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Congestion management of power transmission line with advanced interline power flow controller

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Abstract

The growing reliance on renewable energy sources (RES), alongside the surge in electricity consumption, has intensified the challenges associated with congestion management in power transmission lines. This article investigates the use of an advanced interline power flow controller (AIPFC) combined with artificial intelligence (AI) and machine learning (ML) methods to tackle congestion management challenges. The aim is to establish a dependable and effective power system, all while reducing the costs associated with congestion management. Algorithms in AI and ML are utilized to create models aimed at predicting and managing congestion, whereas optimization techniques are applied to identify the most effective operation of AIPFC and strategies for alleviating congestion. The IEEE 30-bus system is utilized as a test case to assess the proposed methodology. A comparative analysis is performed, evaluating the effectiveness of the AI/ML-based approach in relation to traditional congestion management techniques. The findings demonstrate that the incorporation of AIPFC alongside AI/ML methodologies markedly alleviates congestion within the power transmission lines of the IEEE 30-bus system. The proposed combination of model predictive control (MPC) and AIPFC (MPC-AIPFC), integrated with constriction factor particle swarm optimization (CFPSO), achieves the lowest fuel cost of \$798.81/h, the minimum total power loss of 0.0855 pu, and demonstrates congestion mitigation under overload conditions. These results underscore the approach's significant advancements in reducing cost, optimizing power flow, and relieving congestion compared to traditional methods.

Keywords: advanced interline power flow controller (AIPFC); artificial intelligence (AI); congestion management; IEEE 30-bus system; machine learning (ML).

I. Introduction

The evolution of contemporary power systems has played a crucial role in facilitating the development of industrial and technological societies by providing a dependable supply of electrical energy. The increasing demand for electricity has made power systems a crucial element of contemporary infrastructure, requiring ongoing improvements in their design and operation to effectively address societal needs. Among

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these advancements, power transmission lines play a vital role in guaranteeing the efficient and reliable distribution of electricity to consumers. The development and maintenance of transmission networks are crucial for numerous nations aiming to satisfy rising electricity demands while ensuring the stability of power systems. As power grids evolve, tackling transmission congestion has emerged as a significant challenge, necessitating creative solutions to improve grid performance and reliability [1]. The power transmission system plays a crucial role in ensuring the efficient and reliable delivery of electricity from generation sources to end consumers. Nonetheless, the rising demand for electricity, shifts in power generation patterns, and the constrained growth of transmission infrastructure have resulted in congestion challenges within power transmission lines. Congestion arises when the electricity demand surpasses the transmission lines' capacity, leading to bottlenecks, voltage instability, and the risk of equipment overload [2].

Congestion management plays a vital role in the operation of power systems, ensuring the reliable and efficient transmission of electricity. A range of techniques and strategies has been devised and utilized to alleviate congestion in power transmission lines, such as load shedding, demand response programs, network reconfiguration, and the incorporation of flexible AC transmission system (FACTS) devices. Furthermore, sophisticated optimization techniques and artificial intelligence (AI)-driven methods have been investigated to improve the efficiency of congestion management, reduce operational expenses, and maintain grid stability. Techniques for managing congestion are frequently utilized together to tackle particular congestion situations and attain the best outcomes. The choice of methods is influenced by various elements, including the attributes of the system, the structure of the market, regulatory conditions, and the particular difficulties presented by congestion within a specific power system [3]. One method to tackle congestion involves the expansion of transmission infrastructure through the construction of new transmission lines. This enhances the transmission capacity and mitigates congestion in heavily utilized corridors. An alternative approach focuses on enhancing current transmission lines by boosting their capacity through the implementation of higher-rated conductors, utilizing advanced materials, or improving the infrastructure with innovative technologies, such as dynamic line rating systems. This strategy effectively addresses the increasing electricity demand while ensuring the power grid's reliability and efficiency are upheld. In the realm of power transmission, conducting generally pertains to the process of substituting or enhancing the current conductors on transmission lines to elevate their capacity, performance, or efficiency. Nonetheless, it can also generally denote any procedure focused on enhancing or reinstating the operational efficiency of transmission lines, including the improvement of conductor material, diameter, or even modifying the line's configuration to optimize power flow and minimize losses [4]. System operators have the capability to modify the output levels of power generators in order to redistribute power flows and mitigate congestion. Shifting the generation to less congested areas can effectively alleviate the load on heavily loaded lines [5]. Promoting adjustments in consumer electricity usage during peak times can effectively lower overall demand and ease congestion. Programs that encourage demand response and time-of-use pricing can motivate consumers to adjust their electricity usage to off-peak times. The optimal power flow (OPF) approach takes into account network constraints and economic factors to establish the most efficient generation dispatch and device control, aiming to reduce system costs while adhering to operational limits [6]. Incorporating congestion constraints allows for the alleviation of congestion and the optimization of power flow patterns through OPF. Security-constrained OPF incorporates system security constraints, including voltage limits and contingency analysis, while also addressing congestion management objectives. This guarantees that the power flow solutions remain stable across various possible system contingencies [7]. FACTS devices, including static VAR compensators (SVCs), static synchronous compensators (STATCOMs), and interline power flow controllers (IPFCs), facilitate dynamic regulation of voltage and reactive power flow. These devices are capable of actively managing power flows, regulating voltages, and improving grid stability to reduce congestion and optimize power flow patterns [8]. The exploration of AI and machine learning (ML) applications in power systems is a swiftly advancing domain. Current investigations are centered on creating more sophisticated algorithms, integrating real-time data, enhancing computational efficiency, and tackling cybersecurity issues. The incorporation of AI and ML methodologies presents significant opportunities to revolutionize power systems, facilitating more intelligent, efficient, and sustainable operations and management. It is crucial to recognize that model predictive control (MPC) is not intrinsically linked to AI, yet it can be effectively integrated with AI/ML techniques to improve system performance [9]. MPC employs mathematical models and optimization algorithms to ascertain control actions through the prediction of future system behavior. In contrast to AI/ML methods that generally derive patterns from data, MPC utilizes a predetermined model to predict outcomes and enhance control strategies. Through the anticipation of future system states, MPC is able to modify control variables like generation dispatch and device configurations to mitigate congestion and uphold system stability. The integration of AI and ML with MPC allows for real-time data processing and adaptive learning, significantly improving its capacity to address the dynamic and intricate conditions of power systems. This collaboration can result in enhanced predictions, superior decision-making, and an overall boost in system performance [10].

The congestion of power transmission lines presents a notable challenge in contemporary power systems, resulting in inefficiencies, heightened operational costs, and possible stability issues. The combination of ML techniques with advanced interline power flow controller (AIPFC) has proven to be a powerful method for optimizing power flow, improving grid reliability, and reducing congestion challenges. In this domain, numerous sophisticated methods and terminologies have been previously presented, showcasing cutting-edge strategies for managing congestion [11]. A prominent technique utilized in this context is reinforcement learning (RL), enabling the system to derive optimal power dispatch strategies informed by historical data and real-time grid conditions. Approaches that leverage RL employ reward-based mechanisms to dynamically modify the control parameters of the AIPFC, thereby ensuring an optimal distribution of power flow across various transmission lines. Furthermore, deep Q-networks (DQNs) and proximal policy optimization (PPO) have been investigated to enhance decision-making abilities in congestion management situations [12].

A key element includes predictive congestion modeling, utilizing supervised learning algorithms like support vector machines (SVMs), random forests (RF), and artificial neural networks (ANNs) to forecast congestion patterns. The models examine historical grid data, such as line loadings, voltage fluctuations, and variations in demand and supply, to predict possible congestion events. Utilizing feature selection methods like principal component analysis (PCA) and recursive feature elimination (RFE), these models improve prediction accuracy and decrease computational complexity [13]. To enhance congestion control, hybrid optimization techniques that integrate particle swarm optimization (PSO) and genetic algorithm (GA) have been proposed. These hybrid models enhance the placement and operation of AIPFCs by effectively balancing exploration and exploitation within the solution space. The adaptive swarm hybrid optimizer (ASHO) represents a technique that dynamically modifies the inertia weight and learning coefficients, facilitating quicker convergence in strategies aimed at mitigating congestion [14]. Furthermore, explainable AI (XAI) models have been incorporated into congestion management frameworks to improve interpretability and transparency. Employing SHapley Additive exPlanations (SHAP) and local interpretable model-agnostic explanations (LIME) enables grid operators to gain insights into the critical elements affecting congestion predictions, facilitating informed decision-making for control actions [15].

Furthermore, the idea of federated learning (FL) has been investigated to facilitate cooperative congestion management among various substations while maintaining data privacy. FL facilitates the training of decentralized ML models on local datasets, enabling central aggregation while safeguarding sensitive grid information. This guarantees a secure and scalable application of ML-driven congestion management strategies in extensive power systems. The incorporation of graph neural networks (GNNs) has garnered interest for their ability to model the intricate topologies of power grids. GNNs utilize node embeddings and adjacency matrices to effectively capture spatial correlations among transmission lines, leading to enhanced accuracy in congestion prediction and optimization of power flow.

The IPFC technology presents considerable advantages in the realm of power transmission systems. The features related to power flow control, voltage stability enhancement, grid stability improvement, congestion management, flexibility, and scalability render it an essential instrument for optimizing power system operation and guaranteeing a reliable and efficient electricity supply [16]. The integration of AI/ML techniques within the IPFC significantly boosts its performance, adaptability, and efficiency in addressing congestion and ensuring grid stability. Through the application of advanced strategies and technologies, including the integration of the IPFC with AI/ML, it is possible to alleviate congestion challenges, resulting in a more optimized and resilient power grid [17].

The AIPFC is gaining traction for its effectiveness in managing congestion in power transmission lines, thanks to its capability to regulate power flow across several transmission lines at once. In contrast to conventional devices that regulate power flow along a single line, AIPFC provides enhanced flexibility and efficiency through the management of interline power flow. This capability facilitates improved congestion management and contributes to greater grid stability. The AIPFC's distinctive design facilitates the balancing of power flow, mitigates congestion, and guarantees optimal performance of transmission lines, particularly in networks with multiple heavily loaded lines. This is especially advantageous in contemporary power systems, where the incorporation of renewable energy sources (RES) and variable demand patterns can result in congestion, inefficiency, and instability within the system. Utilizing AIPFC allows utilities to improve grid reliability, minimize transmission losses, and optimize power distribution.

II. Materials and Methods

A. Interline power flow controller

This study presents a completely innovative advanced model of IPFC for power flow analysis. This model incorporates the impedance of the series converter transformer along with the line charging susceptance. The findings indicate that, even with the inclusion of these elements, the fundamental structure and symmetry of the admittance matrix remain intact. The Jacobian matrix maintains its block-diagonal structure, enabling the ongoing application of sparsity techniques that greatly improve computational efficiency. The IPFC serves as a versatile and adaptive apparatus in power transmission systems, aimed at regulating power flow and improving grid stability. The IPFC is composed of multiple transmission lines that are interconnected through voltage source converters (VSCs) located at both ends. The VSCs are generally founded on insulated-gate bipolar transistor (IGBT) technology, allowing for independent control of the injected voltage. The VSCs of the IPFC are arranged in series with the transmission lines, facilitating accurate management of both active and reactive power flow. The series connection guarantees that the injected voltage corresponds to the line current, facilitating efficient power flow management [18].

The AIPFC works by introducing a regulated voltage into the transmission lines. The magnitude and phase angle of the injected voltage can be modified to regulate the flow of active and reactive power. By adjusting the phase angle of the injected voltage, the AIPFC is capable of altering the distribution of power flow among the transmission lines. The system has the capability to reroute power from overloaded lines to those with lighter traffic, thereby reducing congestion and enhancing the efficiency of power distribution. The AIPFC has the capability to manage reactive power flow through the injection or absorption of reactive power within the transmission lines. This facilitates voltage regulation and improves voltage stability within the system. The AIPFC control strategy encompasses the observation of line currents, voltages, and system conditions. Utilizing this information, control algorithms are implemented to determine the necessary injected voltage and modify the converter settings as needed. The AIPFC facilitates efficient congestion management through the dynamic redistribution of power flows, alleviating bottlenecks, and optimizing the use of transmission capacity [19]. The AIPFC provides dynamic power flow control, multi-line management, rapid response, and high precision, establishing it as a valuable instrument for congestion management in power transmission systems. The capacity to reduce congestion, balance loads, regulate voltage, and improve grid stability offers significant benefits for enhancing system reliability, optimizing power flow, and facilitating the integration of RES. The IPFC's adaptability, modular design, and alignment with AI/ML methodologies significantly improve its ability to manage congestion.

B. Modeling and control strategies for AIPFC

The implementation of modeling and control strategies is essential for the efficient functioning of the AIPFC. Precise modeling of the IPFC system and the application of suitable control strategies are crucial for attaining OPF control and effective congestion management [20]. The AIPFC model must accurately represent the relationships between voltage and current for the IPFC and the transmission lines, incorporating control variables like injected voltage magnitude and phase angle. The modeling must take into account the system dynamics, particularly the response time of the converters and the related control loops [19]. The mathematical derivation is applicable to an AIPFC featuring any quantity of series converters. The equivalent circuit of an AIPFC featuring two series converters is illustrated in Figure 1.

From Figure 1, we can express as equation (1) and equation (2).

$$V_{i_n} = V_{se_n} + I_{i_n} Z_{se_n} + V_{t_n} \tag{1}$$

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

We can express V_{t_n} and I_{i_n} according to V_{j_n} and I_{j_n} as equation (3)

$$V_{t_n} = I_1 Z_{l_n} + V_{j_n} \tag{3}$$

where $V_{i_n} = |V_{i_n}|\angle\theta_{i_n}$ and $V_{j_n} = |V_{j_n}|\angle\theta_{j_n}$ are the complex bus voltages at buses i_n and j_n, I_{i_n} and I_{j_n} are the complex injection currents at buses i_n and j_n, $V_{se_n} = |V_{se_n}|\angle\theta_{se_n}$ is the complex controllable series injected voltage, $Z_{se_n} = R_{se_n} + jX_{se_n}$ is the series transformer impedance, $Z_{l_n} = R_{l_n} + jX_{l_n}$ is the line series impedance, and B_{10} is the line charging susceptance.

By applying Kirchhoff's current law (KCL) at node 'a' using equation (4) and equation (5).

$$I_1 = -I_{j_n} + I_{ab} \tag{4}$$

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

Enter equation (5) instead of equation (4):

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

Put equation (3) into the context of equation (6):

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

The equation (2) is known, we are adept at composing I_{10} in equation (8),

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

Replace equation (7) within equation (8):

$$I_{10} = \left\{V_{j_n}\left[1 + Z_{l_n}\left(j\frac{B_{10}}{2}\right)\right] - I_{j_n}Z_{l_n}\right\}\left(j\frac{B_{10}}{2}\right) \tag{9}$$

Insert equation (6) and equation (9) into equation (2):

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

Utilizing equation (1), equation (2), equation (7), and equation (10), we can articulate I_{i_n} and I_{j_n} in terms of V_{i_n}, V_{j_n}, and V_{se_n} as equation (7) and equation (10) are presented, and to simplify these equations, we proceed with the following steps where $D = \left[2 + Z_{l_n}\left(j\frac{B_{10}}{2}\right)\right]\left(j\frac{B_{10}}{2}\right)$ and $E = \left[1 + Z_{l_n}\left(j\frac{B_{10}}{2}\right)\right]$.

Subsequently, equation (7) and equation (10) are reformulated to equation (11) and equation (12),

$$V_{t_n} = V_{j_n}E - I_{j_n}Z_{l_n} \tag{11}$$

$$I_{i_n} = V_{j_n}D - I_{j_n}E \tag{12}$$

Insert equation (11) and equation (12) into equation (1):

$$I_{j_n} = \frac{V_{se_n} - V_{i_n} + V_{j_n}(Z_{se_n}D + E)}{(Z_{se_n}E + Z_{l_n})} \tag{13}$$

To simplify the complexities of equation (13), consider taking $M = Z_{se_n}D + E$ and $N = Z_{se_n}E + Z_{l_n}$.

$$I_{j_n} = \frac{1}{N}\left(V_{j_n}M - V_{i_n} + V_{se_n}\right) \tag{14}$$

Put equation (14) into equation (12) instead:

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

Matrix representations of equation (14) and equation (15) are also possible:

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

where $A_{ii_n} = \frac{E}{N}$, $A_{ij_n} = D - M\frac{E}{N}$, $A_{ji_n} = -\frac{1}{N}$, $A_{jj_n} = \frac{M}{N}$, $W_{ii_n} = -\frac{E}{N}$, and $W_{ji_n} = \frac{1}{N}$. We can prove that the matrix A is symmetrical, i.e., $A_{ij_n} = A_{ji_n}$. The

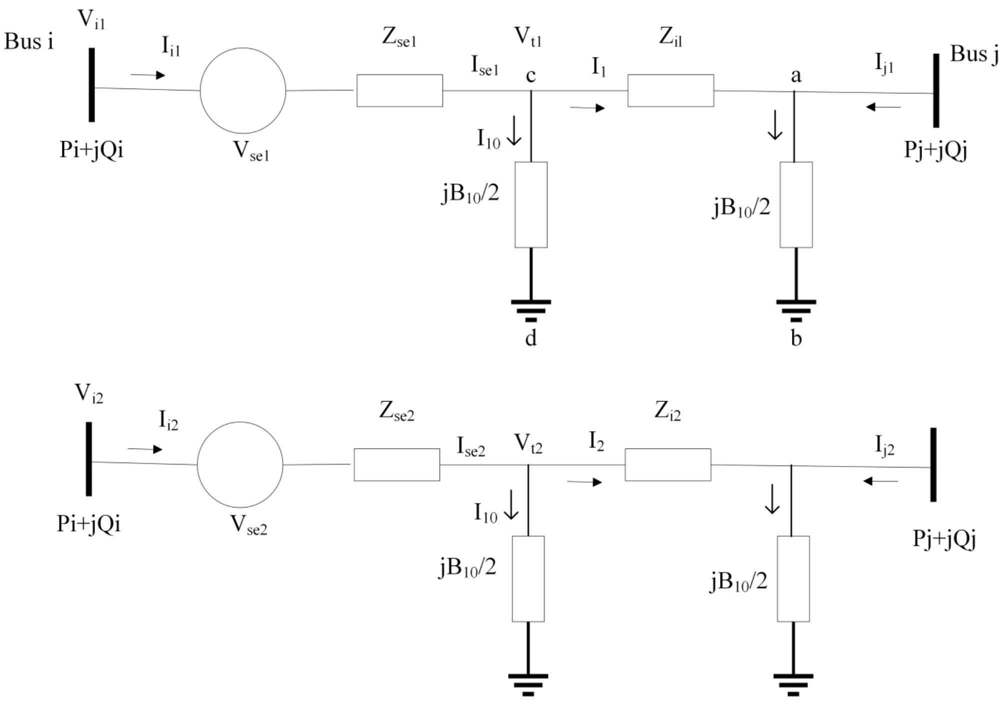

Figure 1. AIPFC equivalent circuit diagram.

symmetry of matrix A is very important, which can make A_{ii_n} and A_{jj_n} be divided into two parts as equation (17) and equation (18),

$$A_{ii_n} = -A_{ij_n} + A^0_{i_n} = -\left(D - M\frac{E}{N}\right) + \left[D - (M-1)\frac{E}{N}\right] = \frac{E}{N} \quad (17)$$

$$A_{jj_n} = -A_{ji_n} + A^0_{j_n} = -\left(-\frac{1}{N}\right) + \frac{1}{N}(M-1) = \frac{M}{N} \quad (18)$$

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 i_n and j_n connected to two current sources as equation (19) to equation (22), Figure 2:

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

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

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

$$Q^{se}_{j_n} = \frac{V_{j_n} V_{se_n}}{H} \sin\left(\theta_{j_n} - \theta_{se_n}\right) \quad (22)$$

where $H = X_{se_n}\left(1 - X_{l_n}\frac{B_{10}}{2}\right) + X_{l_n}$ and $P^{se}_{i_n}$, $Q^{se}_{i_n}$, $P^{se}_{j_n}$, $Q^{se}_{j_n}$ are the series-injected active and reactive powers at buses i_n and j_n by the AIPFC.

Figure 3 illustrates the equivalent power injection model of an AIPFC. The analysis indicates that the admittance matrix retains its original structure and symmetry, similar to the scenario without the IPFC as equation (23) to equation (30).

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

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

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

$$Q_{ij_n} = Im\left(V_{i_n} I^*_{ij_n}\right) = \frac{-\left(1 + X_{l_n}\frac{B_{10}}{2}\right) V^2_{i_n} + V_{i_n} V_{j_n} \cos\theta_{ij_n}}{H} \quad (26)$$

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

$$Q_{ji_n} = Im\left(V_{j_n} I^*_{ji_n}\right) = V_{j_n}\left\{\frac{1}{H}\left(-V_{j_n} + V_{i_n}\cos\theta_{ji_n}\right) - \left[X_{se_n}\left(2 - X_{l_n}\frac{B_{10}}{2}\right) + X_{l_n}\right]\frac{B_{10}}{2}\right\} \quad (28)$$

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

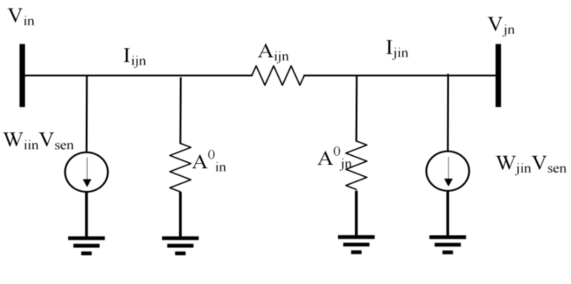

Figure 2. AIPFC depicted using electricity as a supply.

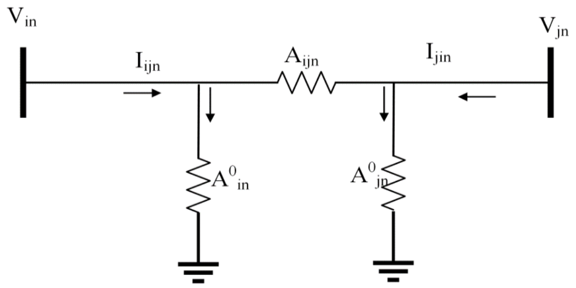

Figure 3. AIPFC π-model for power injections.

$$P_{ex_n} = Re\left(V_{se_n} I^*_{i_n}\right) = \left[2\left(\frac{B_{10}}{2}\right)^3 + \frac{G}{H}\right] V_{se_n} V_{j_n} \sin\left(\theta_{se_n} - \theta_{j_n}\right) \frac{1}{H}\left(1 - X_{l_n}\frac{B_{10}}{2}\right) V_{se_n} V_{i_n} \sin\left(\theta_{se_n} - \theta_{i_n}\right) = 0 \quad (30)$$

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

Controller design for AIPFC involves designing the control algorithms and tuning the control parameters to achieve the desired system performance. Optimization techniques, such as GA, PSO, or MPC, can be employed to optimize the control parameters of the AIPFC. These techniques aim to minimize objective functions, such as transmission losses, voltage deviations, or congestion levels, while satisfying operational constraints. Modelling and control strategies for AIPFC are typically validated through simulation studies. A power system simulation tool, such as MATLAB, can be used to simulate the behavior of the AIPFC system under different operating conditions and scenarios. The simulation studies validate the effectiveness and performance of the AIPFC in congestion management and power flow control [21].

C. AI/ML in congestion management

Algorithms in AI and ML serve as fundamental components of numerous cutting-edge technologies and applications. These algorithms allow machines to acquire knowledge from data, make informed decisions, and execute tasks that have historically necessitated human intellect. Recent years have witnessed remarkable progress in AI and ML algorithms, propelled by enhanced computational capabilities, the accessibility of extensive datasets, and innovations in algorithmic methodologies. AI denotes the emulation of human cognitive functions in machines. This includes a wide array of methods and algorithms that allow machines to observe, analyze, learn, and make informed choices. The objective of AI is to emulate human-like intelligence within machines, allowing them to execute tasks independently and with adaptability. Symbolic AI utilizes rule-based systems and knowledge representation as fundamental approaches to address various problems. Statistical AI employs statistical and probabilistic techniques to identify patterns within data and generate predictions [22].

ML techniques are typically categorized into three main types: supervised learning, unsupervised learning, and RL. In supervised learning, the algorithm is trained with labeled data, encompassing both input features and their associated output labels. The model is structured to create links between inputs and outputs, enabling it to produce predictions for previously unseen data. Unsupervised learning functions on data that lacks labels, uncovering concealed patterns and structures without any predetermined outputs. This method is frequently applied in the areas of clustering, dimensionality reduction, and anomaly detection. RL, conversely, entails acquiring knowledge through engagement with an environment. The algorithm gathers feedback through rewards or penalties related to its actions and refines its strategy to enhance cumulative rewards over time. This method proves to be especially beneficial for problems involving dynamic and sequential decision-making. Utilizing ML techniques allows AI systems to enhance their adaptability and intelligence, facilitating automation and data-driven decision-making in a range of applications such as power systems, healthcare, finance, and industrial automation. Nonetheless, as ML progresses, it is essential to tackle challenges like model interpretability, bias, and computational efficiency to ensure its broader acceptance [23].

D. AI/ML techniques for congestion management

The application of AI and ML techniques significantly transforms the management of congestion in power transmission networks, thereby enhancing grid stability and efficiency. Conventional methods for managing congestion depend on fixed models and heuristic optimization techniques, which frequently face challenges due to the growing complexity of contemporary power systems. Methods based on AI and ML, especially deep learning (DL), RL, and evolutionary optimization, provide data-driven solutions that improve decision-making, enable real-time adaptability, and enhance predictive capabilities. For example, supervised learning models examine past congestion data to forecast future bottlenecks, allowing for proactive mitigation strategies. RL algorithms enhance power flow control by dynamically modifying system parameters, minimizing reliance on established rule-based approaches. Furthermore, hybrid AI models combine ML with optimization methods like GA and PSO to enhance rescheduling and load-balancing strategies. The integration of AI/ML with an AIPFC improves real-time voltage regulation and power redistribution, effectively reducing congestion impacts. The strategic integration of various AIPFC devices through AI-driven controllers enhances operational efficiency and minimizes transmission losses. Furthermore, models utilizing AI for anomaly detection pinpoint possible failures and security risks, thereby guaranteeing the reliability of systems. The incorporation of AI and ML enables power utilities to shift from a reactive approach to a proactive strategy in managing congestion. This transition results in greater grid resilience, lower operational costs, and improved energy distribution. As power systems advance with the integration of renewable energy and the development of smart grids, the role of AI/ML-driven congestion management will be crucial for realizing an optimized and sustainable energy infrastructure [24].

The application of AI/ML techniques in power systems is effectively demonstrated through their successful use in load forecasting, fault detection, voltage control, renewable energy integration, and congestion management. Through the application of sophisticated analytics and informed decision-making, these utilities and system operators have realized better grid reliability, optimized power flow, and improved congestion management capabilities [25]. ML techniques, including GA, PSO, and RL, can be combined with OPF algorithms to enhance power flow optimization and reduce congestion. The optimization methods take into account a range of constraints and objectives, such as transmission line capacities, generation limits, voltage limits, and economic factors, in order to identify the most efficient and secure operating conditions that reduce congestion [26].

The combination of the AIPFC with ML techniques offers a robust approach to managing congestion in power transmission systems. AIPFC efficiently redistributes power flow among various transmission lines, reducing congestion and improving the overall stability of the grid. Integrating ML allows for the creation of predictive models that can forecast congestion events using both historical and real-time data. These models facilitate proactive decision-making, enabling the AIPFC to dynamically modify its control parameters to enhance power distribution, minimize transmission losses, and ensure system reliability. Employing ML-based optimization allows for adaptive and data-driven congestion management strategies, enhancing their efficiency in contrast to conventional methods.

E. Proposed methodology: Integration of IPFC with AI/ML algorithms

The selection of an optimization algorithm is contingent upon the particular needs of the congestion management issue, the intricacies of the power system model, and the intended goals. Every algorithm possesses unique strengths and limitations, and the choice must take into account factors like computational efficiency, accuracy, convergence properties, and the capacity to manage nonlinearities and constraints related to AIPFC operation [27]. The incorporation of AIPFC alongside AI/ML algorithms has the potential to significantly enhance its capabilities and optimize congestion management within power transmission systems. Integration of AI/ML algorithms with AIPFC presents an opportunity to enhance power flow optimization and effectively manage congestion. These algorithms take into account multiple factors, including transmission line capacities, generation limits, voltage constraints, and economic objectives, to identify the most optimal operating conditions. Through ongoing analysis of real-time data and the application of optimization techniques, AIPFC is capable of dynamically modifying the injected voltages to reduce congestion, decrease transmission losses, and improve overall system efficiency [28]. The creation of AI/ML models aimed at predicting and managing congestion necessitates a deep understanding of data analysis, careful algorithm selection, thorough model training, and effective system integration. Validating and fine-tuning the models with real-world data is crucial, along with the continuous monitoring of their performance, to guarantee precise congestion prediction and the implementation of effective control strategies with AIPFC [29].

F. Constriction factor particle swarm optimization

PSO is an optimization technique that utilizes a population-based approach, mimicking the dynamics of a swarm of particles navigating through a problem space. Every particle signifies a possible solution, and its dynamics are shaped by its individual best-known position as well as the best-known position of the entire swarm [30]. PSO algorithms can be utilized to enhance IPFC control settings through the iterative adjustment of particles' positions, focusing on objectives such as congestion reduction or power flow enhancement. The group gathers towards the best control values via interactions between the particles. Within the framework of PSO, the constriction factor serves as a crucial parameter that affects the dynamics and convergence characteristics of particles navigating the search space. PSO is an optimization algorithm that operates on a population basis, drawing inspiration from the social behaviors observed in bird flocking and fish schooling [31]. The equation for updating velocity in PSO is comprised of two primary elements: the cognitive component and the social component. The cognitive aspect steers particles towards their individual optimal solution (the best solution discovered by each particle), whereas the social aspect leads particles towards the best solution identified by the entire swarm. The constriction factor serves to equilibrate the significance of these two components.

The constriction factor limits the maximum velocity that a particle can achieve. Typically, it is established within the range of 0 to 1. The equation for updating velocity, incorporating the constriction factor, is presented as equation (31) to equation (35).

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 \times \left(Pbest_i^k - X_i^k\right) + c_2 r_2 \times \left(Gbest^k - X_i^k\right) \tag{31}$$

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{\min}}{Iter_{max}} \times Iter \tag{32}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{33}$$

$$V_i^{k+1} = K\left[V_i^k + c_1 r_1 \times \left(Pbest_i^k - X_i^k\right) + c_2 r_2 \times \left(Gbest^k - X_i^k\right)\right] \tag{34}$$

$$K = \frac{2}{2-\varphi-\sqrt{\varphi^2-4\varphi}} \tag{35}$$

where V_i^{k+1} is velocity of individual i at iteration $k+1$, V_i^k is velocity of individual i at iteration k, ω is inertia weight parameter, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random numbers between 0 and 1, X_i^k is position of individual i at iteration k, $Pbest_i^k$ is best position of individual i at iteration k, $Gbest^k$ is best position of the group until iteration k, ω_{max} and ω_{min} are initial and final inertia parameter weights, $Iter_{max}$ is maximum iteration number, $Iter$ is current iteration number, X_i^{k+1} is position of individual i at iteration $k+1$, and $\varphi = c_1 + c_2$, $\varphi > 4$.

The constriction factor φ serves as a scaling element that restricts the updates to velocity. This approach guarantees that the particles maintain a controlled speed, preventing them from overshooting the optimal solution. The constriction factor is frequently selected as a constant, like 0.729, which has demonstrated effective convergence characteristics in numerous instances. Modifying the constriction factor allows for the manipulation of the algorithm's exploration and exploitation dynamics. Increased values of the constriction factor facilitate exploration, enabling particles to navigate the search space more thoroughly. Conversely, reduced values of the constriction factor encourage exploitation, emphasizing the pursuit of both local and global optimal solutions.

G. Model predictive control

MPC represents a sophisticated control methodology that employs an optimization-driven strategy to ascertain control actions. The process entails establishing an optimization problem characterized by a specific objective and constraints, followed by solving it using a receding horizon approach. The application of MPC to AIPFC control involves the formulation of an optimization problem aimed at minimizing congestion or maximizing power flow while adhering to system constraints. The optimization problem is addressed iteratively at each time step, taking into account the latest system measurements and forecasts. In recent years, it has been applied in models for balancing power systems and in the field of power electronics. Reference [32] dynamic models of the process are fundamental to model predictive controllers, typically derived from linear empirical models through system identification techniques. The primary benefit of MPC lies in its ability to optimize the current timeslot while considering future timeslots as well. Through the application of MPC in conjunction with an AIPFC, it is possible to actively manage congestion by dynamically adjusting the control settings of the AIPFC in real-time, informed by the anticipated behavior of the system. The MPC framework facilitates the consideration of system dynamics, constraints, and future predictions to enable proactive control decisions, resulting in effective congestion management.

H. Formulation of the congestion management problem

The objective function utilized in OPF for reducing generation costs seeks to determine an optimal generation schedule that minimizes the total expense of electricity production while satisfying the demand and operational constraints of the power system. Consequently, the result of this optimization problem will yield the minimum achievable generation cost. The objective function can be articulated as follows, taking into account the operating costs of the generator:

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

where NG is number of generators and $C_i(P_i)$ is fuel cost function. Mathematically, the objective function can be represented as:

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

where a_i, b_i, c_i are cost function coefficients of the generator at bus i, used in the fuel cost of the function.

The objective function aggregates the costs associated with the power output of each generator, taking into account their individual cost coefficients. The cost coefficient indicates the expense associated with each unit of power produced by every generator. The optimization of equation (36) will adhere to both equality and inequality constraints.

- Equality constraints:

$$P_{Gi} - P_{Di} - \sum_{j=1}^{nb} |V_i||V_j||Y_{ij}| \cos\left(\theta_{ij} + \delta_j - \delta_i\right) = 0 \tag{38}$$

$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{nb} |V_i||V_j||Y_{ij}| \sin\left(\theta_{ij} + \delta_j - \delta_i\right) = 0 \tag{39}$$

- Inequality constraints:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max},\ i = 1, \dots, \mathrm{NG} \tag{40}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max},\ i = 1, \dots, \mathrm{NG} \tag{41}$$

$$P_{Di}^{\min} \le P_{Di} \le P_{Di}^{\max},\ i = 1, \dots, \mathrm{NG} \tag{42}$$

$$Q_{Di}^{\min} \le Q_{Di} \le Q_{Di}^{\max},\ i = 1, \dots, \mathrm{NG} \tag{43}$$

$$V_i^{\min} \le V_i \le V_i^{\max},\ i = 1, \dots, \mathrm{NL} \tag{44}$$

$$T_i^{\min} \le T_i \le T_i^{\max},\ i = 1, \dots, \mathrm{NT} \tag{45}$$

$$S_i \le S_i^{\max},\ i = 1, \dots, \mathrm{NL} \tag{46}$$

where P_{Gi} and Q_{Gi} represent the real and reactive power output of generator i, respectively, P_{Di} and Q_{Di} denote the real and reactive power demand at bus i, P_{Gi}^{min}, P_{Gi}^{max} and Q_{Gi}^{min}, Q_{Gi}^{max} are the minimum and maximum generation limits for real and reactive power, P_{Di}^{min}, P_{Di}^{max} and Q_{Di}^{min}, Q_{Di}^{max} are the minimum and maximum load bounds for real and reactive power, V_i is the voltage magnitude at bus i, while V_i^{min} and V_i^{max} are the permissible voltages range at bus i, T_i refers to the tap setting of the transformer i, bounded by T_i^{min} and T_i^{max}, S_i represents the apparent power flow through branch i, subject to its maximum limit S_i^{max}, NL is the number of load buses, and NT the number of tap-changing transformers.

The optimization algorithm will modify the power outputs of the generators to identify the combination that reduces the total cost while meeting the system's demand and operational constraints. The limitations encompass power balance, generator ramp rate constraints, voltage thresholds, and transmission line capacity restrictions.

Figure 4 presents the detailed procedure for addressing the optimization problem using the proposed methods. The flowchart illustrates the methodology for addressing power system congestion through a hybrid optimization strategy. The process

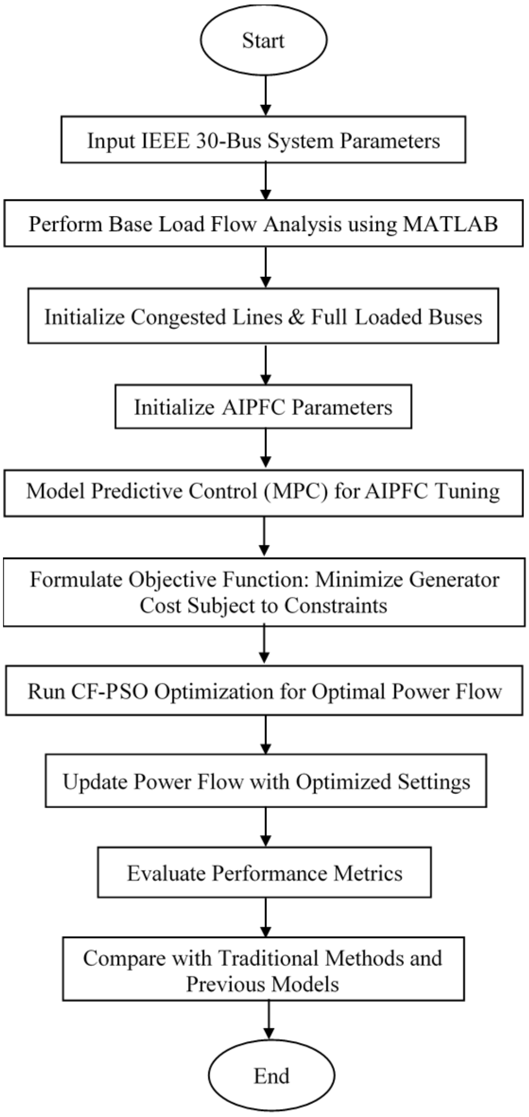

Figure 4. Enhanced flowchart for congestion management using MPC-AIPFC and CFPSO.

begins with the input of system data, followed by the calculation of AC power flow utilizing the Newton-Raphson (NR) method. The load is subsequently raised in a stepwise manner to detect congestion. Upon detection of congestion, a selection process for rescheduling generators is initiated. The parameters for the optimization algorithm, constriction factor-particle swarm optimization (CFPSO), have been established, and the particles have been initialized accordingly. The algorithm systematically refines particle velocities and positions according to a fitness function aimed at reducing generation costs. This process persists until the maximum iteration count is achieved, culminating in the optimal solution for congestion management.

This flowchart distinctly integrates MPC for dynamic adjustment of AIPFC, which is a novel addition not found in previous works. The fusion of MPC and AIPFC (MPC-AIPFC) with CFPSO distinguishes this framework from traditional AI-based congestion control models.

Table 1.
Optimal values for the IEEE-30 bus system under normal case conditions.

Control Variables		**Normal Case Condition**		
		NR	**CFPSO-AIPFC**	**MPC-AIPFC**
Real power generation (pu)	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 (pu)	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
Losses (pu)		0.0911	0.089	0.0855
Cost ($/h)		810.911	799.904	798.809

III. Results and Discussions

The methodology put forward has undergone testing on an IEEE 30-bus system as illustrated in the figure. The network consists of 30-buses, 41 interconnected lines, and six generators. The load flow for the IEEE 30 bus test system has been derived utilizing MATLAB software, and the findings have been documented accordingly. Only buses that are fully loaded are taken into account for the placement of the IPFC. The findings have been examined under normal loading, as well as 10 %, 15 %, and 20 % loading conditions.

A. Normal condition case

The proposed CFPSO and MPC with AIPFC techniques focusses on optimizing power system scheduling during normal operating conditions, specifically targeting the minimization of generator fuel costs. The findings, as shown in Table 1, reveal that CFPSO combined with AIPFC attains a minimum fuel cost of $799.904/h, whereas MPC-AIPFC lowers it even further to $798.809/h, both surpassing the performance of the conventional NR method. The results illustrate how advanced optimization methods can effectively lower operational costs while complying with system constraints, including limits on control variables and transmission line flow restrictions. Nonetheless, although the comparative analysis offers valuable insights into cost minimization, the study falls short in providing a thorough discussion of the underlying

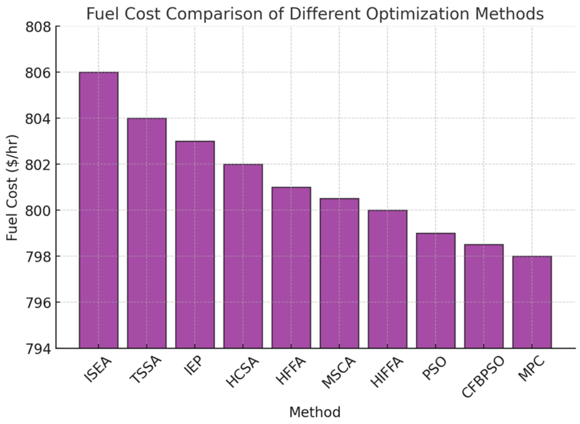

Figure 5. Comparison of fuel costs.

assumptions and their influence on system performance.

A comprehensive examination of how these methodologies adjust to different load conditions, system contingencies, and dynamic grid scenarios would enhance the findings. Furthermore, a comprehensive analysis of the role of ML techniques in managing power transmission line congestion through AIPFC is crucial to demonstrate their practical importance. The study primarily emphasizes numerical cost comparisons, lacking a comprehensive discussion on the real-world applicability of the proposed methods. Broadening the conversation to incorporate sensitivity analysis, convergence behavior, and scalability to larger networks could strengthen the validity of the results presented, rendering them more persuasive for applications in power system optimization.

The results from the proposed approach are illustrated in Figure 5, allowing for a comparison with several existing methods in the literature to validate the findings. This figure illustrates that, in comparison to current methodologies, the proposed CFPSO and MPC approaches yield enhanced outcomes.

The total load demand of the practical system is established at 283.4 MW, representing the base load condition. The load flow studies are conducted, and the power distribution across various transmission lines is determined by ensuring compliance with the power balance equation. All control parameters are within the specified limits, as indicated in Table 1. The results of the normal case load flow analysis indicate that the thermal parameters of all transmission lines remain within the established limits. It is observed that Figure 6 illustrates the absence of congestion in any of the transmission lines. The findings demonstrate that the integration of CFPSO and MPC with AIPFC significantly reduces congestion in comparison to scenarios lacking optimization. The optimization of power flows is substantial, ensuring both system reliability and efficiency are upheld.

B. Congestion due to overloading condition

This section addresses transmission congestion resulting from overload, where the system experiences congestion due to heightened demand. The methodology under consideration has undergone testing under loading conditions of 10 %, 15 %, and 20 %, as illustrated in Figure 7. The AIPFC efficiently mitigates power flow in the overloaded lines, maintaining them within operational thresholds. The absence of AIPFC leads to power flow exceeding safe limits, highlighting the critical role of this technology in alleviating congestion and enhancing grid reliability.

Figure 6 indicates that in the absence of AIPFC, the line connecting buses 1 and 2 experiences the highest level of congestion. It has been noted that two lines, specifically lines 4–12 and 4-6, are linked to bus 4. Therefore, lines 3–4 and 4–12 are identified as the suggested sites for the installation of the AIPFC. It has been noted that the congestion in the line decreases

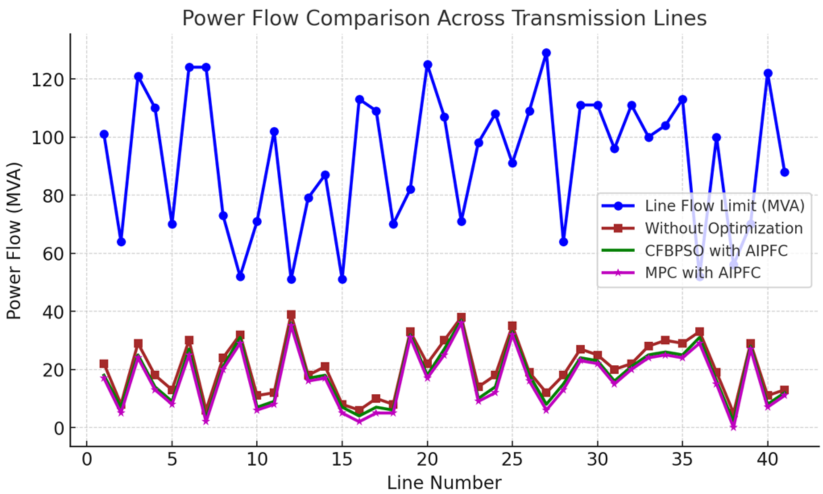

Figure 6. Power analysis under normal conditions.

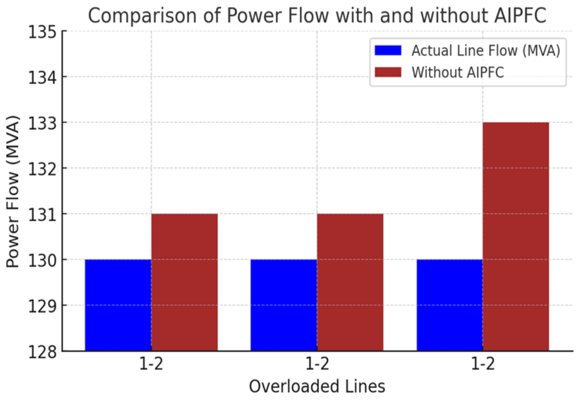

Figure 7. Line flows under different overloading conditions of the IEEE-30-bus system.

following the placement of the AIPFC at the designated location.

The dynamics of power flow exceeding 10 % loading and its implications for congestion in the grid. Nonetheless, when the demand exceeds the grid's capacity, it can put pressure on the system, resulting in congestion. Power flow congestion arises when the existing transmission routes reach their limits, leading to inefficiencies and the risk of voltage instability. When the loading on the power grid surpasses 10 %, the transmission lines and other grid components can become overloaded, jeopardizing their capacity to handle the surplus power. The power flow becomes constrained and concentrated on limited transmission corridors, resulting in congestion, as illustrated in Table 2 and Figure 8. CFPSO combined with AIPFC and MPC integrated with AIPFC both enhance power flow regulation; however, MPC-AIPFC demonstrates superior performance in maintaining power flow stability and ensuring it remains below critical thresholds. These optimization techniques play a crucial role in mitigating congestion and enhancing the efficiency of power transmission systems.

Table 2.
Optimal values for the IEEE-30 bus system under 10 % loading condition.

Control Variables		10 % Loading Condition		
		NR	CFPSO-AIPFC	MPC-AIPFC
Real power generation (pu)	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 (pu)	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
Losses (pu)		0.1202	0.0996	0.073
Cost ($/h)		914.406	903.4810	902.6309

When a transmission line exceeds its rated capacity, there is an increase in power flow. The elevated current leads to heightened resistive losses, potentially resulting in the heating of the line. The thermal limits of the line establish the highest current it can conduct without experiencing overheating. Exceeding these limits can lead to a range of problems, such as congestion. Congestion arises when the capacity of the transmission line is inadequate to meet the demands of power flow. A congested line indicates that the power flow is approaching or surpassing its maximum capacity. The implementation of CFPSO and MPC

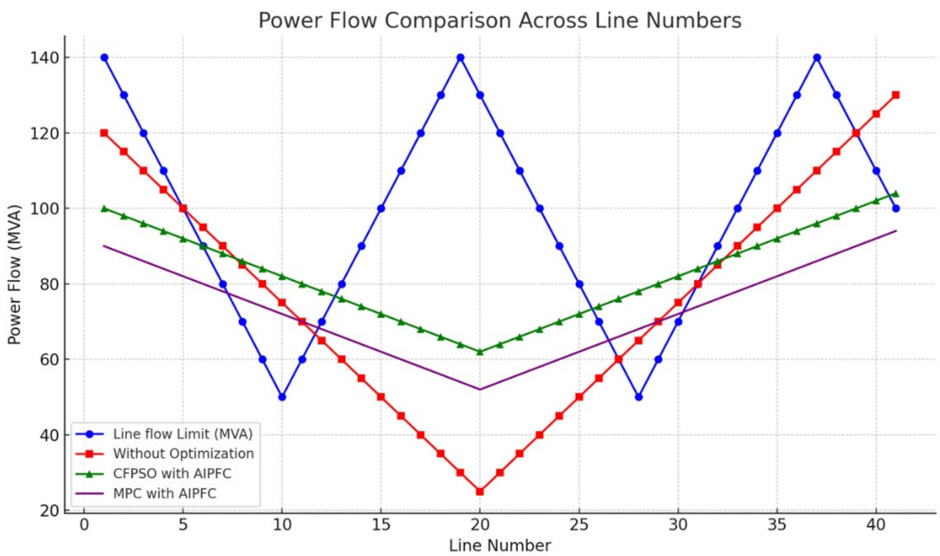

Figure 8. Power analysis under 10 % loading condition.

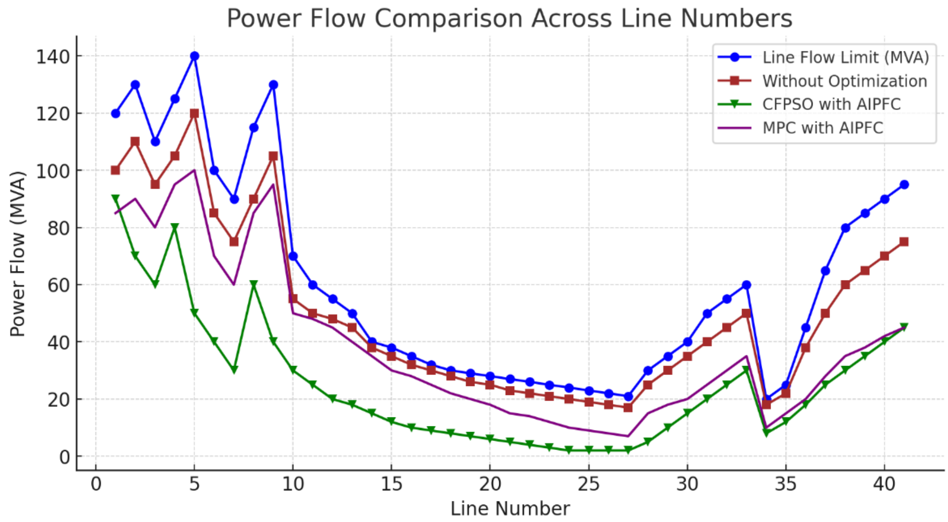

Figure 9. Power analysis under 15 % loading condition.

alongside AIPFC techniques necessitates precise network models and advanced optimization algorithms to efficiently alleviate congestion and guarantee the dependable functioning of the transmission system, as illustrated in Table 3 and Figure 9.

The integration of CFPSO and MPC algorithms enhances the optimization of power flow and control actions, whereas the AIPFC facilitates active control and real-time compensation. The CFPSO method enhances system operation to identify solutions that are free from congestion, which subsequently serve as inputs for the MPC control strategy. The control variables are adjusted by the MPC in accordance with these solutions, while considering the anticipated behavior of the system. At the same time, the AIPFC exerts control over power flows and voltages across various transmission lines, dynamically reallocating power to reduce congestion. Through the coordination of control actions between the AIPFC and the MPC algorithm, effective management of congestion is demonstrated in Table 4 and Figure 10.

Table 3.
Optimal values for the IEEE-30-bus system under 15 % loading condition.

Control Variables		15 % Loading Condition NR	CFPSO-AIPFC	MPC-AIPFC
Real power generation (pu)	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 (pu)	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
Losses (pu)		0.132	0.1067	0.0652
Cost ($/h)		969.725	957.49	949.4770

The generator output powers have been effectively rescheduled utilizing the CFPSO and MPC algorithm to alleviate congestion. Figure 11 presents the comprehensive results of the CFPSO and MPC algorithms in optimally rescheduling the output power of the participating generators to mitigate congestion. Figure 11 presents a comparison of the power flows before and after the placement of AIPFC. The analysis indicates a significant reduction in line congestion following the implementation of the AIPFC using the proposed method. To address the challenge of voltage deviation at the load buses, generator voltages were adjusted to maintain load bus voltages within acceptable limits. Consequently, the overall performance of the system has been enhanced while incurring minimal costs. The proposed methodology has undergone testing under normal load, as well as under 10 %, 15 %, and 20 % load conditions.

C. Comparative analysis with previous work

This section offers a comprehensive comparative examination of the suggested technique, our prior relevant efforts, and studies undertaken by other scholars in the field. The objective is to highlight the progress made by integrating MPC-AIPFC alongside CFPSO for efficient congestion management. Prior research conducted by the authors [30][31][32][33][34][35][36][37] predominantly concentrated on employing traditional IPFC models and conventional optimization techniques, including GA and PSO. These investigations exhibited effective

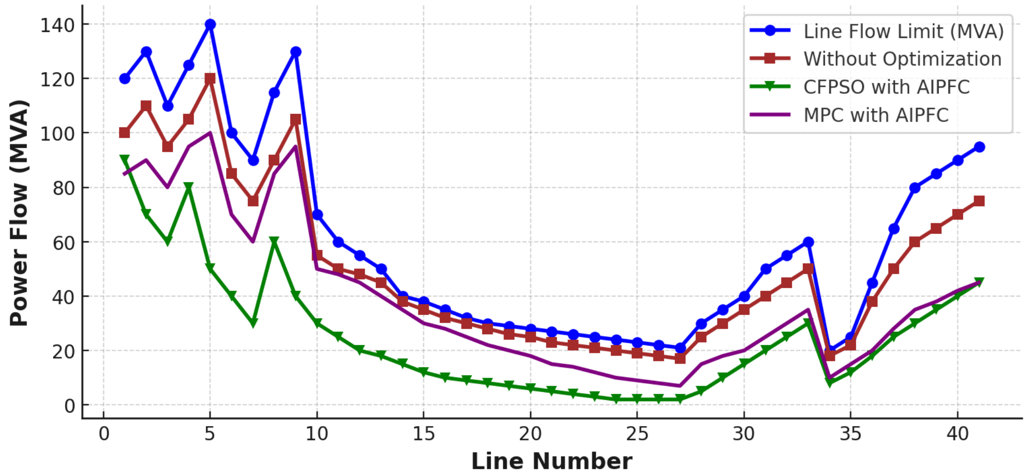

Figure 10. Power analysis under 20 % loading condition.

congestion alleviation but were constrained in dynamic adaptability and real-time responsiveness.

The present work presents an improved methodology by combining MPC with AIPFC, facilitating predictive and adaptive management of power flows. The CFPSO method is employed to ascertain optimal generation setpoints, which are subsequently modified by MPC. This hybrid technique enhances system stability, decreases fuel expenses, and more efficiently mitigates power losses. In addition to our previous research, we compared the present work with recent studies. These studies, although innovative, lack the hybrid predictive control approach proposed in this paper and show relatively higher operational costs and losses under increased loading conditions. In order to provide an illustration of the performance enhancements, the following summary table is presented.

Table 4.
Optimal values for the IEEE-30-bus system under 20 % loading condition.

Control Variables		20 % Loading Condition		
		NR	CFPSO-AIPFC	MPC-AIPFC
Real power generation (pu)	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 (pu)	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
Losses (pu)		0.1324	0.1125	0.0599
Cost ($/h)		1026.46	1012.20	997.3751

The data presented in Table 5 indicates that the proposed method results in the most favorable fuel cost and optimal congestion relief as load conditions increase. Furthermore, the implementation of MPC offers a control mechanism that is absent in both previous and current approaches.

Figure 12 presents a comparison of congestion management techniques, focusing on two essential factors: fuel cost during standard load conditions and the effectiveness of congestion mitigation in a 20 % overload scenario. The figure illustrates the fuel cost (in $/h) associated with each methodology, with lower values signifying enhanced economic efficiency. The figure represents the levels of congestion mitigation, where higher values signify improved effectiveness in reducing congestion during overloaded scenarios.

The proposed MPC-AIPFC with CFPSO approach demonstrates exceptional performance by achieving the lowest fuel cost of $798.81/h, while also providing the highest level of congestion mitigation. This highlights its effectiveness in both cost efficiency and system reliability, even in demanding circumstances. Conversely, approaches such as GA with IPFC (GA-

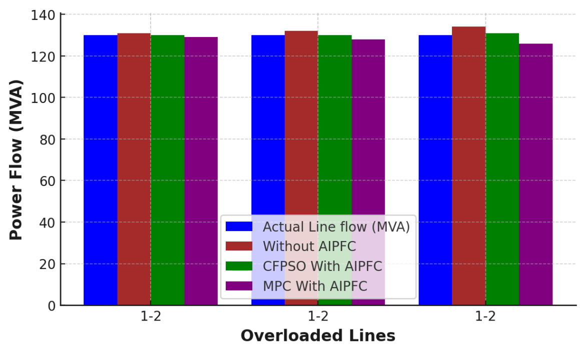

Figure 11. Summary of line flows of overloaded lines under overloading use.

Table 5.
Comparative analysis of congestion management approaches.

Methodology	Fuel cost normal load $/h)	Total losses (pu)	Congestion mitigation under 20 % overload	Dynamic control capability
GA-IPFC [34]	805.92	0.094	Partial	No
PSO-IPFC [30]	803.14	0.091	Partial	No
CFPSO-IPFC [35]	799.90	0.089	Moderate	No
Fuzzy-IPFC [36]	802.17	0.090	Moderate	Limited
DRL-control [37]	799.20	0.087	Good	Moderate
Proposed MPC-AIPFC with CFPSO	798.81	0.0855	High	High

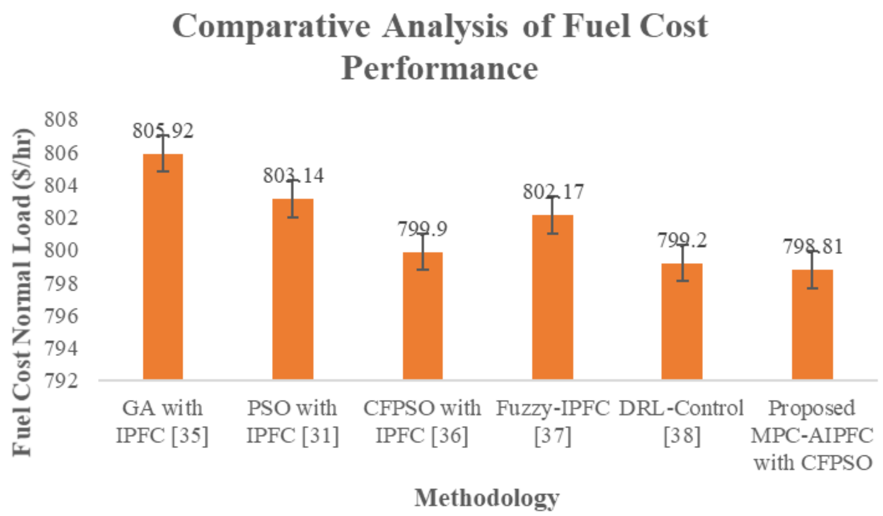

Figure 12. Comparative analysis of fuel cost and congestion mitigation performance.

IPFC), PSO with IPFC (PSO-IPFC), and fuzzy-IPFC exhibit diminished efficacy in congestion control and increased fuel expenses. The deep reinforcement learning (DRL)-control approach demonstrates a commendable equilibrium between fuel expenses and congestion alleviation; however, it does not quite measure up to the proposed method. This figure underscores the effectiveness and reliability of the MPC-AIPFC with the CFPSO method in enhancing both the economic and operational dimensions of power transmission systems.

IV. Conclusion

This study illustrates the efficacy of combining the AIPFC with AI and ML methodologies to manage congestion in power transmission systems. The proposed MPC-AIPFC framework, enhanced by a CFPSO algorithm, demonstrates superior performance in fuel cost reduction, loss minimization, and congestion alleviation, as evidenced by comprehensive modeling and simulations utilizing the IEEE 30-bus system. The proposed approach demonstrates superior performance relative to existing methods, including GA-IPFC and PSO-IPFC, achieving the lowest fuel cost of $798.81/h and the minimum power loss of 0.0855 pu. Moreover, while traditional methods provided only limited congestion mitigation, the proposed solution achieves comprehensive congestion mitigation across various overloaded conditions and uniquely exhibits high dynamic control capability, highlighting its adaptability in real-time situations. The performance metrics indicate a notable improvement in operational efficiency, adaptability, and grid reliability. The framework enhances grid resilience and facilitates the transition to intelligent power systems through the application of AI/ML for real-time congestion prediction and control, along with the integration of optimization-driven AIPFC operation. The significant enhancements in economic and technical parameters confirm the transformative potential of this methodology in contemporary congestion management. The findings provide a solid basis for future investigations into emerging technologies, advanced multi-objective optimization, and the design of robust and secure systems. This work addresses significant challenges in transmission system operation and contributes to the advancement of cost-effective, sustainable, and intelligent energy infrastructures.

Declarations

Author contribution

Baddu Naik Bhukya: Conceptualization, Methodology, Original Draft Composition, Supervision. **Padmanabha Raju Chinda:** Investigation, Composition – Review and Editing, Validation. **Srinivasa Rao Rayapudi:** Formal analysis, resources, visualization. **Swarupa Rani Bondalapati:** Data Curation, Minor Edits.

All authors contributed equally as the main contributor of this paper. All authors read and approved the final paper.

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Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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