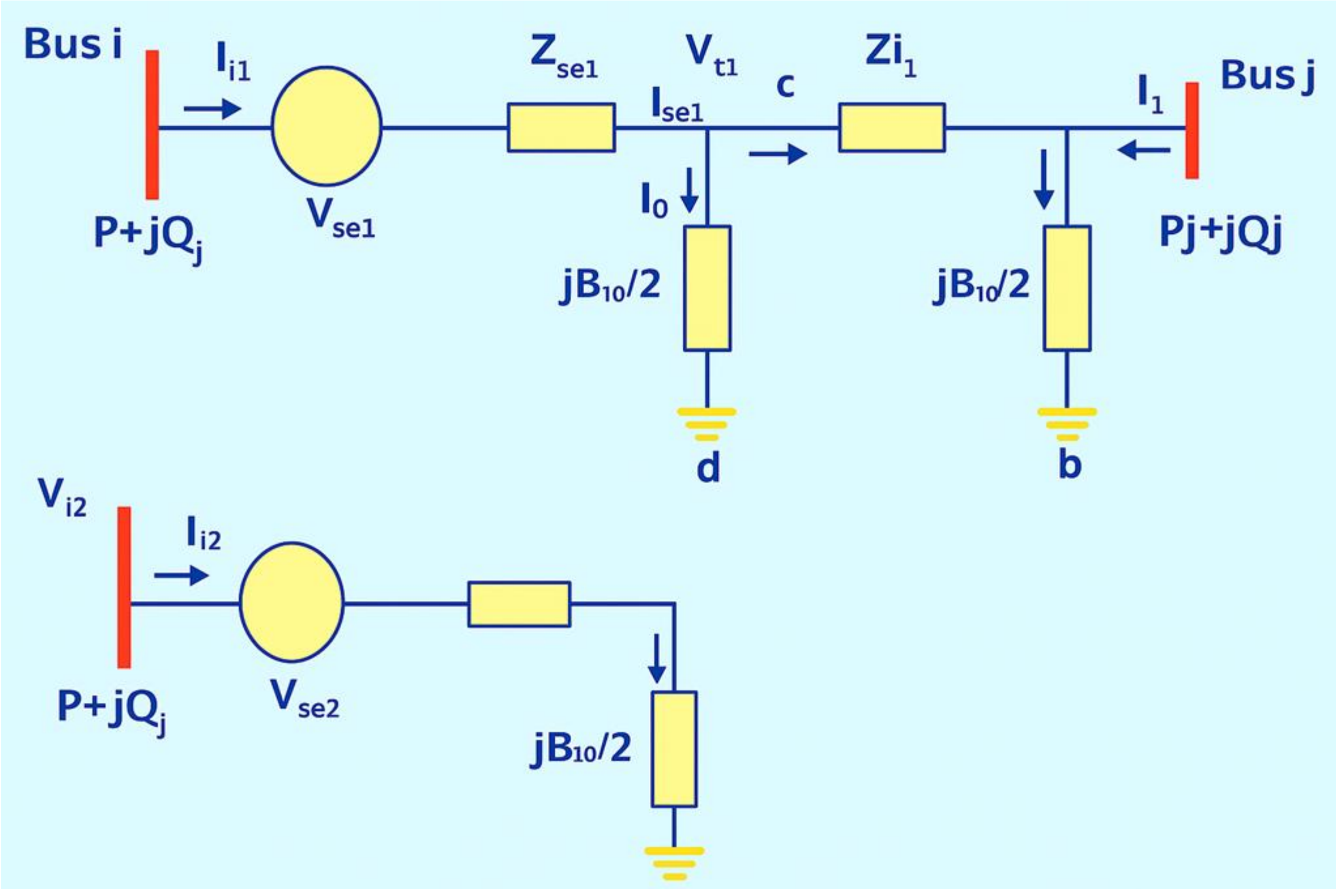

Fig. 1. Equivalent Circuit diagram of IPFC

I_{i_n} and I_{j_n} :The complex currents injection at buses i_n and j_n

$V_{se_n} = V_{se_n} \angle \theta_{se_n}$: The complex controllable series injected voltage

$Z_{se_n} = R_{se_n} + jX_{se_n}$: The series transformer impedance

$Z_{l_n} = X_{l_n} + jX_{l_n}$: The line series impedance

B_{10} : The line charging susceptance

$$V_{t_n} = I_1 Z_{l_n} + V_{j_n} \quad (3)$$

$$I_1 = -I_{j_n} + I_{ab} \quad (4)$$

Where $I_{ab} = \frac{V_{ab}}{Z_{ab}} = \frac{V_{j_n}}{\left(\frac{2}{jB_{10}}\right)} = V_{j_n}\left(j\frac{B_{10}}{2}\right) \quad (5)$

$$I_1 = -I_{j_n} + V_{j_n}\left(j\frac{B_{10}}{2}\right) \quad (6)$$

$$V_{t_n} = V_{j_n} + \left[1 + \left(j\frac{B_{10}}{2}\right) Z_{l_n}\right] - I_{j_n}(Z_{l_n}) \quad (7)$$

$$I_{10} = I_{cd} = \frac{V_{cd}}{Z_{cd}} = \frac{V_{t_n}}{\left(\frac{2}{jB_{10}}\right)} = V_{t_n}\left(j\frac{B_{10}}{2}\right) \quad (8)$$

$$I_{10} = V_{j_n}\left(j\frac{B_{10}}{2}\right) + V_{j_n} Z_{l_n}\left(\frac{B_{10}^2}{4}\right) - I_{j_n} Z_{l_n}\left(j\frac{B_{10}}{2}\right) \quad (9)$$

$$I_{i_n} = V_{j_n}\left[(jB_{10}) + Z_{l_n}\left(\frac{B_{10}^2}{4}\right)\right] - I_{j_n}\left[1 + Z_{l_n}\left(j\frac{B_{10}}{2}\right)\right] \quad (10)$$

$$D = \left[(jB_{10}) + Z_{l_n}\left(\frac{B_{10}^2}{4}\right)\right] \quad E = \left[1 + Z_{l_n}\left(j\frac{B_{10}}{2}\right)\right]$$

$$V_{t_n} = V_{j_n} E - I_{j_n} Z_{l_n} \quad (11)$$

$$I_{i_n} = V_{j_n} D - I_{j_n} E \quad (12)$$

$$I_{jn} = \frac{V_{se_n}}{Z_{se_n}E + Z_{l_n}} - \frac{V_{i_n}}{Z_{se_n}E + Z_{l_n}} + \frac{V_{jn}[Z_{se_n}D + E]}{Z_{se_n}E + Z_{l_n}} \quad (13)$$

$N = Z_{se_n}E + Z_{l_n}$ and $M = Z_{se_n}D + E$

$$I_{jn} = V_{jn}\frac{M}{N} - \frac{V_{i_n}}{N} + \frac{V_{se_n}}{N} \quad (14)$$

$$I_{j_n} = V_{j_n}\left(D - \frac{EM}{N}\right) + V_{i_n}\frac{E}{N} - V_{i_n}\frac{E}{N} \quad (15)$$

Equation (14) and (15) can also be written in matrix form as

$$\begin{bmatrix} I_{i_n} \\ I_{j_n} \end{bmatrix} = \begin{bmatrix} A_{ii_n} & A_{ij_n} \\ A_{ji_n} & A_{jj_n} \end{bmatrix} \begin{bmatrix} V_{i_n} \\ V_{j_n} \end{bmatrix} + \begin{bmatrix} W_{ii_n} \\ W_{ji_n} \end{bmatrix} V_{se_n} \quad (16)$$

Where $A_{ii_n} = \frac{E}{N}$ $A_{jj_n} = \frac{M}{N}$

$A_{ij_n} = D - \frac{ME}{N}$ $A_{ji_n} = -\frac{1}{N}$

$$W_{ii_n} = -\frac{E}{N} \quad W_{ji_n} = \frac{1}{N} \quad A_{ij_n} = A_{ji_n} \quad (17)$$

$A_{ii_n} = -A_{ij_n} + A_{i_n}^0$ $A_{i_n}^0 = D + \frac{E(1-M)}{N}$

$$A_{jj_n} = -A_{ji_n} + A_{j_n}^0 \quad A_{j_n}^0 = D + \frac{M-N}{N} \quad (18)$$

For simplicity's sake, we will ignore the transmission line and series coupling transformer resistances while calculating the active and reactive power injections at buses in and jn connected to two current sources Figure 2:

$$P_{i_n}^{se} = \frac{\left(1 - \frac{B_{10}}{2} X_{l_n}\right)}{H} V_{i_n} V_{se_n} \sin(\theta_{i_n} - \theta_{se_n}) \quad (19)$$

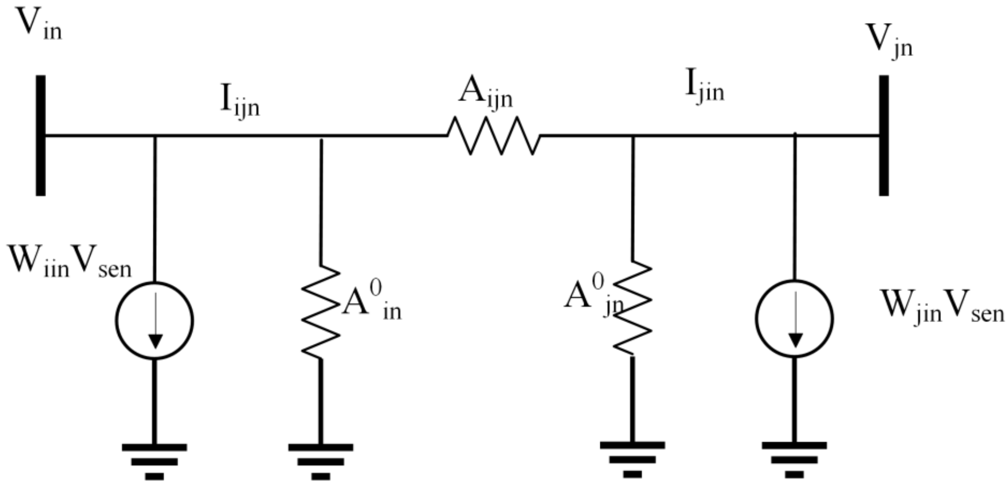

Fig. 2. Representation of IPFC using current source

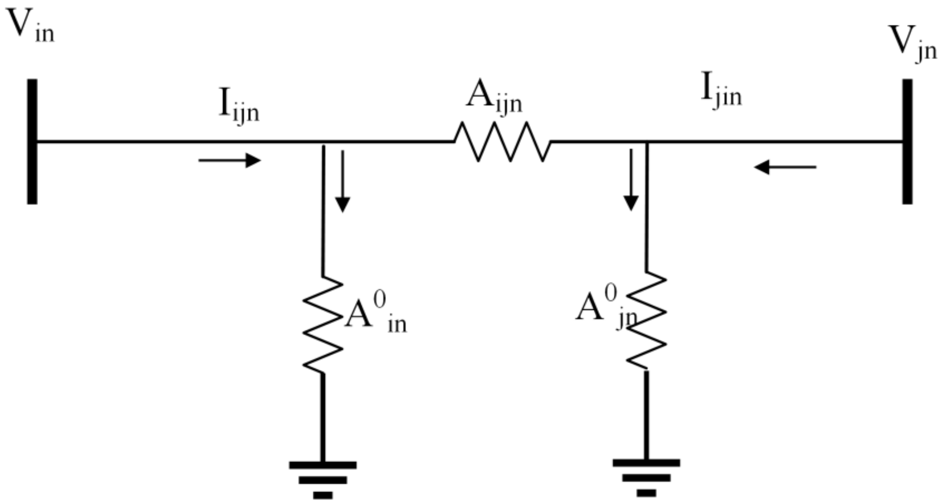

Fig. 3. Power injections π-model of IPFC

$$Q_{i_n}^{se} = \frac{-\left(1-\frac{B_{10}}{2}X_{l_n}\right)}{H} V_{i_n} V_{se_n} \cos\left(\theta_{i_n} - \theta_{se_n}\right) \quad (20)$$

$$P_{j_n}^{se} = \frac{V_{jn}V_{sen}}{H} \sin\left(\theta_{j_n} - \theta_{se_n}\right) \quad (21)$$

$$P_{j_n}^{se} = \frac{V_{jn}V_{sen}}{H} \cos\left(\theta_{j_n} - \theta_{se_n}\right) \quad (22)$$

Where $H = X_{se_n}\left[1-\left(\frac{B_{10}}{2}\right)X_{l_n}\right] + X_{l_n}$

The equivalent power injection model of an IPFC is shown in Figure 3. It can be concluded that the admittance matrix still keeps the same structure and symmetry as that of the case without IPFC.

$$I_{ij_n} = \left(V_{i_n} - V_{r_n}\right)A_{ij_n} + V_{i_n}A_{i_n}^0 \quad (23)$$

$$I_{ji_n} = \left(V_{j_n} - V_{i_n}\right)A_{ij_n} + V_{j_n}A_{j_n}^0 \quad (24)$$

$$P_{ij_n} = Re\left(V_{i_n}I_{ij_n}^*\right) = \frac{-1}{H} V_{i_n} V_{j_n} \sin\theta_{ij_n} \quad (25)$$

$$Q_{ij_n} = Im\left(V_{i_n}I_{ij_n}^*\right) = \frac{-\left(1+\frac{B_{10}}{2}X_{l_n}\right)V_{in}^2 + V_{in}V_{jn}\cos\theta_{ijn}}{H} \quad (26)$$

$$P_{ji_n} = Re\left(V_{j_n}I_{ji_n}^*\right) = \frac{-1}{H} V_{i_n} V_{j_n} \sin\theta_{ji_n} \quad (27)$$

$$Q_{ji_n} = Im\left(V_{j_n}I_{ji_n}^*\right)$$

$$Q_{ji_n} = \frac{V_{j_n}}{H}\left(-V_{j_n} + V_{i_n}\cos\theta_{ji_n}\right) - V_{j_n}\left[X_{se_n}\left(B_{10} - \frac{B_{10}^2 X_{l_n}}{4}\right) + \frac{B_{10}X_{l_n}}{2}\right] \quad (28)$$

$$P_{dc} = \sum_n P_{ex_n} = 0 \quad (29)$$

Where $P_{ex_n} = Re\left(V_{se_n}I_{i_n}^*\right)$

$$P_{ex_n} = \left(B_{10}\frac{B_{10}^2}{4} + \frac{G}{H}\right)V_{se_n}V_{j_n}\sin\left(\theta_{se_n} - \theta_{j_n}\right)\frac{\left(1-\frac{B_{10}X_{l_n}}{2}\right)V_{se_n}V_{i_n}\sin\left(\theta_{se_n} - \theta_{i_n}\right)}{H} = 0 \quad (30)$$

Where

$$G = \left[-X_{se_n}\left(B_{10} - X_{l_n}\left(\frac{B_{10}^2}{4}\right)\right) + 1 - X_{l_n}\left(\frac{B_{10}}{2}\right)\right]\left[1 - X_{l_n}\left(\frac{B_{10}}{2}\right)\right]$$

In order to achieve the required system performance, controller design for IPFC entails creating the control algorithms and fine-tuning the control parameters. Improving the IPFC's control parameters is possible with the use of optimization methods including genetic algorithms, particle swarm optimization, and model predictive control. While meeting operational restrictions, these strategies strive to minimize objective functions like transmission losses, voltage variations, or congestion levels. It is common practice to do simulation studies to validate IPFC modelling and control techniques. The IPFC system can be modelled under various operating conditions and situations using a power system modeling tool like MATLAB. The IPFC's efficiency and efficacy in managing congestion and controlling power flow were confirmed by the simulation studies [17].

III. Artificial Intelligence/Machine Learning in Congestion Management

A great deal of cutting-edge technology and software relies on AI/ML algorithms. Algorithms like this allow computers to do things that have always required human intellect, like learn from data and make smart decisions. Recent years have witnessed remarkable progress in artificial intelligence and machine learning algorithms, thanks to developments in computer power, the availability of massive datasets, and improvements in algorithmic methodologies.

A. *Artificial Intelligence (AI)*

A.I. is the process of teaching computers to think and behave like humans. It includes a wide variety of methods and algorithms that give computers the ability to see, think, learn, and decide for themselves. Machines with artificial intelligence (AI) will be able to learn and adapt to new situations much like humans. When it comes to solving problems, symbolic AI uses rule-based systems and knowledge representation. In contrast, statistical AI learns patterns in data and makes predictions using probabilistic and statistical approaches [18].

B. *Machine Learning (ML)*

Learning from data without explicit programming is the goal of ML, a branch of artificial intelligence. This goal is achieved through the creation of algorithms and models. In order to generate predictions or choices, as well as to enhance their performance over time, ML algorithms learn patterns and relationships from data. Algorithms engage in supervised learning when they are given inputs and labelled data that correspond to their outputs. It can learn to generate predictions using data it has never seen before by mapping input data to accurate output labels. Without any predetermined labels for the output, unsupervised learning algorithms discover patterns and structures in unlabeled data. Clustering, dimensionality reduction, and anomaly detection are among of the jobs that make use of them. By interacting with their surroundings, reinforcement learning algorithms are able to learn. As a result of the positive or negative reinforcement they receive for their activities, they gradually learn to maximize their total reward. Decisions that are both sequential and subject to change frequently employ reinforcement learning [19].

C. *AI/ML Techniques for Congestion Management*

When it comes to managing power system congestion, AI/ML approaches have been the talk of the town and shown encouraging results. In order to improve strategies for managing congestion, these methods make use of data analytics, pattern identification, and optimization. Common artificial intelligence and machine learning methods for traffic control are as follows [20]:

These methods demonstrate how artificial intelligence and machine learning have been effectively integrated into power networks to manage congestion, control voltage, integrate renewable energy sources, and predict future loads. Utilities and system operators have increased grid stability, optimized electricity flow, and expanded congestion management capabilities by employing advanced analytics and intelligent decision-making [21].

D. *Optimal Power Flow (OPF) Optimization*

To optimize power flow and alleviate congestion, OPF algorithms can be linked with ML approaches like reinforcement learning, genetic algorithms, or particle swarm optimization. Finding the most secure and efficient operating conditions that reduce congestion is the goal of these optimization techniques, which take into account a number of limitations and objectives, such as transmission line capacities, generation limits, voltage limits, and economic variables [22].

IV. Proposed Methodology

A. *Integration of IPFC with AI/ML Algorithms*

Congestion management problem specifications, power system model complexity, and desired outcomes inform the choice of optimization algorithm. Computing efficiency, accuracy, convergence characteristics, and the capacity to manage nonlinearities and limits related to IPFC operation are some of the criteria that should be considered while choosing an algorithm [23]. By incorporating AI and ML techniques, IPFC may be made even more effective in managing power transmission system congestion. By combining IPFC with AI/ML algorithms, power flow and congestion management can be optimized. In order to determine the best possible operating conditions, these algorithms can take into account a wide range of parameters, including transmission line capabilities, generation restrictions, voltage restraints, and economic objectives. The injection voltages can be dynamically adjusted by IPFC to reduce congestion, transmission losses, and improve system efficiency by constantly analyzing real-time data and applying optimization algorithms [24]. Skill in data analysis, algorithm selection, model training, and system integration is necessary for the creation of AI/ML models for congestion prediction and control. For accurate congestion prediction and effective control techniques with IPFC, it is crucial to test and fine-tune the models using real-world data and regularly monitor their performance.

Finding the best possible operating conditions for IPFC is essential for efficient congestion management in power transmission systems, and optimization methods are core to this process. Congestion management problem specifications, power system model complexity, and desired outcomes inform the choice of optimization algorithm. Computing efficiency, accuracy, convergence characteristics, and the capacity to manage nonlinearities and limits related to

IPFC operation are some of the criteria that should be considered while choosing an algorithm [25].

B. Constriction factor Particle Swarm Optimization

One population-based optimization method is Particle Swarm Optimization (PSO), which models the solution process as a flock of particles navigating a given environment. Particles' movements are affected by both their own and the swarm's best-known positions; each particle stands for a possible solution [26]. By repeatedly adjusting the particle placements according to goals for congestion reduction or power flow enhancement, PSO algorithms can optimize IPFC control settings. As a result of particle interactions, the swarm converges on optimal control values. The constriction factor is a parameter in Particle Swarm Optimization (PSO) that affects how the particles move and converge in the search space. The social behaviour of flocks of birds or schools of fish served as inspiration for PSO, an optimization method based on populations [27].

There are two primary parts to the velocity update equation in PSO: the cognitive part and the social part. While the social component steers particles toward the optimal solution discovered by the entire swarm, the cognitive component guides particles towards their particular best solutions. These two factors are balanced out by the constriction factor.

A particle's maximum velocity is limited by the constriction factor. Most commonly, it takes on the values 0 and 1. Here is the equation for updating velocity with the constriction factor:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 * (Pbest_i^k - X_i^k) + c_2 r_2 * (Gbest^k - X_i^k) \quad (31)$$

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{Iter_{\max}} * Iter \quad (32)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (33)$$

$$V_i^{k+1} = K[V_i^k + c_1 r_1 * (Pbest_{,i}^k - X_i^k) + c_2 r_2 (Gbest^k - X_i^k)] \quad (34)$$

$$K = \frac{2}{2 - \varphi - \sqrt{\varphi^2 - 4\varphi}}, \text{ where } \varphi = c_1 + c_2, \varphi > 4 \quad (35)$$

The constriction factor Φ acts as a scaling factor that limits the velocity updates. It ensures that the particles do not move too quickly, which can result in overshooting the optimal solution. The constriction factor is often chosen to be a fixed value, such as 0.729, which has been found to provide good convergence properties in many cases.

C. Model Predictive Control (MPC)

Modern PID controllers take an optimization-based approach to control action determination, making them a cutting-edge control technique. Solving an optimization issue in a receding horizon fashion requires defining a goal and constraints. To use MPC to IPFC control, one must first formulate an optimization problem that, given certain restrictions, either maximizes power flow or reduces congestion. Taking into account the most recent system measurements and predictions, the optimization issue is tackled iteratively at each time step. More recently, it has found applications in power electronics and models for balancing power systems [28]. [29] Dynamic process models, often linear empirical models derived from system identification, are the backbone of model predictive controllers. Optimisation of the current timeslot while future timeslots are considered is the key benefit of MPC. Using MPC in conjunction with an IPFC allows for active congestion management through real-time adjustments to the IPFC's control settings based on projected system behavior. To effectively manage congestion, the MPC framework enables proactive control decisions by taking into account system dynamics, limits, and future projections.

V. Problem Formulation for Congestion Management

Finding the best generation plan that minimizes the total cost of producing power while satisfying the power system's demand and operational restrictions is the goal of the objective function employed in OPF for minimizing the cost of generation. Consequently, the output of this optimization issue will include the generating cost with the minimum possible value. Here is one way to define the objective function using generator operating costs:

$$J = \sum_{i=1}^{NG} C_i(P_i) \quad (36)$$

Where

NG = Number of Generators

$C_i(P_i)$ = Fuel cost function

Mathematically, the objective function can be represented as:

$$\min c(x) = min \sum_{i=1}^{N_g} \left(c_i + b_i P_{gi} + a_i P_{gi}^2\right) \quad (37)$$

The objective function sums up the cost of each generator's power output, weighted by their respective cost coefficients. The cost coefficient represents the cost per unit of power generated by each generator. Results and Discussion

The proposed methodology has been tested on an IEEE 30 bus system shown in Figure. The network comprises 30 buses, 41 interconnected lines, and six generators. The IEEE 30 bus test system load flow is obtained using MATLAB software, and the results have been presented. Only loaded buses are considered for IPFC placement. The results have been analysed for normal loading, 10% loading, 15% loading and 20% loading conditions.

A. Normal case condition

To find the optimal scheduling for the power system under base case conditions, the proposed CFBPSO and MPC with IPFC are employed. Keeping the cost of generator fuel to a minimum is the objective function that is considered. When using CFBPSO and MPC with IPFC, the appropriate parameters for the control variables in the usual case scenario are listed in Table 1.

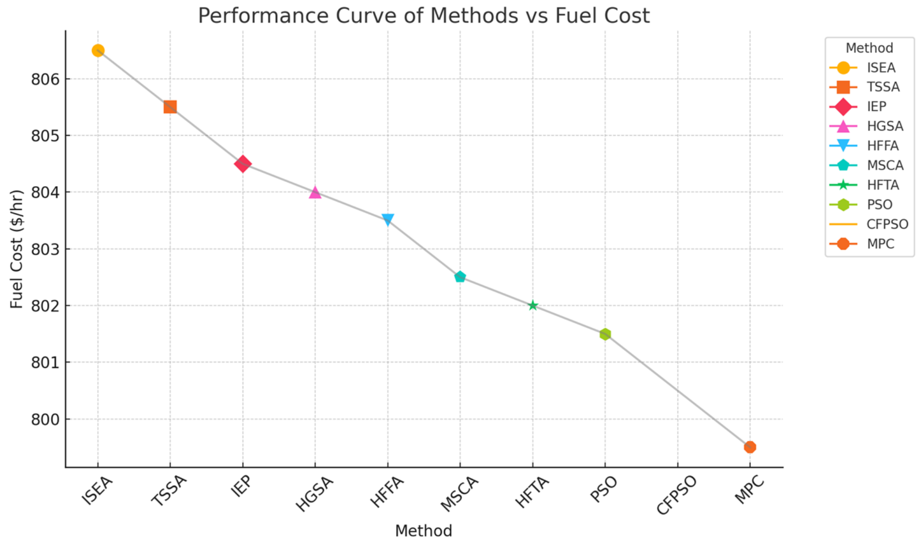

Fig. 4. Comparison of Fuel Costs

TABLE 1
OPTIMAL VALUES FOR IEEE-30 BUS SYSTEM UNDER NORMAL CASE CONDITION

Control variables		Normal Case condition		
		NR	**CFPSO with IPFC**	**MPC with IPFC**
Real Power Generation (MW)	P_{G1}	1.5929	1.7766	1.7695
	P_{G2}	0.5812	0.4882	0.4877
	P_{G3}	0.1287	0.2134	0.2111
	P_{G4}	0.1871	0.12	0.1182
	P_{G5}	0.2242	0.2133	0.2129
	P_{G6}	0.211	0.1115	0.12
Generator Voltages (p.u)	V_{G1}	1.05	1.05	1.1
	V_{G2}	1.045	0.9505	1.0878
	V_{G3}	1.01	0.95	1.0698
	V_{G4}	1.05	1.1	1.1
	V_{G5}	1.01	0.95	1.0619
	V_{G6}	1.05	1.1	1.1
Loss (MW)		**0.0911**	**0.089**	**0.0855**
Cost ($/hr)		**810.911**	**799.904**	**798.809**

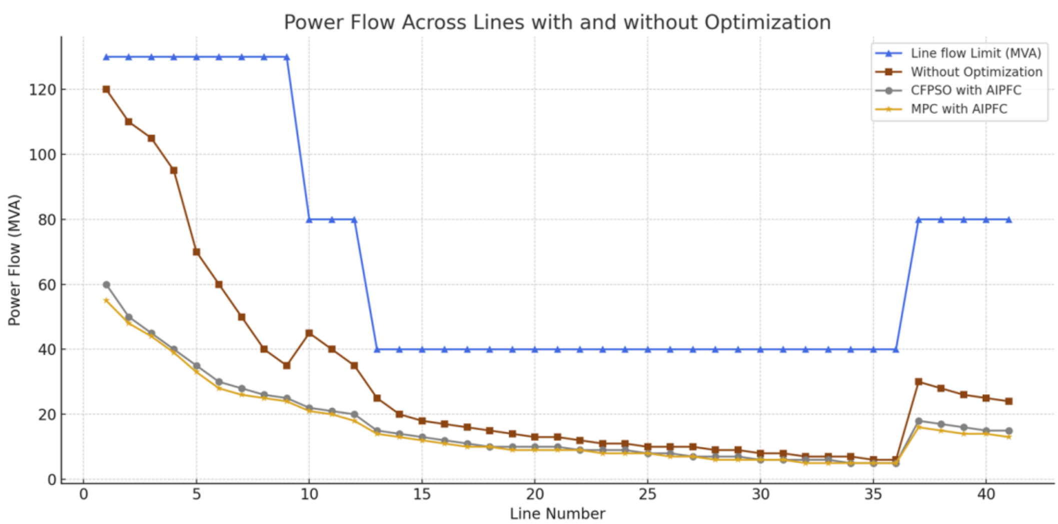

Figure 5: Power analysis under normal case condition

TABLE 2
OPTIMAL VALUES FOR IEEE-30 BUS SYSTEM UNDER 10% LOADING CONDITION

Control variables		10% Loading condition		
		NR	CFPSO with IPFC	MPC with IPFC
Real Power Generation (MW)	P_{G1}	1.9054	1.9057	1.6948
	P_{G2}	0.5812	0.5193	0.6048
	P_{G3}	0.1287	0.2871	0.35
	P_{G4}	0.1871	0.145	0.1734
	P_{G5}	0.2242	0.224	0.2474
	P_{G6}	0.211	0.136	0.12
Generator Voltages (p.u)	V_{G1}	1.05	1.1	1.05
	V_{G2}	1.045	1.0871	0.9501
	V_{G3}	1.01	1.0685	0.95
	V_{G4}	1.05	1.1	1.1
	V_{G5}	1.01	1.0585	0.95
	V_{G6}	1.05	1.1	1.1
Loss (MW)		**0.1202**	**0.0996**	**0.073**
Cost ($/hr)		**914.406**	**903.4810**	**902.6309**

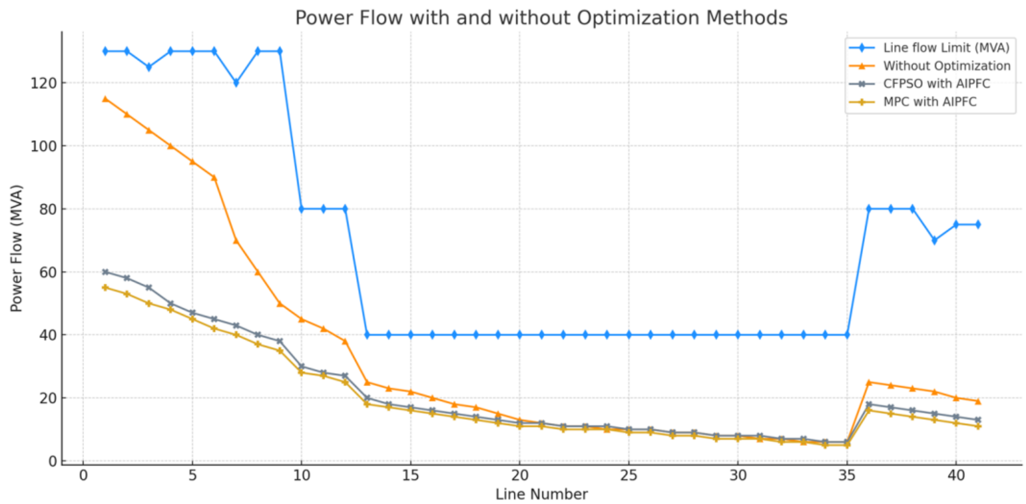

Fig. 6. Power analysis under 10% loading condition

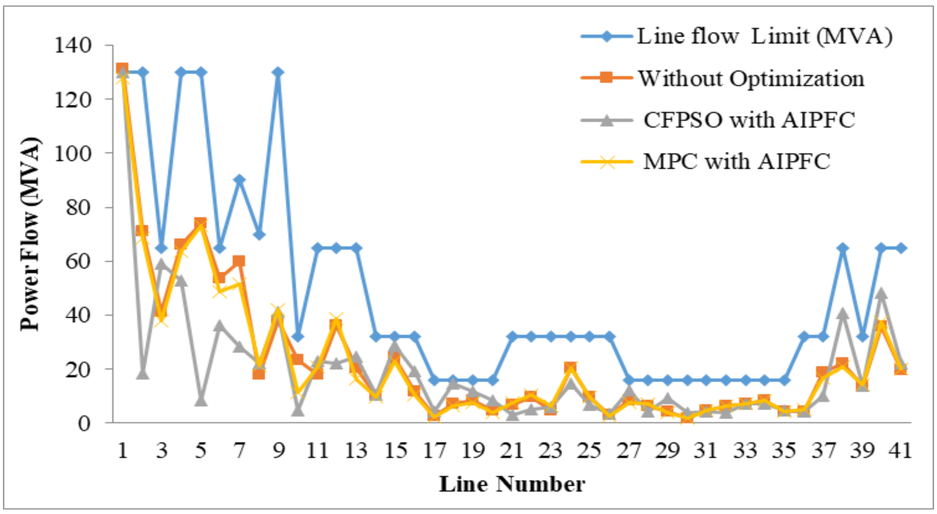

Fig. 7. Power analysis under 15% loading condition

TABLE 3
OPTIMAL VALUES FOR IEEE-30 BUS SYSTEM UNDER 15% LOADING CONDITION

Control variables		15% Loading condition		
		NR	CFPSO with IPFC	MPC with IPFC
Real Power Generation (p.u)	P_{G1}	1.9902	1.9716	1.787
	P_{G2}	0.66315	0.5369	0.6255
	P_{G3}	0.189	0.35	0.35
	P_{G4}	0.1137	0.1569	0.1909
	P_{G5}	0.2597	0.2303	0.2509
	P_{G6}	0.1753	0.12	0.1201
Generator Voltages (p.u)	V_{G1}	1.05	1.1	1.05
	V_{G2}	1.045	1.0873	0.95
	V_{G3}	1.01	1.0688	0.95
	V_{G4}	1.05	1.1	1.1
	V_{G5}	1.01	1.0581	0.95
	V_{G6}	1.05	1.1	1.1
Loss (p.u)		**0.132**	**0.1067**	**0.0652**
Cost ($/hr)		**969.725**	**957.49**	**949.4770**

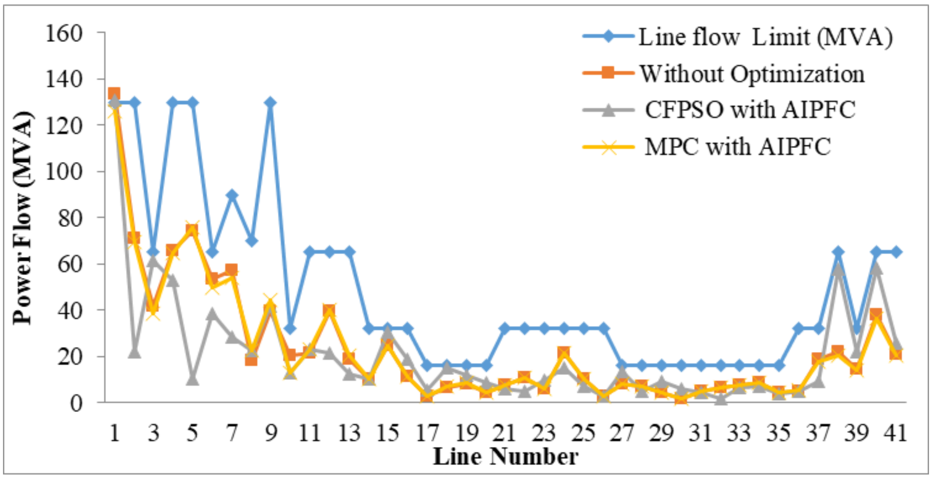

Fig. 8. Power analysis under 20% loading condition

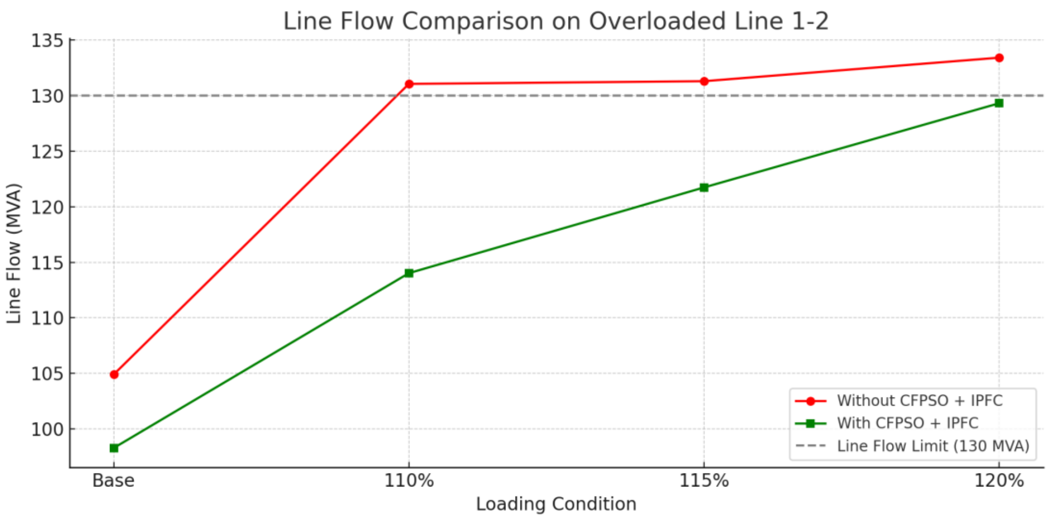

Fig. 9. The line flow comparison on the overloaded transmission line (bus 1–2) under various loading conditions

TABLE 4
OPTIMAL VALUES FOR IEEE-30 BUS SYSTEM UNDER 20% LOADING CONDITION

Control variables		20% Loading condition		
		NR	CFPSO with IPFC	MPC with IPFC
Real Power Generation (p.u)	P_{G1}	1.9721	1.9999	1.8949
	P_{G2}	0.7	0.5707	0.6376
	P_{G3}	0.2553	0.35	0.35
	P_{G4}	0.1559	0.1796	0.202
	P_{G5}	0.2985	0.2423	0.2561
	P_{G6}	0.1514	0.1708	0.12
Generator Voltages (p.u)	V_{G1}	1.05	1.1	1.05
	V_{G2}	1.045	1.0878	0.9501
	V_{G3}	1.01	1.0681	0.95
	V_{G4}	1.05	1.1	1.1
	V_{G5}	1.01	1.0581	0.95
	V_{G6}	1.05	1.1	1.1
Loss (p.u)		**0.1324**	**0.1125**	**0.0599**
Cost ($/hr)		**1026.46**	**1012.20**	**997.3751**

TABLE 5
THE EFFECTIVENESS OF CFPSO IPFC IN ALLEVIATING CONGESTION

	Over loaded lines	Line flow limit (MVA)	Increment in load (%)	Line flow (MVA)	
				Without CFPSO IPFC	CFPSO With IPFC
Case a	1-2	130	Base	**104.9**	**98.2825**
Case b	1-	130	110	**131.062**	**114.021**
Case c	1-2	130	115	**131.305**	**121.742**
Case d	1-2	130	120	**133.423**	**129.318**

TABLE 6
RESULTS SUMMARY UNDER DIFFERENT LOAD CONDITIONS

Load Condition	Fuel Cost (NR)	Fuel Cost (CFPSO + IPFC)	Fuel Cost (MPC + IPFC)	Loss (NR)	Loss (CFPSO + IPFC)	Loss (MPC + IPFC)
Normal	$810.91	$799.90	$798.81	0.0911 MW	0.089 MW	0.0855 MW
10% Load	$914.41	$903.48	$902.63	0.1202 MW	0.0996 MW	0.073 MW
15% Load	$969.73	$957.49	$949.48	0.1320 MW	0.1067 MW	0.0652 MW
20% Load	$1026.46	$1012.20	$997.38	0.1324 MW	0.1125 MW	0.0599 MW

When compared to the Newton Raphson (NR) approach, the minimum generator fuel cost achieved using the CFBPSO with IPFC method is 799.904 $/h, while the MPC with IPFC method yields a cost of 798.809 $/hr. The range of the control variable and the flow limit of the transmission line are both found to be satisfied by all solutions that were found. In order to validate the results, we compare the OPF results from the proposed methodology with some of the existing literature methods. You can see the comparison in Figure 4. You can see that the suggested CFBPSO and MPC approaches outperform the status quo in this graphic.

The total load demand of the practical system is taken as 283.4 MW and it is base load condition. The load flow studies are carried out and the power flows through the different transmission lines are obtained by satisfying the power balance equation.

All control parameters are within limit it is shown in Table 1. It is found from the results of normal case load flow analysis that the thermal parameters of all transmission lines are within the limit. Hence, it is noticed that there is no congestion in any of the transmission lines is shown in Figure 5.

B. Congestion due to Overloading Condition

This section deals with transmission congestion is due to overload, where the congestion has been created in the system by increasing the demand. The proposed methodology has been tested for 10% load, 15% load and 20% loading condition.

It is observed from that without IPFC, the line connecting buses 1 and 2 is the most congested line. It is observed that two lines, namely, lines 4–12 and 4-6, are connected to bus 4. Hence, lines 3–4 and 4–12 are the proposed locations for the placement of the IPFC. It is observed that reduces the congestion in line after placement of the IPFC at the proposed location.The phenomenon of power flow over 10% loading and how it contributes to congestion within the grid. However, when the demand surpasses the capacity of the grid, it can strain the system, leading to congestion. Power flow congestion occurs when the available transmission paths become saturated, causing inefficiencies and potential voltage instability. When the loading on the power grid exceeds 10%, the transmission lines and other grid components may become overloaded, compromising their ability to carry the excessive power. As a result, the power flow becomes constrained and concentrated on limited transmission corridors, leading to congestion it is shown in Table 2 and Figure 6. When a transmission line is loaded beyond its rated capacity, the power flow increases. The increased current generates more resistive losses, which can cause the line to heat up. The line's thermal limits define the maximum current that it can carry without overheating. If the loading exceeds these limits, it can result in various issues, including congestion. Congestion occurs when the transmission line's capacity is insufficient to accommodate the power flow demands. When a line is congested, it means that the power flow on the line is near or exceeds its maximum capability. The application of CFPSO and MPC with IPFC techniques requires accurate network models and sophisticated optimization algorithms to effectively relieve congestion and ensure the reliable operation of the transmission system are shown in Table 3 and Figure 8.

The combination of CFPSO and MPC algorithms optimizes the power flow and control actions, while the IPFC provides active control and compensation in real-time. CFPSO optimizes the system operation to find congestion-free solutions, which are then used as inputs for the MPC control strategy.

The combination of CFPSO and MPC algorithms optimizes the power flow and control actions, while the IPFC provides active control and compensation in real-time. CFPSO optimizes the system operation to find congestion-free solutions, which are then used as inputs for the MPC control strategy. MPC adjusts control variables based on these solutions, taking into account predicted system behaviour. Simultaneously, the IPFC actively controls power flows and voltages in multiple transmission lines, dynamically redistributing power to alleviate congestion. By coordinating the control actions of the IPFC with the MPC algorithm, congestion can be effectively managed it is shown in Table 4 and Figure 8.

The line flow comparison clearly demonstrates the effectiveness of the CFPSO-based IPFC approach in alleviating congestion on the overloaded transmission line connecting buses 1 and 2 in Figure 9. Under base loading conditions, the line operates safely below the thermal limit of 130 MVA. However, as the system load increases to 110%, 115%, and 120%, the line flow without any control measures rapidly exceeds the permissible limit, reaching as high as 133.42 MVA at 120% loading. This excessive flow indicates a high risk of overheating and potential system instability.

In contrast, when the CFPSO algorithm is applied in conjunction with IPFC, the line flow is significantly reduced under the same loading conditions. At 110% load, the line flow drops from 131.06 MVA to 114.02 MVA, and even at 120% load, the flow is brought down to 129.32 MVA—just within the safe operational boundary. These results confirm that the proposed method not only redistributes power flows efficiently but also maintains system security by keeping the line loading within acceptable limits, even under stress. This validates the suitability of CFPSO + IPFC for dynamic congestion management in modern power systems.

The generator output powers have been optimally rescheduled using the CFPSO and MPC algorithm to reduce congestion. The detailed results of CFPSO and MPC algorithm optimally rescheduling the output power of the participating generators to alleviate congestion. The power flows before and after placement of IPFC has been compared it is observed that the congestion in the lines reduces to a great extent after the placement of the IPFC by the proposed method. Also, to conquer the hassle of voltage deviation at the load buses, generator voltages were rescheduled to hold load bus voltages within acceptable boundaries. Hence, the overall system performance has been improved at a minimum cost. The proposed methodology has been tested for normal load, 10% load, 15% load, and 20% load conditions.

The congestion in all the lines has been effectively mitigated, as evident from the data presented in the table below. The comparison between line flow without CFPSO IPFC and with CFPSO IPFC demonstrates a significant reduction in line flow, ensuring the system operates within the specified limits is presented in Table 5. At 110% load (Case B), the line flow decreases from 131.062 MVA to 114.021 MVA. At 115% load (Case C), the line flow reduces from 131.305 MVA to 121.742 MVA. At 120% load (Case D), the line flow drops from 133.423 MVA to 129.318 MVA. The results demonstrate the effectiveness of CFPSO IPFC in alleviating congestion and maintaining the line flow within permissible limits, even under increasing load conditions.

The results summarized in the Table 6 clearly demonstrate the effectiveness of the proposed CFPSO and MPC methods integrated with the Interline Power Flow Controller (IPFC) for congestion management under varying load conditions. As system loading increases from normal (100%) to 120%, both fuel cost and transmission line losses also rise. However, the proposed AI-based techniques consistently outperform the traditional Newton-Raphson (NR) approach in minimizing operational cost and power losses. For example, under the normal load condition, the fuel cost using NR is \$810.91/hr, while it is reduced to \$799.90/hr and \$798.81/hr using CFPSO + IPFC and MPC + IPFC, respectively. This trend continues under 10%, 15%, and 20% increased load conditions, where the MPC approach yields the lowest cost of \$997.38/hr at 120% load, compared to \$1012.20/hr for CFPSO and \$1026.46/hr for NR.

In terms of system efficiency, the power losses observed with NR are significantly higher than those achieved with the proposed methods. At 20% overload, NR results in 0.1324 MW of loss, while CFPSO + IPFC and MPC + IPFC bring it down to 0.1125 MW and 0.0599 MW, respectively. The performance gap becomes more pronounced as the loading increases, indicating that the proposed AI-enhanced IPFC models are highly scalable and robust under stressed grid conditions. These findings confirm that integrating AI/ML optimization strategies with FACTS devices not only improves economic performance but also enhances grid reliability and stability.

VI. Conclusion

The research findings presented in this paper demonstrate the effectiveness of utilizing an Advanced Interline Power Flow Controller (IPFC) with AI/ML techniques for congestion management in power transmission lines. Extensive modeling and simulation have yielded useful insights into how AI/ML might be applied to tackle power system congestion. The study's results show how powerful IPFC may be when combined with AI and ML to handle electricity transmission line congestion. In order to alleviate congestion and enhance system reliability, the suggested methodology provides answers that are efficient, flexible, and inexpensive. The power sector and grid reliability could be greatly enhanced with the integration of IPFC with AI/ML approaches. It aids in the development of a more robust and intelligent power grid by improving its stability, resource usage, resilience, and the ability to make decisions in real time. Integrating new technology, optimizing for several objectives at once, and creating secure and resilient congestion management systems are all areas that could benefit from further investigation as a result of this study.

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