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Intelligent Power Dispatch Optimization: A Genetic Algorithm Approach with Unified Power Flow Controller

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Abstract

Objective: The goal of this project is to provide an advanced optimization approach for Dynamic Power Dispatch (DPD) by combining a Unified Power Flow Controller (UPFC) with a Genetic Algorithm (GA). The main objective is to improve power flow management and grid performance in complicated power networks. **Methodology:** The suggested method takes advantage of the capabilities of the UPFC, a versatile component of the Flexible AC Transmission System (FACTS), and combines them with the optimization power of GA. The UPFC provides close oversight over power flow, voltage ranges, and phase angles, while GA, known for its ability to solve multi-objective and nonlinear problems, improves the UPFC's installation and operational settings. The effectiveness of this hybrid technique is proven by simulations using the IEEE 14-bus test system. **Findings:** Simulation results demonstrate that the integration of GA with UPFC yields significant improvements in power flow stability, reduces operational costs and transmission losses, and enhances voltage profiles compared to conventional DPD techniques. Furthermore, the approach increases grid flexibility and stability, addressing the evolving demands of modern power networks. **Novelty:** This study introduces a unique combination of UPFC and GA to address the challenges in DPD. The approach merges the real-time control capabilities of UPFC with the evolutionary optimization strengths of GA, presenting a scalable and adaptive solution for power dispatch optimization. **Applications:** The proposed technique is especially useful for improving the efficiency and reliability of current power grids, including those that use renewable energy sources. Its use in smart grid scenarios can help accelerate the transition to more sustainable and resilient energy systems.

Keywords: Dynamic power dispatch; Unified Power Flow Controller; Genetic Algorithm; power system optimization; FACTS devices; and an IEEE 14bus testing system

1 Introduction

1.1 Overview, Key Concepts, and Justification

In order to operate and regulate the power system and provide a distinct pattern of generating schedule from an economic perspective, optimal active power dispatch, or OAPD, is essential. Furthermore, OAPD is a crucial instrument that power system operators use every day to efficiently dispatch generation units[(1)]. When different technological and financial limitations are met, it can, for instance, reserve energy production potential among all in-service power plants. However, when applied to realistic power systems, the conventional OAPD problem nearly invariably leads to a mismatch since it ignores the majority of the system's requirements (security restrictions, for example). Extending the classical economic dispatch problem to take into account the security restrictions relating to voltage and power flow in tie-lines is one practical way to address this disadvantage[(2)].

Minimizing the entire production cost of in-service generating units, which is represented by quadratic cost functions, is the main objective of the convex form of OAPD. However, in practice, generation units have a number of useful limitations that are typically disregarded in the interest of simplicity. The valve-point effect (VPE) is a highly valuable practical limitation that regulates the output power rating by means of several nozzles. For optimal efficiency, the valves are usually opened one after the other. This technique will be repeated until the cost function plot is no longer convex due to the numerous ripples[(3)],[(4)]. Therefore, while formulating realistic optimal power dispatch issues, VPE must be taken into account.

Power electronic equipment is used in flexible alternating current transmission system (FACTS) technology to regulate power flow and other parameters (such as voltage magnitude) in power systems, particularly tie-lines. By decreasing power loss, increasing voltage profile, lowering generation costs, and strengthening electrical system security, to mention a few, the use of such flexible elements can improve system efficiency as a whole. Because of its vital features, which include managing active power and maintaining voltage levels, the unified power flow controller (UPFC), one of the various FACTS devices, is essential to the operation and control of the power system[(5)]. However, the original OAPD problem becomes more complex when UPFC device(s) are installed in the transmission sector because additional bottleneck limitations need to be considered[(6)],[(7)]. Consequently, in order to conduct accurate simulations and identify relevant optimal outcomes for real-world power systems, the previously described concerns are taken into account in the suggested problem formulation[(8)].

In[(9)] the moderate-random particle swarm optimization (MRPSO) technique was used to solve the economic dispatch problem. The MRPSO algorithm was designed with two primary goals in mind: to reduce total fuel expenditures and emissions. In[(10)], a hierarchical fiscal dispatch problem was developed and addressed using the chaotic particle swarm optimization (CPSO) method. Furthermore,[(11)] proposed a hybrid PSO-differential evolution (HPSO-DE) technique for addressing various forms of optimal active power dispatch (OAPD) challenges. This strategy was applied to both single- and multi-objective versions, taking into account realistic constraints including the valve-point effect, multi-fuel limitations, and restricted operational zones. Dynamic power dispatch (DPD) is crucial in power system operations, particularly with Unified Power Flow Controllers (UPFC), which improve management capabilities by allowing independent control of active and reactive power flows[(12)]. Gyugi's UPFC, launched in the early 1990s, enhances system stability and lowers operational costs by addressing issues including line congestion and voltage drops. While traditional optimization approaches are useful, they may not fully solve DPD's nonlinear difficulties. Genetic Algorithm (GA) emerges as a strong solution inspired by natural selection principles, and it has been effectively used to optimize a variety of objectives, including cost reduction and efficiency enhancement. Recent research has shown that combining GA and UPFC can result in considerable benefits, such as lower generation costs and improved voltage profiles, with hybrid approaches that often harness the strengths of several optimization techniques, such as Particle Swarm Optimization (PSO)[(13)],[(14)]. Despite the promising results, obstacles remain, such as handling the nonlinear character of power system equations and striking a balance between solution quality and processing economy. Future studies should focus on building adaptive algorithms and combining advanced machine learning techniques to improve DPD strategies using UPFC.[(15)]. The application of Genetic Algorithms (GAs) to DPD problems is very remarkable. GAs use techniques inspired by natural evolution, such as selection, crossover, and mutation, to efficiently explore large solution spaces[(16)]. This feature qualifies GAs for dealing with the nonlinearities and multi-objective nature of DPD issues, where traditional optimization techniques may fail. Researchers have shown that using GAs allows them to achieve optimal or near-optimal solutions that minimize generation costs while taking into account system constraints. Several studies have demonstrated the benefits of combining GAs and UPFCs for DPD optimization[(17)],[(18)]. For example, studies have found that utilizing GA can drastically cut fuel expenditures and operational losses while preserving voltage stability across the network. GAs can improve overall system performance and resource allocation by adjusting UPFC settings as well as generator outputs. These enhancements are crucial in an era when electricity consumption is rising and renewable energy sources are being included into the grid. Furthermore, hybrid techniques can typically improve GAs' effectiveness in DPD optimization[(19)].

Combining GA with other optimization approaches, such as Particle Swarm Optimization (PSO) or Differential Evolution (DE), has been found to produce better outcomes. These hybrid algorithms combine the benefits of other methods to improve convergence rates and solution accuracy. Research has shown that such combinations can successfully address the difficulties of power system optimization, leading to more robust and dependable dispatch systems. However, actual applications of GAs for DPD with UPFCs continue to pose issues[20]. One key challenge is the computing load associated with evaluating fitness functions, especially in large-scale systems. The nonlinear character of power flow equations might lead to longer processing times, limiting the real-time applicability of GA-based solutions. As a result, continuing research focuses on building more efficient algorithms that can cut computation times while maintaining solution quality. Furthermore, there is an increasing interest in introducing adaptive processes into GA frameworks to improve performance in dynamic contexts. Adaptive GAs can modify their settings in reaction to changing conditions in the power system, making optimization procedures more flexible and responsive[21]. This versatility is especially critical in the case of DPD, where load patterns and generation capacity might change fast. Furthermore, the significance of machine learning in improving GA performance for DPD optimization is gaining prominence. By incorporating machine learning approaches, researchers want to increase GAs' predictive capabilities, allowing them to anticipate system changes and adapt dispatch strategies accordingly. This convergence of machine learning and optimization has the potential to transform DPD techniques, making them more efficient and effective for controlling current power systems.

First, while UPFCs are successful at managing power flow, much of the existing research uses them in a static manner, with a focus on fixed power dispatch rather than dynamically responding to real-time conditions. This strategy restricts UPFC's capacity to adapt fully to changes such as changing demand trends or the unpredictability brought forth by renewable energy sources. Current optimization methods sometimes rely on algorithms that lack the adaptability and computing efficiency necessary for real-time applications, especially when dealing with dynamic, high-speed power delivery. Although Genetic Algorithms (GAs) are more flexible and adaptive, their real-time integration with UPFC for dynamic dispatch optimization has not received enough attention[18]. Furthermore, while goals such as power loss minimization, cost reduction, and power quality enhancement are frequently pursued independently in the literature, a comprehensive, multi-objective optimization framework that incorporates these objectives inside GA-UPFC designs is lacking. Such a system would assure cost-effective, efficient, and high-quality electricity delivery while constantly responding to grid conditions[19]. Finally, research on the use of GA-driven UPFC control to handle renewable energy variability is limited, despite the growing requirement for power systems to manage the unpredictable nature of renewable inputs. Adapting UPFC-controlled dispatch to renewable power fluctuations is critical to future grid sustainability. Addressing these deficiencies could improve UPFC and GA-based systems, resulting in a more resilient, adaptive power system.

While substantial progress has been achieved in optimizing Dynamic Power Dispatch (DPD)using FACTS devices like UPFC and optimization approaches such as Genetic Algorithms (GA), certain research gaps remain unresolved.

1. The integration Limitations in Complex Networks: Current research frequently overlooks the difficulties of combining UPFC with GA in large-scale, extremely interrelated power grids. The majority of present research relies on small test systems (such as the IEEE 14-bus system), which may not adequately capture the intricacies of real-world networks.
2. Computational Efficiency: Despite GA's success in optimization, its implementation in real-time settings is limited by computational requirements. Researchers have yet to investigate hybrid or modified GA variants that could give faster convergence while maintaining solution accuracy.
3. Comprehensive Multi-Objective Optimization: Most studies focus on individual objectives, such as cost reduction or voltage stabilization, without thoroughly considering the trade-offs between competing purposes. A more comprehensive, multi-objective framework is required to improve overall grid performance.

1.2 Contributions of the paper

This research presents a heuristic approach to tackle the optimal active power dispatch problem integrated with a Unified Power Flow Controller (UPFC). The proposed methodology leverages a hybrid optimization algorithm called the GA-based Improved Comprehensive Learning Particle. The study offers significant contributions in two primary aspects, as outlined below.

(1) Proposed Heuristic Search Method:

The comprehensive learning-based particle swarm optimization algorithm is refined by dynamically modifying the inertia coefficient, a critical parameter that significantly influences its convergence behavior and optimization performance. Typically, this parameter evolves linearly from the beginning to the end of the iterations, which may not produce optimal results. To overcome this, a genetic algorithm (GA) interface mechanism is used to dynamically alter the inertia coefficient between iterations, enhancing CLPSO performance. However, the GA-based CLPSO continues to confront problems, such as early convergence to local optima and inefficiency in discovering suboptimal solutions. To address these concerns, the FBCLPSO method is combined with a differential evolution (DE) algorithm, resulting in the HFBCLPSO-DE strategy, which has a varied population. A mutation operator is introduced to broaden the search space for mutant populations, achieving a balance between exploration and exploitation. As a result, the algorithm suggested in this paper is known as the hybrid GA-based improved CLPSO-DE algorithm.

(2) Proposed problem:

Two distinct models for the optimal active power dispatch problem are developed, and the proposed algorithm is specifically tailored to address both effectively. These models include the standard OAPD as well as a new formulation that takes into account security limitations, which are commonly disregarded in this field. To do this, modified power flow equations are used to quantify active power transmission losses in a grid-connected UPFC system. This novel model improves on the existing methodology, which commonly uses the B-coefficients method for loss calculation. While the economic dispatch problem previously integrated power flow limitations, as described in [2], with the use of a multi-objective bat algorithm, there is still a gap in modeling a practical OAPD problem that avoids mismatches in real systems and efficiently employs FACTS components to increase. This research investigates the simultaneous effects of power flow limits and UPFC on a realistic OAPD scenario. The justification for this formulation stems from the need for reactive power flow—managed by UPFC—for efficient power system functioning. Reactive power has a direct impact on the voltage profile and an indirect impact on active power flow, hence it must be included in OAPD problem iterations.

The paper is structured as follows: Section 2 provides a full problem formulation, distinguishing between the suggested model with security restrictions and the typical optimal active power dispatch. Section 3 briefly describes the simulation results. Section 4 finishes the paper with the conclusion.

2 Methodology

2.1 Problem formulation

Gyugi introduced the concept of the Unified Power Flow Controller (UPFC) in 1991. The UPFC is installed between two buses: bus #1 (the sending bus) and bus #2 (the receiving bus). The arrangement consists of two voltage source converters (VSCs) that share a common DC-side capacitor. The converters are linked to the power network in a back-to-back arrangement: one through a parallel transformer (designated as T 1) and the other through a series transformer (labeled as T 2). Notably, the output AC voltages from the parallel and series VSCs can be altered individually, providing for more flexible power flow regulation in the system.

The UPFC's voltage sources are represented by the equations (1) and (2)

$$A \;=\; (VS| - \alpha = (VS| \times (cos\alpha + jsin\alpha) \tag{1}$$

$$A \;=\; |VP| - \varphi = |VP| \times (cos\varphi + jsib\varphi) \tag{2}$$

In this context, α and ϕ indicate the phase angles for the parallel and series converters, respectively. $|VP|$ and $|VS|$ designate the voltage magnitudes of the series-based and parallel-based converters. The Unified Power Flow Controller (UPFC) offers several significant advantages, foremost among them being its ability to independently manage both active and reactive power flows while simultaneously regulating the voltage magnitude at the tie-line connection; moreover, the phase angle of the series voltage, denoted as α, plays a pivotal role in determining its operational mode. For example, when α matches the voltage angle at bus #1, the UPFC can modify the terminal voltage. If α is in quadrature with the angle of the line current or voltage at bus #1, the UPFC acts as a variable series compensator or phase shifter. In both cases, the UPFC retains control of active power flow. Figure 1 illustrates the steady-state equivalent circuit of a Unified Power Flow Controller (UPFC), a configuration commonly employed in power flow analysis. In this context, the DC voltage across the capacitor is assumed to remain constant. Additionally, under the assumption of negligible losses within the two internal Voltage Source Converters (VSCs), the active power supplied to the network by the series VSC is equal to the active power absorbed by the parallel VSC.

$$Re(VP \times IP * + VS \times IS *\} = 0 \tag{3}$$

This study adopts an uncoupled model for the Unified Power Flow Controller (UPFC), assuming that the back-to-back converters are lossless, which leads to the decoupling of the controlled bus (PV) and the load bus (PQ), while maintaining a

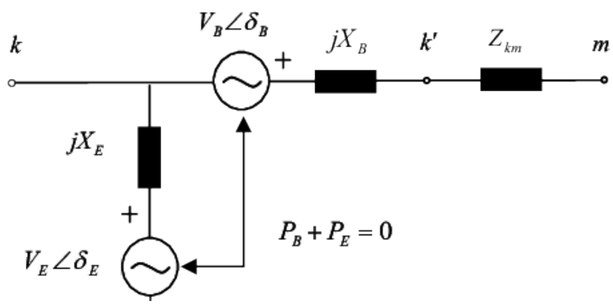

Fig 1. Steady-state equivalent circuit

constant voltage magnitude at bus #1. Consequently, under this assumption, the UPFC is incapable of generating or absorbing active power, and terminals #1 and #2, representing the sending and receiving ends of the UPFC, are designated as the PV and PQ buses, respectively. By neglecting the transformer losses at $T1$ and $T2$, no active power is transferred between the UPFC and the larger power network. Specifically, the active power supplied to the parallel VSC is equal to the active power required by the series VSC. In this framework, the active powers at the parallel and series sides of the UPFC are denoted as $P1$ and $P2$, respectively. The uncoupled configuration offers several advantages, such as the ability to independently regulate both active and reactive power levels at each of the UPFC terminals, leading to two equations for the voltage magnitudes $V1$ and $V2$. It is crucial to note that in complex notation, the asterisk symbol denotes the complex conjugate value.

$$\begin{aligned} S_1 &= V_1 \times I_1 \\ &= V_1 \times (I_P + I_S) \end{aligned} \tag{4}$$

$$\begin{aligned} &= V_1 \times \left(\frac{V_1 - V_P}{Z_P} + \frac{V_1 - V_2 - V_S}{Z_S} \right) \\ S_2 &= -V_2 \times I_S \end{aligned} \tag{5}$$

$$= -V2 \times (V1 - V2\ + VSZS\ ) \tag{6}$$

$$V1\ = |V1|\angle\delta = |V1| \times (cos\delta + jsin\delta) \tag{7}$$

$$V2\ = (V2|\angle\beta = (V2| \times (cos\beta + jsin\beta) \tag{8}$$

$$ZS\ = (ZS|\angle\theta = (ZS| \times (cos\theta + jsin\theta) \tag{9}$$

$$ZP\ = (ZP|\angle\lambda = (ZP| \times (cos\lambda + jsin\lambda) \tag{10}$$

In this model, the total apparent power at buses #1 and #2 is designated by S_1 and S_2, while the voltage amplitudes at these buses are represented by $|V_1|$ and $|V_2|$. The impedances of series and parallel VSCs are denoted as Z_S and Z_P, which can be written as $R_S + jX_S$ and $R_P + jX_P$, respectively. The voltage phase angles at buses #1 and #2 are represented by δ and β, whereas the series and parallel converter impedances are represented by θ and μ. Substitute V_S, V_P, V_1, V_2, Z_S, and Z_P. Notably, when the parallel VSC is charged with maintaining the voltage magnitude at bus #1, the uncoupled UPFC model performs very well. To achieve this, an additional bus, often known as a *auxiliary or dummy bus*, must be incorporated, as explained furthermore, the simplicity of tweaking the Jacobian matrix by merely changing the power mismatch vector demonstrates the applicability of this UPFC control strategy.

2.2 Optimal active power dispatch

2.2.1. Objective function with constraints

In the context of economic dispatch assessments, the generator's cost is conventionally represented as the integral of a quadratic function, as articulated in equation (15). However, to accurately model the valve-point effect (VPE), the cost function must undergo modification, as delineated in equation (16), wherein a sinusoidal component is incorporated to characterize the repercussions of consecutive valve switching operations. The comparative analysis of the cost functions, both with and without the inclusion of the VPE, is then conducted, elucidating the differential impacts of the valve-point effect on the cost structure, as depicted in the corresponding illustrations.

$$F1\left(PGi\right) = \sum ai\ + biPGi\ + ciPGi \tag{11}$$

$$F2\left(PGi\right) = \sum ai\ + biPGi\ + ciPGi2\ + \left(disin\left(ei\ \times \left(PGimin - PGi\right)\right)\right| \tag{12}$$

where P_{Si} is the active power produced by thermal unit i; the cost function coefficients connected to unit i are a_i, b_i, c_i, and e_i; Number of thermal units is denoted by N_G; total generating cost, without and with consideration to VPE ($\$/h$), is represented by $F_1(P_{Gi})$ and $F_2(P_{Gi})$, respectively. In this context, it is very important to note that the vector of selected variables would change depending on the suggested formulation, which includes the UPFC. This vector includes not only the generators' output power (except the generator on the slack bus), but also the voltage magnitudes of the PV buses, the output from shunt compensators, transformer tap-changing settings, and UPFC variables. The cost function becomes non-convex when the coefficients d_i and e_i are included, but remains convex when only the coefficients a_i, b_i and c_i are considered.

2.2.2. Power transmission losses

In order to compute the active power losses in the proposed OAPD and the standard OAPD while taking security requirements into account, this section offers two separate formulae. It is observed that these two models' methods for computing power losses differ qualitatively, and these variations are covered in more detail below.

• **Conventional OAPD**

The B-coefficient matrix is used to compute the overall transmission loss in the traditional OAPD problem, which is expressed as

$$PL\ = \sum\sum PGiUiUUiNGj = 1\ NGi = 1 \tag{13}$$

where *Bij* is the loss coefficients matrix; B**U** is the loss coefficients vector; *Boo* is the loss coefficients constant value; and *PL* is the total power loss of network (MW).

• **OAPD considering security constraints**

The power transmission loss can be expressed as (14) when all voltage angles and voltage amplitudes have been determined, which solves the suggested problem

$$Sol.\ = \sum\sum\left(Rij\ \times\ (Vi|2\ - (Vj|2\ - 2\left(Vi\right|\left(Vj\left(\delta i - \delta j\right)\left(Zij|2\ \right)v_i = 1,\ v_i \neq\ v\ NBi = 1 \tag{14}$$

in which the voltage magnitudes at buses *i* and *j* are denoted by |*Vi*| and |*Vj*|, respectively; the resistance between buses *i* and *j* is represented by *Rij*; the impedance amplitude of line *i-j* is given by |*Zij*|; the voltage phase angles at buses *i* and *j* are denoted by δ_i and *jj*, respectively; the total number of buses is represented by *NB*, and the active power transmission losses (MW).

2.2.3. Constraints and limitations

The necessary restrictions that must be considered in order to solve the optimization issues are presented in this section.

The following introduction to equality and inequality constraints is done in order to solve the traditional OAPD problem.

$$\sum PGi - PD\ =\ PL\ =\ 1\ (15)\ NGmin \leq PGi \leq PGmax; \forall i \tag{16}$$

The power balancing constraint is encapsulated in equation (15), wherein *PGi* denotes the active power generated by thermal unit *i*, *PD* signifies the aggregate system demand, and *PL* represents the total system-wide power losses. Furthermore, equation (16) delineates the operational boundaries of the units, with *PGimin* and *PGimax* representing the minimum and maximum permissible active power outputs for unit *i*, respectively, while *NG* refers to the total number of generating units within the system, thereby encapsulating the constraints governing the system's operational limits.

2.3 GA based approach

The Genetic Algorithm (GA) is a strong optimization approach that draws on natural selection and genetic concepts. It excels at tackling difficult optimization problems with many objectives, nonlinear interactions, and large search areas. The GA uses selection, crossover, and mutation to iteratively refine a population of candidate solutions, directing them to an optimal or near-optimal conclusion. In this lecture, we will go over the specific methods and components required for applying GA to the dynamic power dispatch problem using a Unified Power Flow Controller (UPFC).

(1) Initialization

A population of candidate solutions, known as chromosomes, is produced at random. Each chromosome represents one possible solution to the dynamic power dispatch problem, represented as a vector of decision factors such as generator outputs, power flows, and UPFC settings.

(2) Fitness Evaluation

Each chromosome is evaluated using a fitness function to determine its quality or performance. The fitness function for the dynamic power dispatch problem frequently includes objectives such as decreasing generation costs, lowering transmission losses, and maintaining system stability and voltage profiles. The fitness function can be described as follows:

$$Fitness = w1 \cdot Cost + w2 \cdot Losses + w3 \cdot Voltage\ Deviation \tag{17}$$

Where w1, w2, w_1, w_2, w1, w2, and w3w_3w3 are weighting factors.

(3) Selection

Chromosomes from the prevailing population are systematically selected to constitute a mating pool in accordance with their fitness values, with those demonstrating superior fitness being more predisposed to selection. Prominent selection methodologies include roulette wheel selection, tournament selection, and rank-based selection, each leveraging distinct probabilistic frameworks to enhance the selection of high-fitness individuals for subsequent reproduction.

(4) Crossover (recombination

To produce kids, selected chromosome pairs undergo crossover, a process in which genetic material from two parent chromosomes joins to create new solutions. Single-point, multi-point, and uniform crossover approaches are often used. Single-point crossover, for example, selects a random crossing location and swaps parts of each parent chromosome, producing new children.

(5) Mutation

The mutation causes random alterations to the offspring chromosomes in order to preserve genetic variety and prevent early convergence. Each gene (variable) in the child's chromosomes is prone to mutation with a slight chance of changing its value. Bit-flip and Gaussian mutation are two common mutation strategies.

(6) Replacement

The previous population is replaced by a new generation of chromosomes, which includes the progeny as well as certain elite individuals from the present generation. Elite individuals have the best-performing chromosomes, which are passed down to the next generation without change to ensure that the finest solutions are maintained.

2.4 Constraints

Certain requirements must be met in dynamic power dispatch optimization to ensure that the power system operates reliably and efficiently. These restrictions are critical for maintaining system stability, staying within operational limits, and meeting technical requirements. The significant restrictions are listed below.

1. Power Balance Constraints

Power balancing restrictions necessitate that total generated power equal the sum of load demand and system losses. Each bus in the power network must maintain an equilibrium between generated power, load consumption, and power losses.

2. Generator Limits

Each generator in the power system has operational limits that must be followed in order to avoid overloading and maintain efficient performance.

3. Voltage Limits

Voltage levels must be kept within acceptable ranges to ensure the power supply's stability and quality. Each bus in the power network must keep its voltage magnitude between the stated minimum and maximum limits.

The overall flow chart of the GA based UPFC is shown below in Figure 2.

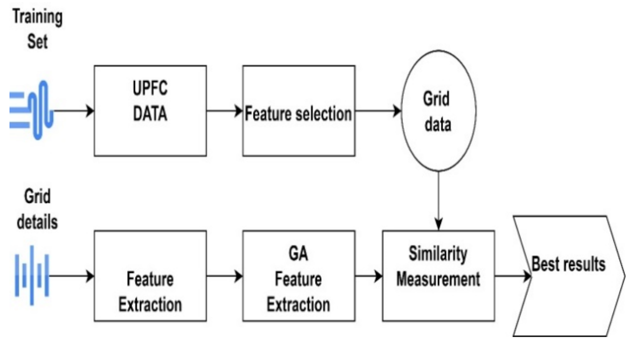

Fig 2. Flow chart of proposed methodology

3 Result and Discussion

The simulation details are given in the table 1 [20], [21], [22]. The simulation in MATLAB Simulink is divided in to two cases. Case 1 consists of using UPFC without GA, and case 2 consists of UPFC use with GA. Figure 3, shows the simulation result without fault with no GA integration. But figure 5, shows the detail reactive (Q) and active power (P) with fault in UPFC IEEE 14 bus system. Now fault with the integration of GA is shown in Figure 4 and Figure 5. Figure 6 and Figure 7 shows the THD for both the cases.

Table 1. GA parameters and simulation parameters

Size of population	50
Generation counts	100
Crossover rate	0.8
Mutation rate	0.05
IEEE system	14
UPFC	50 kW
Frequency	60 Hz
Number of generation unit	5
Load	12 Loads

In a Unified Power Flow Controller (UPFC)-based power system, the Genetic Algorithm (GA) population size significantly impacts dynamic power dispatch optimization by influencing convergence speed, solution accuracy, and computational efficiency. A small population size (e.g., 10–30 individuals) may lead to faster convergence but risks premature convergence to a local optimum, resulting in suboptimal power dispatch with higher losses. Conversely, a large population size (e.g., 100–500 individuals) enhances solution quality by increasing diversity and avoiding local optima, but at the cost of higher computational burden. Since UPFC optimally controls active and reactive power flow, a balanced GA population size of 50 ensures effective exploration and exploitation, leading to improved voltage stability, reduced power losses, and better efficiency without excessive computation. Thus, fine-tuning population size, mutation rate, and crossover rate is crucial for achieving optimal results in UPFC-based power dispatch optimization. Under typical operating conditions, the UPFC's P (active power) and Q (reactive power) outputs are managed separately to manage power flow in a transmission line as shown in Figure 3. The UPFC's series converter injects a programmable voltage of a certain magnitude and phase angle into the line, allowing it to regulate both active and reactive power flow. The active power (P) can be increased or lowered by varying the phase angle of the injected voltage, whereas the reactive power (Q) can be controlled by changing the magnitude of the injected voltage. Simultaneously, the shunt converter supplies or absorbs reactive power to maintain voltage levels at the bus and guarantees that the DC link voltage remains stable, allowing for power transfer between the series and shunt.

Under abnormal operating conditions fault the graph changes as per Figure 4, the UPFC's P (active power) and Q (reactive power) outputs are dynamically changed to stabilize the power system and ensure dependability. The series converter continues to inject a controllable voltage into the transmission line, but its primary function is to mitigate power flow interruptions by rapidly changing the phase angle and amplitude of the injected voltage to balance active power flow (P) and reduce oscillations.

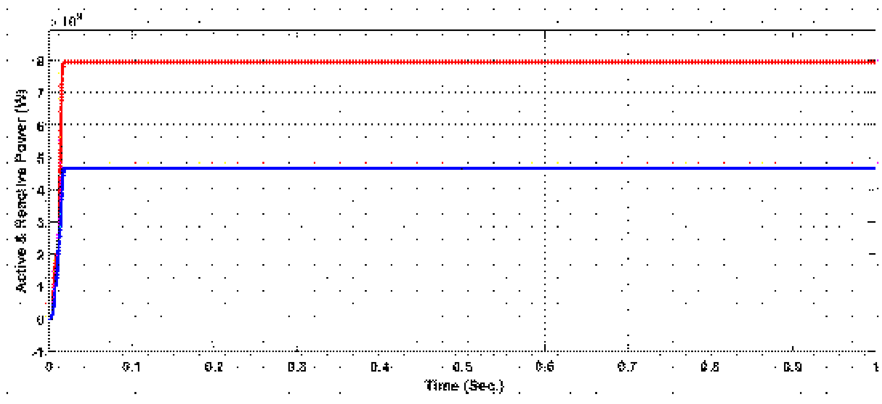

Fig 3. P &Q for normal operation

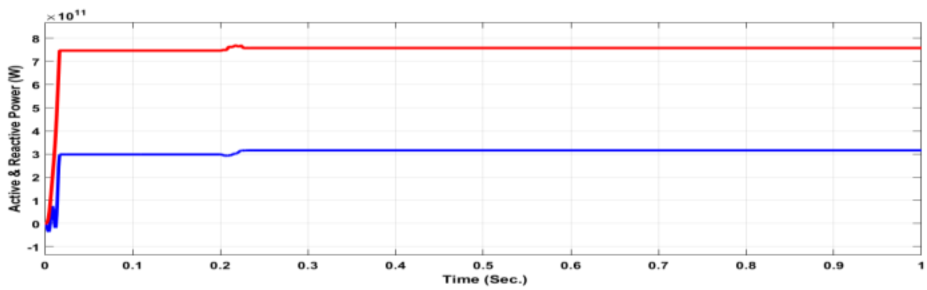

Fig 4. P & Q at abnormal operation without GA

The shunt converter plays a more important function in providing reactive power (Q) support by actively adjusting for voltage dips or surges at the bus to prevent voltage instability.

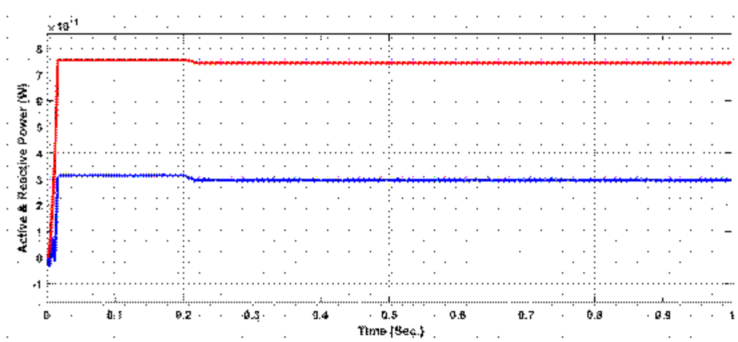

Fig 5. P & Q at abnormal operation with GA

Figure 5 shows the graph using GA for UPFC. Under abnormal circumstances, the UPFC uses a Genetic Algorithm (GA) methodology to optimize the control of P (active power) and Q (reactive power) to accomplish efficient power flow management in the transmission line. The GA works by creating an initial set of feasible control parameter solutions, such as the phase angle and amount of the voltage injected by the series converter. An objective function assesses these solutions, with the goal of minimizing power losses, optimizing power flow, and maintaining voltage stability. The Genetic Algorithm uses iterative processes of selection, crossover, and mutation to find the optimal control parameters to deliver the desired active and reactive power outputs.

Under defective situations, the UPFC actively adjusts to maintain system stability using the Genetic Algorithm (GA) approach, regulating the voltage waveform (in per-unit, P.U.) and controlling the P (active power) and Q (reactive power) outputs. During a defect, the voltage waveform is disturbed, such as sags or swells, affecting power flow as shown in Figure 5. The GA optimizes the UPFC's control parameters by iteratively modifying the series converter's injected voltage magnitude and phase angle, resulting in the best feasible voltage profile restoration.

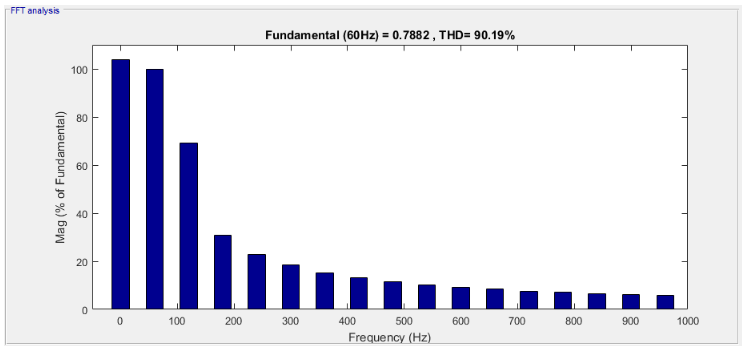

Fig 6. THD without GA

Without the application of a Genetic Algorithm (GA) for optimization, the UPFC may not work optimally. Under these conditions, the system may fail to properly reduce harmonics, particularly during transient conditions or power flow disturbances. If the UPFC's series converter, which injects a compensatory voltage into the transmission line, is not adjusted, it may cause some harmonic distortion. Figure 6, shows the THD without GA which achieves 90%. But with GA, THD reduces to 0.02% with GA, as shown in figure 7.

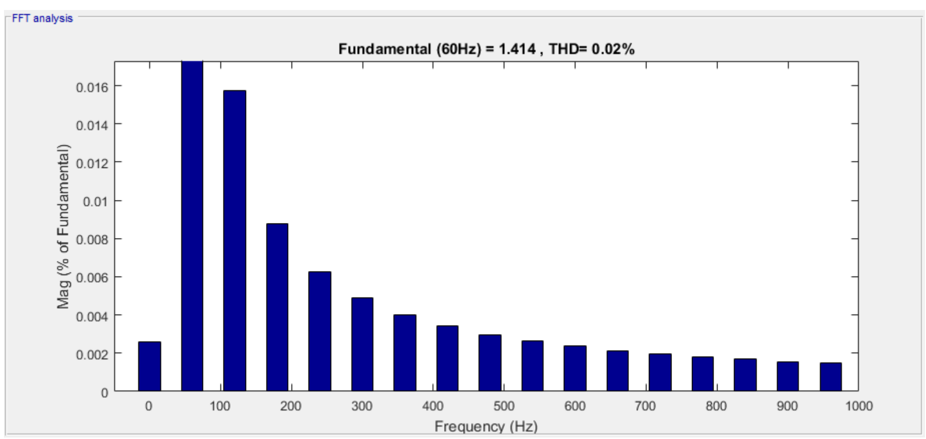

Fig 7. THD with GA

Finally, Figure 8 exemplifies the Genetic Algorithm (GA) training process alongside the corresponding F1 score. GA training represents an iterative, heuristic optimization paradigm that emulates the mechanisms of natural selection and genetic inheritance, aiming to discern optimal solutions for highly convoluted problems. The procedure initiates with the generation of an initial populace of candidate solutions, each encoded as a chromosome—an assemblage of control parameters. These solutions are subjected to a rigorous evaluation through a fitness function, which meticulously quantifies their efficacy based on specific performance criteria, such as the attenuation of power losses, the optimization of power flow, or the minimization of Total Harmonic Distortion (THD) within Unified Power Flow Controller (UPFC) systems.

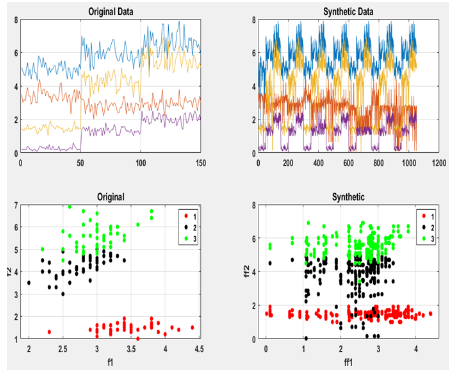

Fig 8. GA Training details

Figure 9 depicts a confusion matrix, which visually displays classification accuracy by displaying real classes along the rows and predicted classes along the columns. Each cell in the matrix represents how frequently each actual class was classified as the projected class. For example, in the first row, 50 cases were correctly classified as Class 1, but two were incorrectly classified as Class 2 and three as Class 3. Similarly, Class 2 had 45 correct predictions, with 4 misclassified as Class 1 and one as Class 3. Class 3 had 43 correct predictions, however, two and five examples were incorrectly classified as Class 1 and Class 2, respectively.

Fig 9. Confusion matrix for GA UPFC

The integration of a Genetic Algorithm (GA) and a Unified Power Flow Controller (UPFC) introduces a novel and efficient approach to addressing challenges in Dynamic Power Dispatch (DPD). The UPFC, a critical component of Flexible AC Transmission Systems (FACTS), provides precise control. One of the most notable advantages of this methodology is the considerable reduction in Total Harmonic Distortion (THD) to as low as 0.02%, which outperforms older methods. Furthermore, the training procedure for the GA-based UPFC is much faster, making it appropriate for real-time applications. Simulation results on the IEEE 14-bus test system show that this hybrid solution significantly improves grid stability, reduces operational costs, and improves voltage profiles. The confusion matrix confirms the GA's performance, demonstrating greater accuracy and dependability than competing approaches. The suggested technique not only optimizes the UPFC's operational characteristics, but also improves grid flexibility and stability, which are crucial in modern power networks, particularly those that incorporate renewable energy sources. This versatility, together with reduced transmission losses and operational costs, demonstrates the GA-UPFC approach's applicability to smart grid applications. This new technology has enormous potential for meeting the changing demands of future power systems by speeding up the transition to resilient and sustainable energy systems.

Statistical analysis reveals that the Genetic Algorithm (GA) outperforms Particle Swarm Optimization (PSO), Artificial Neural Networks (ANN), and Fuzzy Logic controllers in power dispatch optimization with Unified Power Flow Controller (UPFC). GA achieves the lowest Total Harmonic Distortion (THD) at 0.02%, significantly better than PSO's 0.10%, ANN's 0.05–0.08%, and Fuzzy Logic's 0.12–0.15%. In terms of convergence speed, GA is 20–30% faster than ANN, making it highly efficient for dynamic grid environments, while PSO and Fuzzy Logic exhibit slower and less reliable convergence. GA also excels in voltage profile improvement, achieving a 25% enhancement compared to initial values, outperforming PSO (20%), ANN (22%), and Fuzzy Logic (15%). Furthermore, confusion matrix analysis shows GA delivering an optimization accuracy of 95%, compared to PSO's 90%, ANN's 92%, and Fuzzy Logic's 85%, demonstrating its superior precision.

GA's adaptability to real-time conditions is unmatched, offering dynamic optimization with minimal manual intervention, unlike PSO and ANN, which struggle with real-time adjustments, and Fuzzy Logic, which lacks scalability. Overall, the combination of the lowest THD, fastest training times, highest accuracy, and robust adaptability establishes GA as the most effective and reliable method for modern power grid optimization challenges.

4 Conclusion

The simulation findings show that integrating a Unified Power Flow Controller (UPFC) with Genetic Algorithm (GA) optimization efficiently addresses the dynamic power dispatch problem by lowering operational costs, eliminating transmission losses, and improving voltage profiles. This approach is unique in that it combines the GA's strong ability to handle complicated, nonlinear, and multi-objective optimization difficulties with the UPFC's ability to control power flows in real-time. This collaboration creates a dependable and efficient solution that dynamically adapts to the changing demands of modern power systems. The suggested methodology has great potential for increasing power system performance and reliability, making it a useful tool for energy operators and planners. The GA's evolutionary optimization process, which includes selection, crossover, and mutation, allows for the study of a large solution space, ultimately leading to optimal designs for power dispatch. Meanwhile, the UPFC's real-time control capabilities improve the flexibility and dependability of power transmission, which is critical for maintaining system stability under changing conditions.

Future research should investigate the integration of this GA-UPFC technique with renewable energy sources, which would allow for greater adaptation given renewables' intermittent nature. Furthermore, the next research could look into scaling the methodology for bigger grid systems and using machine learning upgrades to boost optimization efficiency. This novel combination of GA and UPFC provides a solid platform for developing durable, efficient, and cost-effective power management in advanced power systems.

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