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Optimal Reactive Power Dispatch in Electric Transmission Systems Using the Multi-Agent Model with Volt-VAR Control

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Abstract: The optimal dispatch of reactive power is a fundamental task in the operational planning of electrical power systems. This task aims to minimize active power losses and improve voltage levels within the electrical power system. This paper presents the application of the particle swarm optimization methodology to achieve optimal reactive power dispatch. The methodology's performance is demonstrated by its high processing speed and the results obtained through a comprehensive global search for reactive power dispatch. Additionally, experimental results confirm the algorithm's effectiveness in optimizing the objective function across different case studies, highlighting its ability to achieve optimal reactive power dispatch. This study represents a significant advancement in the field of power system optimization and provides a useful tool for managing and controlling these systems.

Keywords: ORPD; Volt-VAR control; multi-agent system; particle swarm optimization (PSO)

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1. Introduction

The optimal reactive power dispatch (ORPD) aims to determine the setting of the control variables, such as the voltage of the generator nodes, positions of transformers' tap changers, and the reactive power of the VAR compensators [1].

It has a direct relationship with the optimal reactive power dispatch (RPD), for which researchers have applied deterministic techniques, among which we can mention gradient search, Newton's method, interior point approach, linear programming, quadratic dynamics, and the Lagrangian method; these are the same methods that have definitions that lack the ability to handle functions, demonstrate limitations in handling constraints, and lack the computational process needed to maneuver a high number of iterations [2–4].

The ORPD is also known as a linear optimization problem, which contains a few equality and inequality constraints on the variables [4]. Although in [5] it organizes it as a combinatorial optimization problem, which applies the algorithm based on ant colony optimization (ACO), to minimize power losses, under control and independent variable constraints [5].

Currently, to solve these restrictions, techniques based on computational intelligence, which is based on the behavior of animals or natural phenomena, are being adopted [2,5]. Among the most popular methods among researchers are variants of genetic algorithms (GA), differential evolution (DE), and particle swarm optimization (PSO), as well as improvements or hybrid implementation to obtain a more efficient solution to the ORPD problem [4].

A study by [1] proposes the pseudo gradient search particle swarm optimization (IPG-PSO), which is a variation of PSO that uses the linearly decreasing chaotic inertia weight factor and is guided by a pseudo gradient search, which determines a suitable direction of the particles towards a globally optimal solution. In [6,7], reinforcement learning is

proposed, while in [6] deep multi-agent learning is proposed, which aims to address voltage limits and reactive power capacity constraints; for these, agents acquire the knowledge offline for an optimal voltage control strategy, then they are responsible for measuring the voltage to regulate the reactive power. At the same time, in [7], reinforcement learning is applied directly to the variants which have state safety constraints; according to the author, this method reflects a high superiority in terms of efficiency over other reinforcement learning variants. For [8], who proposes a multi-agent deep deterministic policy gradient (MADDPG) system for agents to learn optimal policies under centralized training and provides optimal actions with only local observations, the same method does not require specific communications between agents coordinating several regions to simultaneously minimize voltage deviations and lost network power [7,8].

With the excessive and advanced introduction of distributed renewable sources, which require efficient control techniques, the irregularity of renewable sources and the restrictions they have at the time of communication transfer increase [9].

The widespread and continuous integration of renewable energies into electric power systems presents several vital considerations. Firstly, there is the challenge of incorporating the intermittent nature of renewable sources, such as solar and wind energy, which are influenced by variations in solar radiation and wind patterns. This calls for careful management to ensure the stability and reliability of the electricity supply, as the fluctuating nature of renewable generation can impact the quality and dependability of the energy delivered.

There is also an additional challenge related to demand and supply management, as renewable energy generation does not always match prevailing energy demand patterns. For example, solar production may peak during daytime hours, while energy demand may be highest during afternoon and evening peaks. To address this discrepancy, precise coordination between supply and demand and the implementation of strategic storage and load management strategies is essential to balance such disparities and ensure a reliable and uninterrupted power supply.

The continued massive penetration of renewables into power systems presents significant sustainability and emissions reduction opportunities but also requires careful planning and management to address the associated technical, economic, and regulatory challenges.

Multi-agent systems (MAS) can contribute to the solution of this type of definition; this term is being used in the current research of intelligent systems. This system is applicable for solving problems of distributed generation (DG), management of electric vehicles, microgrids, stability improvement, protection, and other problems that have a relationship with the electricity market and smart grids [9].

Another way to implement multi-agent concepts is proposed in [10], which is based on the concept of active distribution networks (ADN), the same concept that aims to divide networks into multiple zones, to allow more efficient management of all components that are responsible for facilitating communication between MAS agents. The modularity of the MAS makes it easy for a central agency to assign tasks to different agents, manage them and coordinate among them; in the same way, agents could be added if the number of subtasks increases, giving the system a scalability feature [9,10].

One of the most widely used systems relating to the MAS concept is the PSO system. This system is among the most popular among researchers and is used to solve complicated optimization problems [10–12]. PSO is a population-based metaheuristic technique that has proven to be one of the most efficient nature-inspired algorithms for dealing with constrained and unconstrained global optimization problems such as single or multiple objectives, containing convergence goodness in power flow analysis with quality and efficiency constraints [13,14].

The PSO method has variants such as HMPSO, CLPSO, ALC-PSO, improved MPSO, and IPG-PSO, among others; among these, it is mentioned that the HMPSO contains features of the PSO multi-agent base in the same way. Hybrid PSO-GA is based on the integration of particle swarm optimization, genetic algorithms, and conventional multi-

agent systems. The author notes its superiority over PSO, GA, HPSO, modified PSO, and MPSO algorithms [2].

To solve the ORPD problem within which, we can mention the time-varying inertia weight (PSO TVIW), PSO with time-varying inertia weight acceleration coefficients (PSO-TVAC), self-organized PSO with TVAC (SPSO-TVAC), stochastic weight compensation (SWT-PSO), integral learning PSO (CL-PSO), and the pseudo gradient PSO (PG-PSO); the latter magnifies its applications in economic dispatch [1]. The improved variant of the PSO named IPGS-PSO is used for solving RPD with three objective functions (Ploss, TVD, and VSI), by which it can specify a suitable direction to arrive at a globally optimal solution using pseudo gradient theory [2].

Volt VAR Control has the purpose of managing acceptable voltage profiles and reactive power flow by establishing reactive power compensation and voltage regulation devices at points in the electrical system and obtaining responses periodically [7,14]. It intelligently determines set points for the operability of regulators and compensators. Most power utilities worldwide adopt this form of regulation to keep the threshold voltage within the limits of operability [4,7,14].

The established VVC formulation has been borrowed from a significant set of robust optimization or stochastic programming formulations to address uncertainties with distributed generations or loads. Among the variants are some genetic algorithms (GA), particle swarm optimization (PSO) algorithms, and parallelized PSO with high computational performance [2,14] are mentioned as methods to provide solutions to this problem.

In [14], the researchers implement a method for optimal capacitor placement and sizing in a microgrid with bidirectional power flow characteristics. It also applies to closed-loop distribution systems with different types of local busbar generation. In [3], the researchers present a workshop focused on a VVC/VVO control based on machine learning and MAS, and based on artificial intelligence techniques, with the concept of training and suitably configuring artificial intelligence algorithms to establish voltage stability indicators of power systems. The model takes a decision tree form for an intelligent VVC/VVO and decentralized multi-agent control (MACS) to avoid a voltage collapse. A graphical representation of this scheme can be seen in Figure 1.

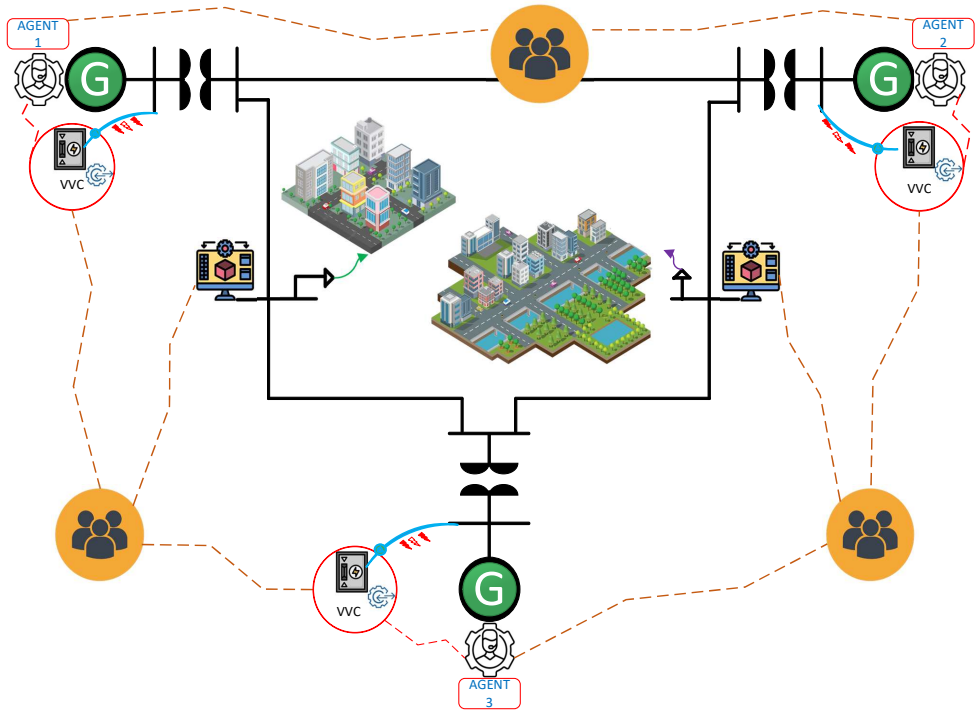


Figure 1. General diagram of the multi-agent system related to reactive power dispatching.

2. Theoretical Background

Within the power systems, addressing the reactive power dispatch dilemma is a crucially important activity to minimize power losses and improve voltage profiles; these objectives will be reached through a defined control of the voltages in the generation bars, the configurations in the transformer taps, and the allocation of resources for reactive energy. In this way, the concept of a multi-agent system is taken into account, where the approach is to work collectively to perform a defined task, which is limited to the capacity of a single agent. Within these systems, given the voltage control needed in recent years, the VVC is a mechanism employed to manage voltage profiles and regulate reactive power flows, thereby ensuring adherence to predefined operational limits.

2.1. Optimal Reactive Power Dispatch (ORPD)

One of the optimal power flows (OPF) subproblems that manage reactive power flow is the ORPD, which involves the optimal configuration of terminal voltages at generation points, compensators, transformer tap ratios, and output points at shunt Q sources [15–17].

The integration of volatile energy sources, such as renewables, into the grids requires more important considerations, as wind farms, for example, produce serious problems in terms of voltage stability due to the variability and intermittency of their generation [16]. This leads to the problem of optimal reactive power dispatch (ORPD), one of the most important actions to establish safe, reliable, and economical operations in the electrical system. This leads us to the challenge of optimal reactive power management, which is one of the key actions to ensure safe, reliable, and efficient operations in the power system [17]. It should be taken into consideration that the ORPD is a complex problem that involves different discrete and continuous variables resulting in a non-linear, non-convex, discontinuous, and multi-model system [18]. The ORPD process is illustrated in the flow diagram of Figure 2.

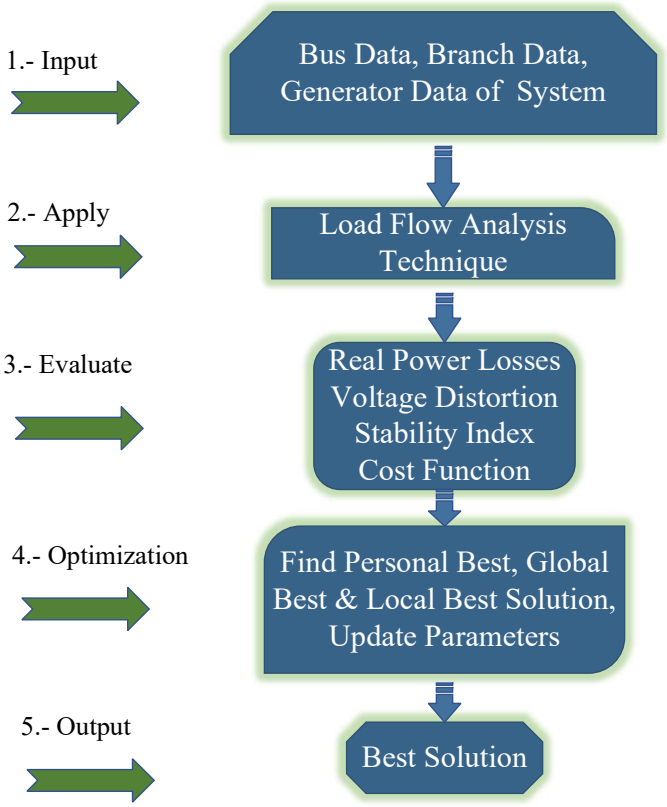


Figure 2. ORPD.

The ORPD succeeds by handling a significant complexity in nonlinear programming that combines successive decision variables that refer to the voltage at the generation busbars, while the discrete variables are referenced concerning the transformer taps and reactive power compensators [18]. The electrical power system uses active power while reactive power circulates within it; the importance of reactive power must be considered since it plays a major role in voltage stability and real power transfer [18].

The objective of ORPD is to increase power system performance in terms of minimizing line losses, outage management, improving transmission line capacity, improving voltage levels, improving network security, and minimizing overall costs while satisfying different groupings of physical and operational constraints [15,19]. Traditional objectives considered in studies are as follows: minimization of total system cost, minimization of transmission line losses, maximization of power handling capacity, and minimization of stability index [19].

2.1.1. Minimization of Line Losses

These losses are calculated using load flow methods in electrical networks, which depend on parameters such as conductance, bus voltage aptitudes, and related angles that are expressed mathematically [19,20].

$$P_{loss} = min \sum_{i}^{n} \sum_{j}^{n} G_{ij} \cdot (V_i^2 + V_j^2 - 2 \cdot V_i \cdot V_j \cdot cos\theta_{ij}) \quad (1)$$

where, V_i and V_j are voltage magnitudes at the i and j, n consigns to the total number of transmission lines, G_{ij} is the conductance of the line, θ_{ij} angular difference between the voltages of Vi and Vj [19,20].

The tap setting on the transformers has an impact on the reactance of the transmission lines. To limit the constraints, a penalty function is implemented to limit the decision variables, but if the limits are not exceeded, the penalty will take a value of zero, thus avoiding serious damage to the system [16,19].

$$Minimize: \ F: P_{loss}(Z) + f(C_h, C_g) \quad (2)$$

The transmission line losses derive from variables $Z \in [Q, T, V]$ such as shunt reactive power compensators Qi, control bus voltages Vi, and transformer tap positions Ti. $f\ (C_h, C_g)$ is awarded to the penalty where C_h and C_g are the penalty coefficients for the constraints being of inequality or equality as appropriate [15,16,19].

2.1.2. Minimization of Voltage Deviations

To obtain a stable operation of the power system, it should be taken into account that the voltages should be as uniform as possible. The effectiveness of the voltage adjustment can be evaluated through the total voltage deviation (TVD) index, which determines the voltage phase shift at the busbars compared to the reference voltage $(Vref)$ set at 1.0 $[p.u]$. That is, if the minimum value of (TVD) implies that all bus voltages are close to Vref, which makes it more level [19,20].

$$VD = \sum_{i=1}^{NL} [Vi - Vref] \quad (3)$$

where:

NL is the transmission lines number

$Vref$ reference voltage 1.

2.1.3. Cost Minimization

It is a priority to refer to costs such as installed technologies, system operating costs, and the cost of energy losses; the first one refers to devices such as FACTS or of other

nature, and the operating cost tends to be disregarded as long as it is hydro energy and is the final one included as a penalty for losses in the TLs. That is why the ORPD not only aims to reduce costs for losses but also focuses on reducing capital costs of technologies implemented for reactive power compensation, such as TCSC and SVC [19].

$$C_{Total} = C_{cpex} + C_{Opex} + C_{Energy} \tag{4}$$

where:

$$C_{Energy} = X \cdot 365 \cdot 24 \cdot P_{loss} \tag{5}$$

The cost associated with energy losses will take a value for each electrical system X \$/kWh, hours/day is 24 days/year are 365. The CCpex cost is linked to the capital cost of the FACTS, which must be valued concerning the manufacturer's database of the technology used [19].

2.1.4. Additional Control Parameters for the ORPD

In recent years, several technologies have been inserted to improve the ORPD's performance, considering the configuration and location of the transmission system. FACTS is one of these technologies with the function of controlling different variables, voltage magnitudes, active power, and reactive power, to improve the safety and stability of electrical systems. There are also devices such as static VAR compensator (SVC), thyristor-controlled series capacitor (TCSC), and thyristor-controlled phase-shifting transformer (TCPST) to minimize system losses. Some of them can be seen in Figure 3 [15,20].

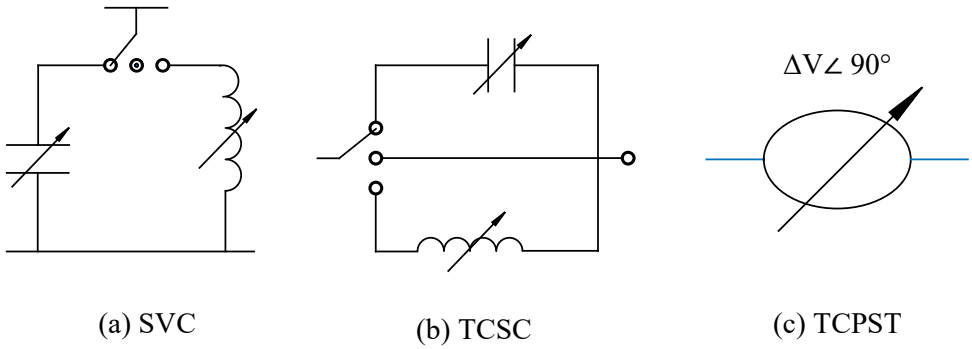


Figure 3. Additional controls.

Static VAR Compensator (SVC): It has two representations, inductive and capacitive. The first one consumes reactive power, while the other one introduces it. The static compensator can be presented as two parallel ideal switched elements, in capacitance and inductance [15].

Thyristor Controlled Series Capacitor (TCSC): It can possess capacitive or inductive properties aimed at decreasing or increasing the impedance of the TL. It is represented by three components interconnected in parallel, including capacitance, inductance, and a single conductor, which gives the TCSC the potential to achieve an absolute null value. Capacitance and inductance are variable, and their values are a function of the reactance of the TL in which this type of technology is installed. Thyristor-controlled phase-shifting transformer (TCPST): Its function is composed of adding a quadrature component to the bus voltage to raise or lower the angle; the modeling implemented by the device is an ideal phase shifter with a series impedance equal to zero. It is inserted in series and can take values of perceived angles in the range of -5 degrees to 5 degrees; zero is also a value that may become possible for the TCPST [15].

There are different structures for the ORPD problem, where each of them has a specific objective and wants to solve something. One example of such a single-objective ORPD aims to minimize total costs by taking into account the costs of adjusting the installed control

devices and the energy losses generated in the grid. Multi-objective ORPD (MO-ORPD) focuses on voltage deviation resolution and a voltage stability improvement index called L-index [16,18].

ORPD with voltage stability restrictions, emphasizing the L index as a stability measure applied by the search engine optimization algorithm (SOA), the same one that seeks harmony. ORPD taking into account the impact of Renewable Energy Sources (RESs), is directly linked to the MO-ORPD, but it is expanded due to the imminent penetration of RESs, resulting in a complex management of reactive power control by the uncertain and volatile nature of these types of resources [16,18].

Several optimization methods have been implemented to define the optimal values of the variables for control. In addition, constraint management methods that favor these methods are applied to highlight the conditions [17]. Different meta-heuristic optimization strategies have been applied to solve the optimization problem that gives an approximation and is usually non-deterministic. The applied methods have high efficiency concerning conventional methods, which are directed to the direct application of ORPD, for example, particle swarm optimization (PSO), genetic algorithm (GA), whale optimization algorithm (WOA), ant colony algorithm (ACA), and gravitational search algorithm (GSA), among others [17,20].

2.2. Multi-Agent System (MAS)

The multi-agent system (MAS) is a structure that consists of single or multiple intelligent agents. An intelligent agent can be understood as a software program or a computational entity that can store information from its environment and act accordingly without the assistance of human mediation. A set of several agents working collectively to execute a specific task that goes beyond the capabilities of a single agent is called a multi-agent system (Figure 4) [21,22].

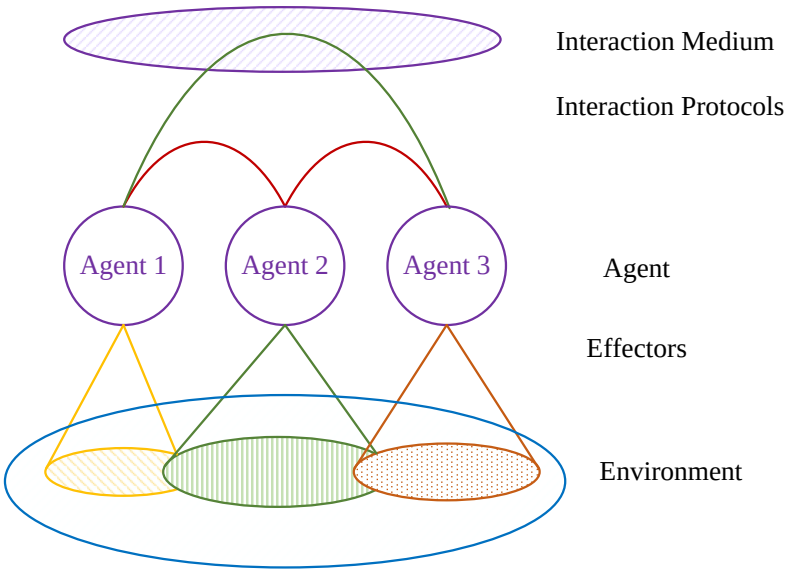


Figure 4. General Characterization of MAS.

They operate and share data collaboratively to achieve the desired result. A representative entity receives inputs from surrounding detectors and subsequently creates an action as an output. The interaction between the agent and its environment is a continuous space of information gathering and action. Communication between the agents is the most important part of the process that helps to achieve the intended solution [21–23].

2.2.1. Characteristics ofIntelligent Agents

Autonomy: They exercise partial control over their internal state and behavior. They affect the outcome of the system without interference from humans or external means.

Reactivity: They can react in time to all changes in the environment. They also act on these changes and implement the intended functionality.

Proactive: Intelligent agents exhibit dynamic behavior, aiming to achieve the desired objectives. An agent's initiative can be defined as its ability to take the initiative.

Social Competence: They can communicate and collaborate, as well as with other entities, such as installed devices and humans, to set their course of operation and achieve their objectives. An MAS has no overall system goal but has local goals that individual agents must achieve separately [21,23].

2.2.2. Main Advantages

1. MAS allocates resources and computing power in a network of interconnected agents. Although centralized systems may suffer from resource limitations, resource limitations, performance bottlenecks, or critical failures, MAS is not centralized and therefore does not suffer from the "single point of failure" problems associated with centralized systems [23].
2. MAS improves overall system performance, particularly in terms of computational efficiency, reliability, scalability, robustness, maintainability, responsiveness, flexibility, and reusability [23].

2.3. VOLT-VAR Control (VVC)

A recurring problem in recent years is the increase in renewable energies and the growing demand for clean energy. These changes have become beneficial to the power system, contributing to the development of active distribution networks and taking research in new directions regarding the control and optimization of these systems so this power can be exploited in the best possible way. This is a highly complex problem, especially when controlling the voltage and challenging the traditional control of the same [24,25].

To solve the problem of controlling voltage stability with the high incidence of renewable energy as a generative source, and as power systems adapt their capacities to accept these sources, various research works have contemplated Volt-VAR control, which has been a great discovery in recent years [26]. Voltage regulation is traditionally performed only on the medium voltage (MV) side of the power grid; most distributed generation systems are installed on low voltage grids, which makes a priority front of the unidirectional power flow in power grids responsible for distribution [24].

Volt-VAR control is an instrument whose essential function is to control voltage levels and reactive power flow, which determines an operating program to mitigate losses in the electrical network, correcting the voltage profile until it stabilizes within the established operating ranges. It is generally characterized as a non-linear problem, where the variables represent the strategies of the voltage regulation elements and reactive compensation sources; usually, the Volt-VAR control system adjusts with the positions of the on-load tap changers (OLTC) supported by LT droop compensators [7,26,27].

Electric utilities adopt the patented VVC control through the VVC algorithm, continuously monitor voltage magnitudes throughout the system, and make decisions based on voltage readings where substation capacitors and field capacitors are disturbed by simple rules concerning the capacitor. The control trips when the voltage drops below the voltage levels contemplated as permissible and shuts down when it exceeds the upper limit of the same permissible level, correcting in both cases [7,28].

The Volt-VAR control operates in an elementary way that currently brings together and exploits a set of rules based on mathematical methods or heuristic optimization techniques. However, these methods tend to be inefficient and sometimes unfeasible when taking into account the high magnitude and large-scale electrical systems; essentially, they struggle when it comes to considering the spatial level and time scales as operational uncertainties [7,8].

With this method, three main conditions need to be considered for effective reactive power definition: voltage operating limits, voltage collapse, and transient faults. The

voltage collapse related to effective reactive power delivery is more comprehensive than the one based on voltage limits. In addition, the definition of effective reactive power output focused on transient faults is one-sided [25].

The Volt-VAR Control problem can be divided into groups according to the model and communication scheme: centralized model-based, distributed model-based, centralized data-based, and distributed data-based methods [26,27]. Model-based centralized methods take full responsibility for all measurements that are collected by a central controller, which is aware of the distribution network parameters. The technical methods contain deterministic optimization, robust optimization, and meta-heuristic solving methods; the deterministic methods include dynamic programming, among other methods commonly applied by researchers to provide solutions [27].

Each sub-grid as a control center is modeled as an agent and learns to optimize inverter Q and power output setpoints by exploration in a virtual environment and a renewed neural network training procedure [8].

To consider the uncertainties in loads and distributed generation, robust Volt-VAR control algorithms have been developed under this premise. Accordingly, meta-heuristic algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been adopted to decrease the communication overhead and thus improve the resilience of the applied methods [27].

2.3.1. Dynamic VAR Controllers

Dynamic VAR controllers (DVC) are utility-implemented devices that effectively maintain voltage levels on the low voltage side of distribution transformers. An adequate number of VAR dynamic controllers can also attenuate the voltage drop on the MV side and can make up for or appease capacitor insufficiency by providing reactive power support. These types of controllers are shunt-connected, single-phase technologies that can be designed to operate with three phases on the LV side voltages [29].

In addition, they can accurately regulate the voltage and provide reactive power when the detected voltage levels fall below the allowable limit. At the same time, they decrease reactive power delivery when the voltage exceeds the allowable limit. They can provide Q in 1 kvar increment and up to a maximum of 10 kvar in discrete periods [29].

2.3.2. Volt-VAR Control Method

Volt-VAR control is classified into three categories depending on the communication regime, centralized control, decentralized autonomous control, and decentralized coordinated control. The centralized control approach involves a control entity with very distinct characteristics from each other and from those of the distribution system operator that contains the information, objectives, and indicators of the optimization problem; the distribution operator uses the centralized optimal power flow to reach an optimal solution. The continuous increase in distributed generation makes it difficult to provide a real-time solution due to the computational limitations of this problem. Decentralized coordinated control requires an advanced metering structure and multiple control centers to perform the optimization. Decentralized autonomous control methods assign little or no communication overhead between control devices; as a result, they are very simple and less expensive to install [26,27]. The graphic detail can be seen in Figure 5, where the processes carried out within the Volt-VAR control are shown.

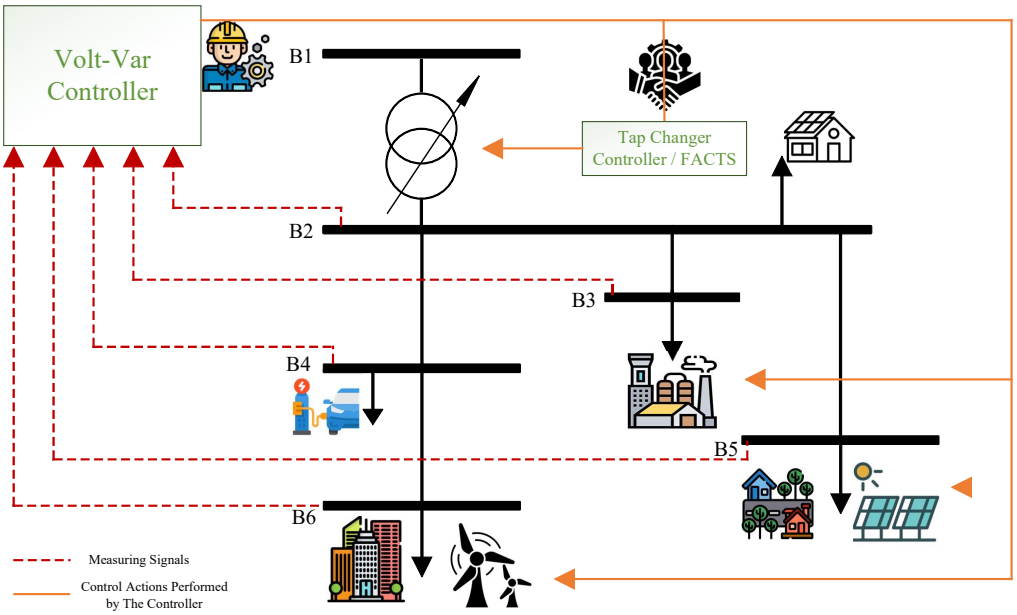


Figure 5. Volt-VAR Control Representation.

3. Problem Formulation and the Proposed Approach

3.1. Problem Formulation

Properly adjusting the reactive power distribution in a power system can solve the problem of reactive power dispatch, which is aimed at improving voltage levels and lowering total losses in the network while complying with operational constraints.

$$FO: minP_{loss} = min \sum_{i}^{n} \sum_{j}^{n} G_{ij} \cdot (V_i^2 + V_j^2 - 2 \cdot V_i \cdot V_j \cdot cos\theta_{ij}) \quad (6)$$

where:

V_i Voltage at bus i.
V_j Voltage at bus j.
θ_{ij} Angular difference between the voltages of V_i and V_j.
G_{ij} Real components of the elements of the matrix Y_{bus}.

Objective Function Constraints

Equality constraints refer to the power balance for each bus of the electrical system:

$$P_{g_i} - P_{d_i} - \sum_{i}^{n} \sum_{j}^{n} V_i \cdot V_j \cdot [G_{ij} \cdot \cos(\theta_{ij}) + B_{ij} \cdot sin(\theta_{ij})] = 0 \quad (7)$$

$$Q_{g_i} - Q_{d_i} - \sum_{i}^{n} \sum_{j}^{n} V_i \cdot V_j \cdot [G_{ij} \cdot \sin(\theta_{ij}) + B_{ij} \cdot cos(\theta_{ij})] = 0 \quad (8)$$

where:

P_{g_i} Generation active power of bus i.
Q_{g_i} Generation Reactive power of bus i.
P_{d_i} Demand active power at bus i.
Q_{d_i} Demand reactive power at bus i.
B_{ij} Imaginary components of the elements of the matrix Y_{bus}.
Inequality constraints refer to all operating constraints:
Generation reactive power limits.

$$Q_{g_i}{}^{min} \leq Q_{g_i} \leq Q_{g_i}{}^{max} \quad (9)$$

Limits of generation active power.

$$P_{g_i}{}^{min} \leq P_{g_i} \leq P_{g_i}{}^{max} \tag{10}$$

Voltage limits.

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{11}$$

Link capacity limits.

$$S_{ij} \leq S_{ij}{}^{max} \tag{12}$$

The control variables mentioned above are incorporated into the power flow calculation. Specifically, the AVR operating values are treated as the specified operating voltage values for the generating unit, while the tap changer position is considered a component of each actual tap.

The P_{loss} function is determined through a power flow analysis. Continuous variables, which refer to the voltage regulator settings, are included, as well as discrete variables, such as the position of switchgear and the location of compensation equipment. Voltage and power conditions are verified about the power flow and, in case of exceeding the admissible ranges, the power flow will be subject to penalty values:

$$FA : min\{P_{loss} + k \cdot f(x)\} \tag{13}$$

$$f(x) = \begin{cases} 0 & x_{min} \leq x \leq x_{max} \\ (x - x_{max})^2 & if \;\; x > x_{max} \\ (x_{min} - x)^2 & if \;\; x > x_{min} \end{cases} \tag{14}$$

where:

$f(x)$ Penalty function.

k Vector of penalty factors.

3.2. Particle Swarm Optimization (PSO)

The concept of swarm optimization is considered very popular. It was introduced by Eberhart and Kennedy (1995), who were inspired by flocks of birds and schools of fish that show intelligent behaviors. Although popular, the simple PSO has a deficiency, as it can become stagnant when applied to complex problems and can be inefficient if viewed from a computational point of view. This is why, considering these limitations, variants of PSO have been introduced to regulate and control the optimal search process by resolving these limitations [30–32].

The PSO is considered within the optimization techniques as the technique that uses swarm intelligence with more efficiency and is very useful; it is applied to different optimization problems. The cloud or swarm is based on a finite number of particles within which each is a possible solution in the search space. Each particle represents a dimension position vector, which includes a search space that contemplates a candidate solution of the given optimization problem and is determined in a velocity resultant [30,33,34].

The PSO can be represented in its mathematical form by velocity and position formulas:

$$v_{id}^{t+1} = \omega v_{id}^{t} + c_1 r_1 \cdot (Pbest_{id} - x_{id}^{t}) + c_2 r_2 \cdot (Gbest_{gd} - x_{id}^{t}) \tag{15}$$

$$x_{id}^{t} = x_{id}^{t} + v_{id}^{t+1} \tag{16}$$

$$i = 1, 2, ..., n; \qquad d = 1, 2, ..., m$$

where:

Pbest best known local position and *Gbest* best global position.

i, d, and t denote the particle index, the dimension, and the discrete-time index under consideration, correspondingly.

n and m represent the population of particles in a group and the size of a particle, respectively.
ω, $r1$, $r2$, and $c1$, $c2$ are the inertia weight factor, the randomization parameters, and the social and cognitive social and cognitive components, respectively [30,33,35].

The inertia takes a value for each iteration k; it is represented as follows:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{total}} \cdot iter \tag{17}$$

where:
ω_{max}: initial weight.
ω_{min}: final weight.
$iter_{total}$: total iterations.
$iter$: current iteration.

The PSO method is known for its efficiency in solving optimization problems. It can effectively explore and exploit the search space, allowing it to find optimal or near-optimal solutions quickly. That is how optimal reactive power dispatch fits, which involves adjusting multiple variables, such as machine voltage levels, to achieve efficient electrical system operation. The PSO method is suitable for dealing with optimization problems with multiple variables and can find an optimal combination of these variables simultaneously. Additionally, the PSO method can adapt to different problems and constraints. It can handle both convex and non-convex objective functions and linear and nonlinear constraints, making it suitable for addressing the complexity of optimal reactive power dispatch.

3.3. Optimization Constraints

Evolutionary algorithms have a high superiority when it comes to handling complex parameter spaces, which are defined by equality and inequality constraints. Within this type of algorithm, all the information of the values of the objective function is considered, and the violation of the prohibitions must be denoted by a single register that takes the name of fitness value. The fitness function can be represented in such a way that the particles have a complete approach to the feasible space, and these can be transformed into efficiency solutions; the evaluation and evolution of the particles are highly dependent on the mentioned value [36].

General constrained optimization problems can be posed in this way:

$$minimize\ f(x), \qquad x = [x_1, x_2, \ldots\ \ldots\ \ldots, x_n] \in R^n \tag{18}$$

where:
$f(x)$: Objective function subject to constraints.
Inequality:

$$g_i(x) \leq 0, \qquad i = 1, 2, \ \ldots\ \ldots\ \ldots, I \tag{19}$$

Equality:

$$h_i(x) = 0, \qquad i = 1, 2, \ \ldots\ \ldots\ \ldots, J \tag{20}$$

The equality and inequality constraints are known as active constraints, which satisfy the condition $g_i(x) = 0$. The search space is delimited by the variables x_1 and x_n; on the other hand, a particle is considered viable if it complies with all the restrictions $I + J$, while if it does not comply with at least one of the restrictions, it is considered unfeasible and cannot be taken into account [36].

$$x_{1,k} \leq x_k \leq x_{u,k} \qquad k = 1, 2, \ \ldots\ \ldots\ \ldots, n \tag{21}$$

The convergence between the constraints and the search space defines the feasible space. Equality constraints are transformed into inequalities by considering the tolerance value ξ in this way:

$$|h_j(x)| - \xi \leq 0 \tag{22}$$

The most significant difficulty in setting up constrained optimization problems is how to operate on infeasible particles. Some constraint management techniques are mentioned:

Rejection Strategy: During the search, infeasible particles are discarded. In case the initial swarm contains an infeasible particle, it is replaced by another feasible particle at random.

RepairStrategy: Rules that act together and are based on the problem to be solved are used to transform an infeasible particle into a feasible one.

SpecialOperatorStrategy: Ensures that particles continuously lie within the feasible search space.

PenaltyStrategy: Particles add a penalty value for each constraint violation.

The advantages and disadvantages of the strategies can be evaluated by observing the fitness value of the various viable (B, D, E, G, H) and non-viable (A, C, F) particles with the optimal solution located at "H".

If the rejection strategy is followed and the infeasible particles such as "C", which contain useful information about the optimal location, are removed, the viable particles "D, E, G" must overcome their respective local minima or the particle "B" must move from its peak position to find the optimal solution (Figure 6) [36].

The use of penalty strategies is frequently resorted to in order to operate the feasible particles in evolutionary optimization. The most important problem is considered in formulating the penalty function and the resulting penalized function. Another important consideration in the application of this strategy is the modeling of the fitness function, i.e., how to compare a viable particle with a non-viable one.

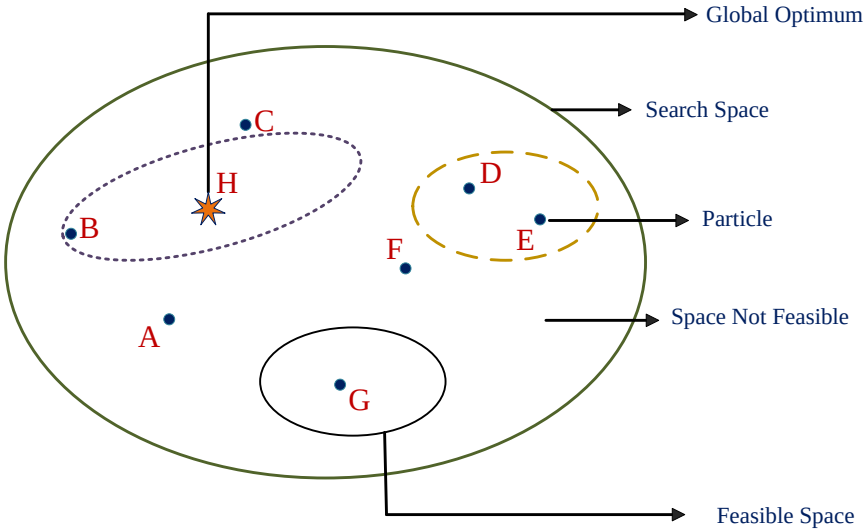


Figure 6. Two-Dimensional Search Space.

3.3.1. Penalty Function

The application of penalty techniques is the most prevalent method for incorporating constraints in programming. This approach allows converting a problem with constraints into a constraint-free problem by adding the penalty function to the objective function, as shown below:

$$F(k, x) = f(x) + p(k, x) \tag{23}$$

$$p(k,x) = 0, \qquad if\ x\ is\ feasible$$

$$= \begin{cases} k_i \cdot |g_i(x)|^2, & i = 1,2, \ \dots \ \dots \ \dots, I \\ k_j \cdot (|h_j(x)| \ - \xi)^2, & j = 1,2, \ \dots \ \dots \ \dots, J \end{cases} \tag{24}$$

where:

$F(k,x)$: Fitness function.

$f(x)$: Objective function.

$p(k,x)$: Penalty function.

The penalty function stores the infeasible particles for each constraint violation. When plotting the penalty functions, the following aspects should be considered:

1. The distance from the feasible boundary.
2. Difficulty level.

The assessment of penalties' intensity should be based on specific attributes. Overly harsh penalties for unfeasible particles may overlook the data that these particles contain outside the feasible area. If the optimal solution lies beyond the searchable feasible boundary, the swarm will not be capable of guiding particles to that outcome. Rigid penalties discourage exploration by particles, resulting in mediocre solutions. Lighter penalties, on the other hand, allow particles to explore a broader area and prolong their time outside the feasible space. In the absence of adequate penalties, unfeasible particles may dominate the search process, and the process may conclude without finding a suitable solution. When the optimization problem has numerous restrictions, finding feasible solutions can be a challenging task. One approach to solve this is by determining non-critical constraints, i.e., weak constraints. Another important aspect is the limited feasible search space in comparison to the global space, which makes meeting all constraints difficult. The penalty function must account for these features and assign the appropriate magnitudes to penalties. The efficacy of any penalty function is contingent on the selection of the penalty coefficient k. The definition of these coefficients classifies the search process. Penalty techniques are generally divided into three categories based on the definition of these coefficients, including the fixed penalty, dynamic penalty, and adaptive penalty [35].

3.3.2. Fixed Penalty

One method of incorporating penalties into constrained optimization is to employ fixed or static penalty functions. Here, penalties become increasingly significant as constraint violations grow. The fitness value is determined by summing the objective function and the penalties for any constraints that are not met.

The formula for the fixed penalty function is expressed as follows:

$$F(k,x) = f(x) + \sum_{m=1}^{I+J} k_m \cdot {d_m}^2 \tag{25}$$

$$d_m = \begin{cases} 0, & if\ (x)\ is\ feasible \\ |g_m(x)|, & m = 1, \ ...., I \\ |h_m(x)|, & m = I+1, ..., I+J \end{cases} \tag{26}$$

where:

d: Measure of violation level.

k: Vector of penalty coefficients.

The selection of the coefficient k is determined based on the extent of the violation, enabling the incorporation of multiple penalties for each constraint depending on the degree of non-compliance. The violation extent for each constraint is divided into segments, with each segment assigned a distinct penalty coefficient. However, a drawback of this method is the requirement to specify numerous k coefficients, and there is no standardized approach available for determining them [31].

3.3.3. Dynamic Penalty

The adaptive nature of the dynamic penalty function takes into account both the magnitude of constraint violations and the progression of the optimization process. The penalties are modified based on the extent of infractions and the progress made by the algorithm. Initially, mild penalties are imposed on particles that are not feasible, but as the search continues, the penalties become more stringent, enabling the feasible particles to lead the swarm toward the optimal solution.

The dynamic penalty function is described as:

$$F(\rho, x) = f(x) + {\rho_k}^{\alpha} \cdot \sum_{m=1}^{I+J} {d_m}^{\beta}(x) \tag{27}$$

$$d_m(x) = \begin{cases} 0, & if\ (x)\ is\ feasible \\ |g_m(x)|, & 1 \le m \le I \\ |h_m(x)|, & I+1 \le m \le I+J \end{cases} \tag{28}$$

$$\rho_k = C \cdot iter \tag{29}$$

where:

$iter$: Number of the current iteration.
α, β: Variables controlling the weighting of the penalty values.
C: Constant.
ρ_k: Control penalties based on the progress of the search process.
d_m: Metric distance.

3.3.4. Adaptive Penalty Function

The adaptive penalty technique allows penalties to be kept within defined ranges based on swarm performance, with penalties reflecting the previous performance history of the particles. This allows particles to reject viable areas already visited and approach promising areas. This ensures that a high-quality solution is only obtained if the cloud can produce viable particles during the initial iterative process and approach promising zones, rejecting feasible zones that have already been visited.

The optimization technique using an adaptive function based on feasible-near boundary NFT allows the algorithm to automatically adapt to the level of difficulty of the optimization. This is achieved by identifying the most critical constraints and increasing the penalty in areas close to the feasible frontier. In this way, the algorithm is prevented from getting trapped in infeasible regions and is steered towards more promising solutions. This technique is especially useful with nonlinear and highly nonconvex constraints. The adaptive function is:

$$F(x,t) = f(x) + \left(F_{feasible}(t) - F_{total}(t)\right) \cdot \sum_{m=1}^{I+J} \left(\frac{d_m}{\mathrm{NFT}_m}\right)^2 \tag{30}$$

where:

$F_{feasible}(t)$: Best feasible solution generated.
$F_{total}(t)$: Best penalized solution.

The adaptive method being proposed involves creating a boundary near the feasible region for each constraint. This boundary, known as the near-feasible frontier (NFT), is where the search results are close enough to the most viable region to account for a significant difference. The penalties are adjusted based on the best results achieved in each iteration, ensuring that they are neither too harsh nor too lenient. The swarm is kept within the feasible region or near the NFT boundary, which prevents non-feasible particles from straying too far from the penalty area. However, it is worth noting that during the early stages of the search process, when the feasible function is significantly larger than the total function, large penalties will be assigned to all infeasible particles [33].

3.4. Development of Volt-VAR Control Algorithm by Means of PSO

Step 1 The starting positions and movements of each particle are established through the utilization of randomly generated state variables.

Step 2 The active power losses, Ploss, at the positions of each particle are calculated by means of a power flow. If the constraints violate the allowable limits, a penalty for the losses is included.

Step 3 Each search point has its known local position, referred to as P_{best}. The best-evaluated value, which is the sum of the loss and penalty, from all the P_{best} is then set as the global best, or G_{best}.

Step 4 The new search velocities and positions are calculated using (15)–(17).

Step 5 The losses (Ploss) in the new search positions are calculated, and a valuation is performed for each one.

Step 6 The evaluation of each particle is compared to its previous P_{best} and updated if it is better. The best of the P_{best} is then compared to G_{best} and updated if it is better. The updated G_{best} values are stored as potential solutions.

Step 7 When the maximum number of iterations determined is reached, and if the result meets the expectations, the search process will end. Otherwise, the process will return to step 4.

Step 8 Using the results obtained for the new AVRs, the power flow calculation is performed to determine the reactive power dispatch by the rotating machines.

4. Case Study

This case study's objective revolves around applying the Particle Swarm Optimization (PSO) algorithm. This research focuses on implementing the PSO algorithm within a standardized IEEE system. The study aims to subject the algorithm to various technical conditions to obtain auspicious outcomes. Specifically, the algorithm will optimize reactive power (Q) to dispatch within the system. It will undergo an examination under different search space scenarios to derive the most optimal results for system enhancement. These outcomes will be manifested through the minimization of losses across the entire system and the improvement of its response time.

The presented one-line diagram depicts the IEEE 14 Bar system (Figure 7), which has five synchronous machines with IEEE type 1 exciter. Among them, three are synchronous compensating generators used exclusively to provide reactive power. The system has a total of 11 loads distributed along the network, with a total power of 259 MW and 73.5 Mvar. It also has three transformers equipped with tap changers. The voltage limit for the system is set at 1.06 p.u for the Slack generator, while for the other machines, it is limited for voltage levels up to $\pm 10\%$ with steps of $\pm 2\%$ relative to 1 p.u. The data to implement are derived considering a base power of 100 MVA.

For transformers 4–7, 4–9, and 5–6, the values of 0.978, 0.969, and 0.932, respectively, for the taps of these are established. The acceleration coefficients c_j of the velocity equation are set in 1.5. Values of 0.9 and 0.4 were set as initial and final weights for ω_{max} and ω_{min}, respectively. The initial particle velocity is set to 1 based on the constant k, and the penalty constants ki are set to $1 \cdot 10^6$. Limits are set for the transmission line loading, including a thermal limit of 80%. For this process, 10 particles will be selected to perform the search in space with a limited number of iterations, up to 200 iterations.

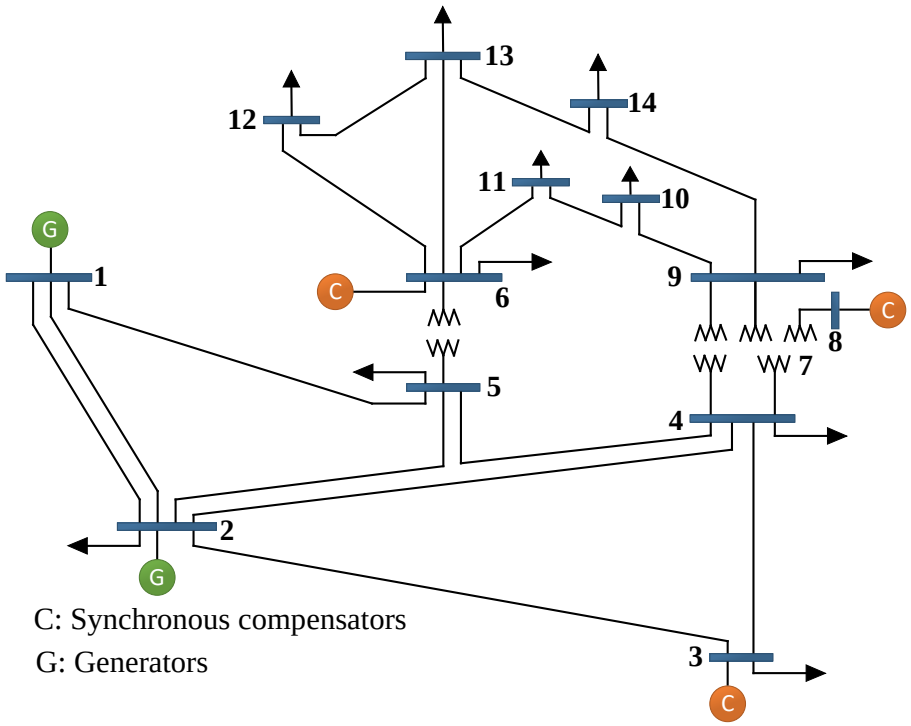


Figure 7. IEEE 14 Bar System.

5. Analysis of Results

The original system presents an initial active power loss of 15.358 MW under normal operating conditions without the use of the PSO algorithm. The application of the PSO algorithm results in an optimization of the AVR variables, achieving a reduction in active power losses, as can be seen in Table 1. These results can also be observed graphically in Figure 8.

Table 1. AVRs variation results for the case studies.

Case	AVR G2 [p.u.]	AVR C3 [p.u.]	AVR C6 [p.u.]	AVR C8 [p.u.]
Base	1	1	1	1
±2%	1.0349	1.0076	1.0207	1.0203
±4%	1.0389	1.005	1.0402	1.0401
±6%	1.0376	1.0057	1.0601	1.0601
±8%	1.0366	1.0059	1.073	1.0801
±10%	1.0361	1.006	1.0766	1.1

The reactive power dispatch presented in Table 2 and Figure 9 is determined from the results obtained in the power flow analysis, ensuring a balanced distribution among the generating machines and supplying the required demand.

Table 2. Dispatch of reactive power by generators.

Case	G2 [Mvar]	CS-3 [Mvar]	CS-6 [Mvar]	CS-8 [Mvar]
Base	–54.97	62.74	2.12	3.77
±2%	33.86	40.3	1.21	1.46
±4%	40.72	31.17	6.62	6.34
±6%	29.76	29.54	14.12	10.07
±8%	21.7	27.93	18.2	14.98
±10%	21.7	27.93	18.2	14.98

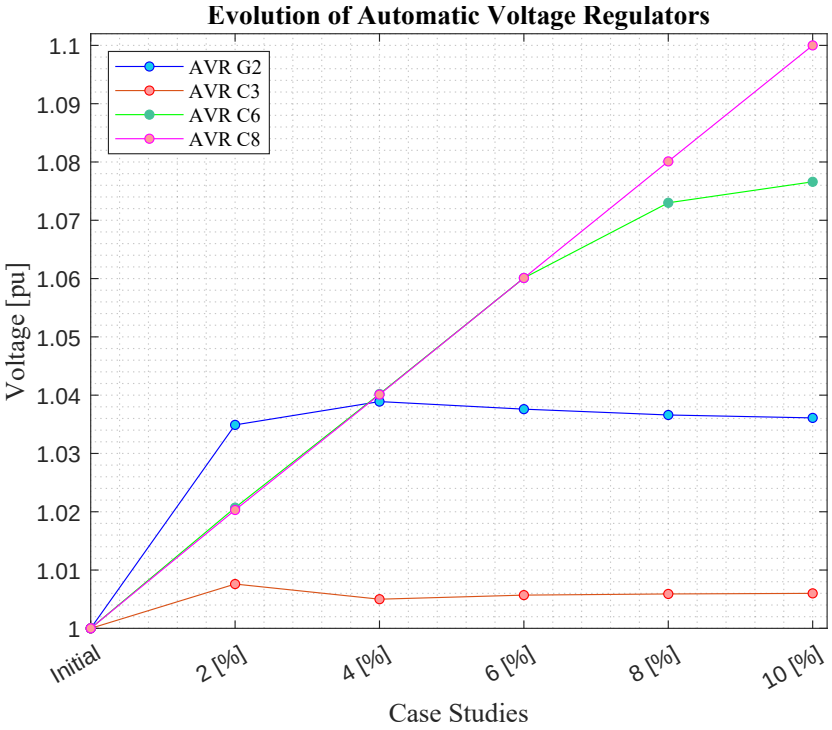


Figure 8. Automatic Voltage Regulators.

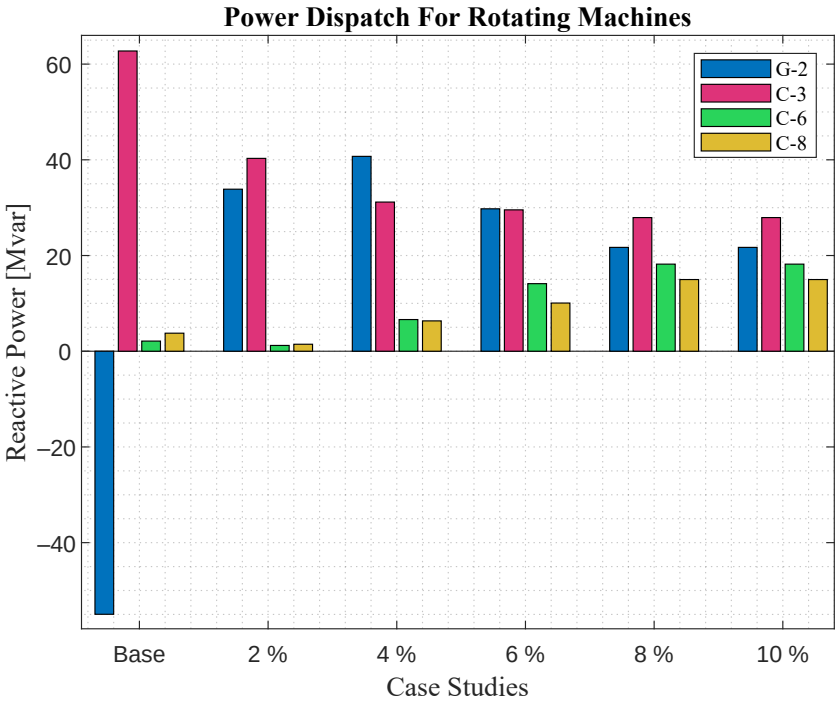


Figure 9. Reactive Power Dispatch.

The application of the particle swarm algorithm has allowed the optimization of the control variables in the analyzed system, achieving a significant reduction in total system losses by 12.61% (Table 3). In Figure 10, it is evident that increasing the voltage band can lead to lower active power losses.

In addition, an average processing time of 9.07 seconds has been recorded for the study cases (Table 4), which also depends on the voltage band (Figure 11). These results demonstrate the algorithm's effectiveness in optimizing electrical systems.

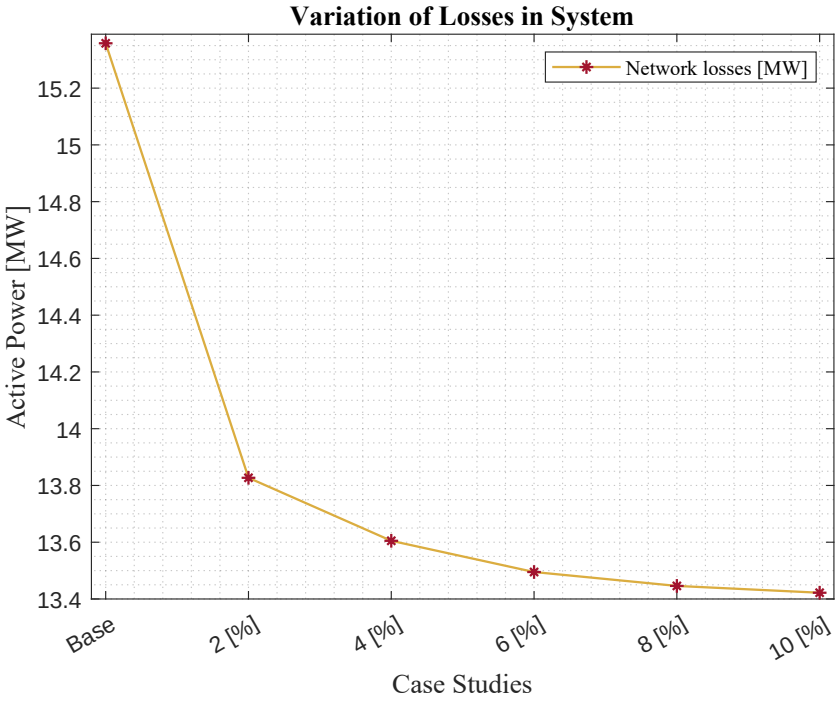


Figure 10. Losses in System.

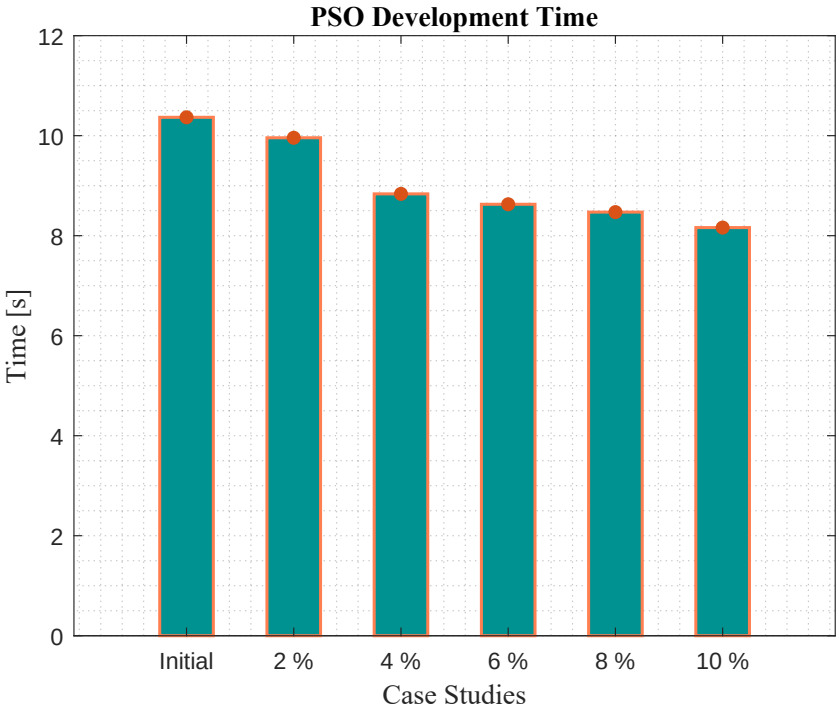


Figure 11. Processing time.

Table 3. System active power losses .

Base Loss [MW]	±2% [MW]	±4% [MW]	±6% [MW]	±8% [MW]	±10% [MW]
15.358	13.827	13.605	13.495	13.446	13.421

Table 4. Algorithm processing time.

Base Case [s]	±2% [s]	±4% [s]	±6% [s]	±8% [s]	±10% [s]
10.367237	9.957719	8.835776	8.628039	8.471272	8.161734

The results obtained show that the behavior of the voltage variation (Table 5 and Figure 12) in the system busbars are also influenced by the setting proposed by the algorithm. It can be observed that bus 3 is the one that suffers the least variation compared to other buses, while bus 8 reaches its limit value to meet the established requirements.

On the other hand, the losses in transmission lines 1–2, 1–5, 2–3, and 3–4 are the ones that experience the most significant reduction compared to the base system (Table 6). In the case of the other lines, a reduction in losses is also observed, although it is smaller and not as noticeable, this fact can be seen in Figure 13. Finally, as an example, Figure 14 shows the detail of the loss reduction in transmission line 6–13, where the reduction is less while the voltage band is ±10%.

Table 5. Voltage Response.

System Voltage Response						
Bus	**Base [p.u.]**	**±2% [p.u.]**	**±4% [p.u.]**	**±6% [p.u.]**	**±8% [p.u.]**	**±10% [p.u.]**
1	1.06	1.06	1.06	1.06	1.06	1.06
2	1	1.0349	1.0389	1.0376	1.0366	1.036
3	1	1.0076	1.005	1.0057	1.0059	1.006
4	0.976	0.9974	1.0037	1.0089	1.0129	1.0154
5	0.979	1	1.0067	1.0118	1.0155	1.0175
6	1	1.0207	1.0402	1.0601	1.073	1.0766
7	0.993	1.015	1.0294	1.0434	1.0557	1.0658
8	1	1.0203	1.0401	1.0601	1.0801	1.100
9	0.988	1.0104	1.0256	1.0403	1.0521	1.0600
10	0.982	1.0045	1.0205	1.0363	1.0483	1.0556
11	0.987	1.0089	1.0267	1.0445	1.057	1.0625
12	0.984	1.0055	1.0249	1.0447	1.0577	1.0617
13	0.979	1.0007	1.0200	1.0395	1.0524	1.0568
14	0.965	0.9873	1.0046	1.0217	1.0342	1.0407

Table 6. Segment Loss Evaluation.

Segment Loss Response							
Branch	**Line**	**Base**	**±2%**	**±4%**	**±6%**	**±8%**	**±10%**
1	1–2	4.976	4.3	4.284	4.254	4.235	4.227
2	1–5	3.071	2.822	2.792	2.792	2.795	2.796
3	2–3	2.733	2.428	2.382	2.365	2.353	2.347
4	2–4	1.792	1.728	1.709	1.694	1.695	1.704
5	2–5	0.958	0.953	0.936	0.918	0.913	0.913
6	3–4	0.674	0.491	0.415	0.392	0.38	0.374
7	4–5	0.543	0.519	0.513	0.506	0.507	0.516
8	4–7	0	0	0	0	0	0
9	4–9	0	0	0	0	0	0
10	5–6	0	0	0	0	0	0
11	6–11	0.057	0.055	0.058	0.067	0.069	0.06
12	6–12	0.081	0.078	0.076	0.075	0.074	0.072
13	6–13	0.239	0.229	0.225	0.224	0.221	0.213
14	7–8	0	0	0	0	0	0
15	7–9	0	0	0	0	0	0
16	9–10	0.017	0.016	0.014	0.01	0.009	0.011
17	9–14	0.141	0.134	0.124	0.11	0.105	0.11
18	10–11	0.012	0.012	0.013	0.018	0.019	0.015
19	12–13	0.007	0.007	0.007	0.007	0.007	0.007
20	13–14	0.057	0.055	0.057	0.063	0.064	0.057

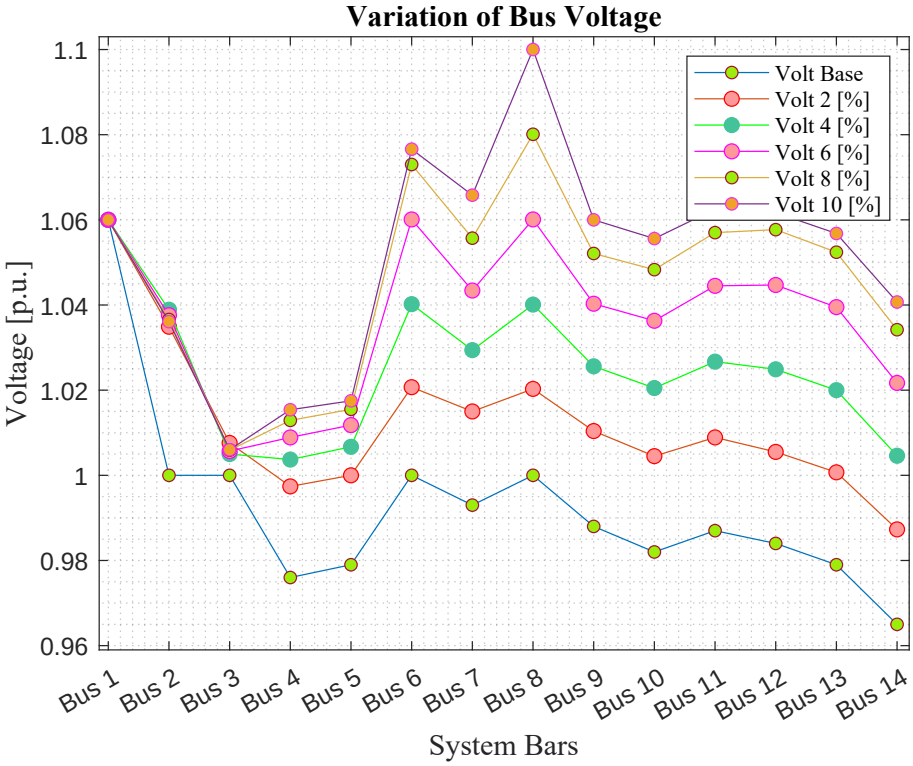


Figure 12. Voltage Response on Busbars.

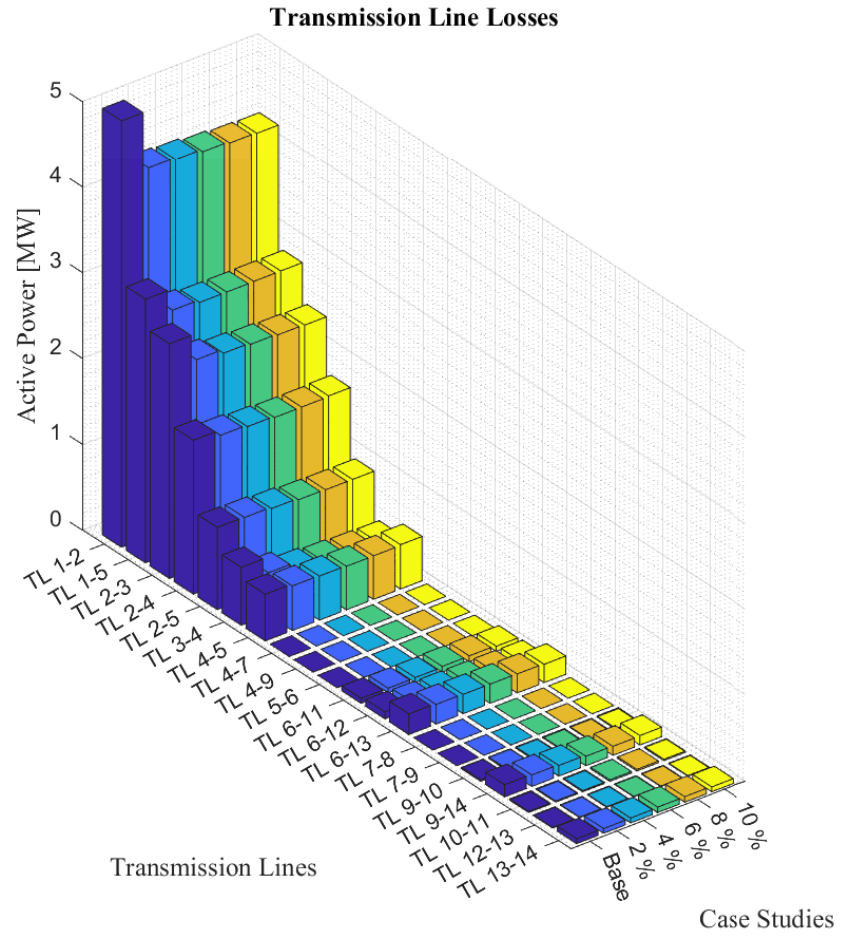


Figure 13. Segment Loss Response.

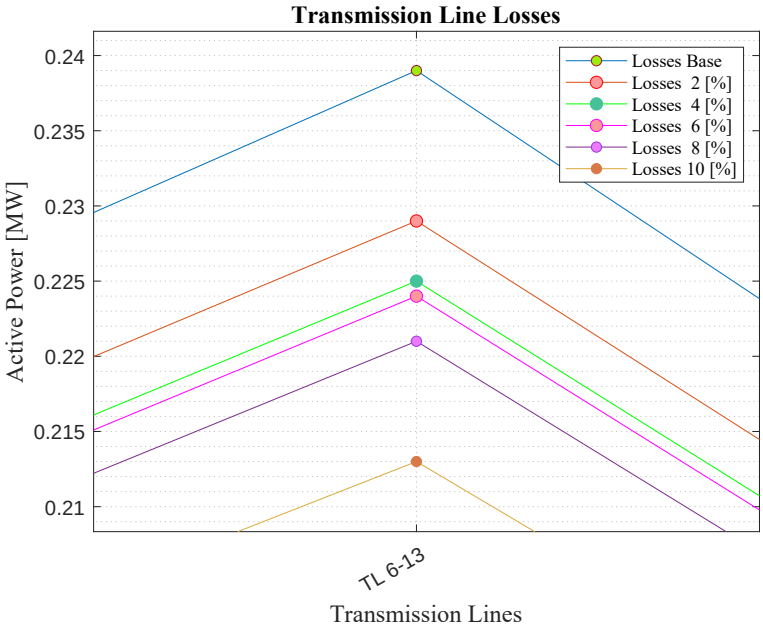


Figure 14. Loss response on transmission line 6–13.

As for the evolution of the losses as more iterations are performed, it can be seen in Figure 15 that after iteration 68, the value remains stable at a value of 13.428 MW, suffering a minimum reduction of 0.0465% until reaching the value of 13.421 MW in iteration 137.

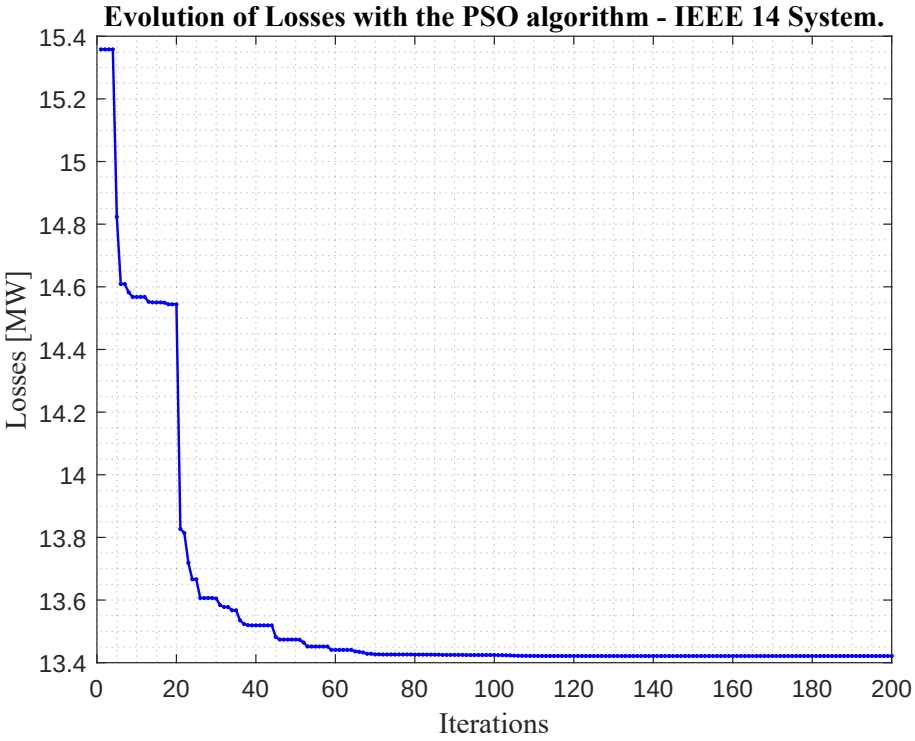


Figure 15. Evolution of the Objective Function.

6. Conclusions

The proposed algorithm demonstrates efficiency in solving the optimal reactive power dispatch problem by determining optimal values for control variables such as machine voltage levels. These values are adjusted based on the sensitivity parameters of the specific case study being considered. This approach leads to a more effective determination of reactive power dispatch, resulting in a substantial reduction of total system losses.

It can be observed that the reactive power forecast for each one of the rotating generation machines, according to the established criteria, is within a permissible search range. These allocations seek uniformity among the machines when dispatching the reactive power. A significant contrast is also observed in machines G2 and C2, which experience the most significant changes compared to the base case and the last case of the study. These results can be analyzed in future works related to economic dispatch to study them further.

The response time of the algorithm in the application has shown highly encouraging results by significantly reducing the response time compared to the base case. A remarkable difference of 2.205 [s] has been observed. This result can be interpreted as an upper threshold for real-time monitoring of the system, implying a substantial improvement in the responsiveness of the algorithm.

The analysis of the system indicates that a wider search range for voltage variables in the rotating machines yields more efficient solutions in terms of reactive power dispatch values. The results obtained were validated through evidence of decreased total system losses following the algorithm's application. Implementing the algorithm ensures uniform power delivery from the generating machines and significantly reduces system losses, achieving reductions of up to 12.61%.

The particle swarm method employed is optimized by considering initial weights, final weights, acceleration, and a penalty constant, as mentioned in the paper. It was observed that increasing these values makes the method less sensitive to changes with higher weights. However, reducing these values may have a negative impact on the efficiency of the optimal solution, potentially increasing solution time or leading to less efficient solutions.

The applied metaheuristic optimization allows solving efficiently complex mathematical problems that include nonlinearity or nonconvexity, as is the case of the reduction of active power losses in electric power systems.

The real application of the proposal has a simple implementation since the operating personnel can be trained to modify the operating points of the generators to change the reactive power delivered by them according to the results of the different possible demand scenarios.

Using the particle swarm optimization method in optimal reactive power dispatch can contribute to reducing greenhouse gas emissions and mitigating climate change. By achieving more efficient management of reactive power in electrical systems, energy losses can be reduced, and resource consumption can be optimized.

Future works that can be developed from this research are related to adding other reactive power control elements which participate in Volt-VAR control, such as transformers, capacitor banks, or FACTS. In addition, other metaheuristic techniques can be explored to solve the problem and thus compare the results regarding objective function and convergence time.

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References

1. Polprasert, J.; Ongsakul, W.; Dieu, V.N. Optimal reactive power dispatch using improved pseudo-gradient search particle swarm optimization. *Electr. Power Components Syst.* **2016**, *44*, 518–532. [CrossRef]
2. Nasouri Gilvaei, M.; Jafari, H.; Jabbari Ghadi, M.; Li, L. A novel hybrid optimization approach for reactive power dispatch problem considering voltage stability index. *Eng. Appl. Artif. Intell.* **2020**, *96*, 103963 . [CrossRef]

3. Tomin, N.; Kurbatsky, V.; Panasetsky, D.; Sidorov, D.; Zhukov, A. Voltage/VAR Control and Optimization: AI approach. *IFAC-PapersOnLine* **2018**, *51*, 103–108. [CrossRef]
4. Ettappan, M.; Vimala, V.; Ramesh, S.; Kesavan, V.T. Optimal reactive power dispatch for real power loss minimization and voltage stability enhancement using Artificial Bee Colony Algorithm. *Microprocess. Microsyst.* **2020**, *76*, 103085. [CrossRef]
5. Abou El-Ela, A.A.; Kinawy, A.M.; El-Sehiemy, R.A.; Mouwafi, M.T. Optimal reactive power dispatch using ant colony optimization algorithm. *Electr. Eng.* **2011**, *93*, 103–116. [CrossRef]
6. Sun, X.; Qiu, J. Two-Stage Volt/Var Control in Active Distribution Networks with Multi-Agent Deep Reinforcement Learning Method. *IEEE Trans. Smart Grid* **2021**, *12*, 2903–2912. [CrossRef]
7. Gao, Y.; Yu, N. Model-augmented safe reinforcement learning for Volt-VAR control in power distribution networks. *Appl. Energy* **2022**, *313*, 118762. [CrossRef]
8. Liu, H.; Zhang, C.; Chai, Q.; Meng, K.; Guo, Q.; Dong, Z.Y. Robust Regional Coordination of Inverter-Based Volt/Var Control via Multi-Agent Deep Reinforcement Learning. *IEEE Trans. Smart Grid* **2021**, *12*, 5420–5433. [CrossRef]
9. Sujil, A.; Verma, J.; Kumar, R. Multi agent system: Concepts, platforms and applications in power systems. *Artif. Intell. Rev.* **2018**, *49*, 153–182. [CrossRef]
10. Mohamed, A.A.; Omran, W.A.; Sharkawy, R.M. Centralized/Decentralized Power Management Strategy for the Distribution Networks based on OPF and Multi-Agent Systems. In Proceedings of the 2021 IEEE PES Innovative Smart Grid Technologies Europe: Smart Grids: Toward a Carbon-Free Future, ISGT Europe 2021, Espoo, Finland, 18–21 October 2021; pp. 1–5 . [CrossRef]
11. Naderi, E.; Pourakbari-Kasmaei, M.; Abdi, H. An efficient particle swarm optimization algorithm to solve optimal power flow problem integrated with FACTS devices. *Appl. Soft Comput. J.* **2019**, *80*, 243–262. [CrossRef]
12. Anand, H.; Narang, N.; Dhillon, J.S. Multi-objective combined heat and power unit commitment using particle swarm optimization. *Energy* **2019**, *172*, 794–807. [CrossRef]
13. Lalwani, S.; Sharma, H.; Satapathy, S.C.; Deep, K.; Bansal, J.C. A Survey on Parallel Particle Swarm Optimization Algorithms. *Arab. J. Sci. Eng.* **2019**, *44*, 2899–2923. [CrossRef]
14. Alexander, A.T.; Gonzalo Manuel, G.S.; DIego Luis, G.S.; Leony, O.M. Optimum location and sizing of capacitor banks using VOLT VAR compensation in micro-grids. *IEEE Lat. Am. Trans.* **2020**, *18*, 465–472. [CrossRef]
15. Karthikaikannan, D.; Ravi, G. Optimal reactive power dispatch consideringmulti-type FACTS devices using harmony search algorithms. *Automatika* **2018**, *59*, 303–314. [CrossRef]
16. Mohseni-Bonab, S.M.; Rabiee, A. Optimal reactive power dispatch: A review, and a new stochastic voltage stability constrained multi-objective model at the presence of uncertain wind power generation. *IET Gener. Transm. Distrib.* **2017**, *11*, 815–829. [CrossRef]
17. Yapici, H. Solution of optimal reactive power dispatch problem using pathfinder algorithm. *Eng. Optim.* **2021**, *53*, 1946–1963. [CrossRef]
18. Saddique, M.S.; Bhatti, A.R.; Haroon, S.S.; Sattar, M.K.; Amin, S.; Sajjad, I.A.; ul Haq, S.S.; Awan, A.B.; Rasheed, N. Solution to optimal reactive power dispatch in transmission system using meta-heuristic techniques—Status and technological review. *Electr. Power Syst. Res.* **2020**, *178*, 106031. [CrossRef]
19. Muhammad, Y.; Khan, R.; Raja, M.A.Z.; Ullah, F.; Chaudhary, N.I.; He, Y. Solution of optimal reactive power dispatch with FACTS devices: A survey. *Energy Rep.* **2020**, *6*, 2211–2229. [CrossRef]
20. Khan, N.H.; Wang, Y.; Tian, D.; Jamal, R.; Kamel, S.; Ebeed, M. Optimal siting and sizing of SSSC using modified salp swarm algorithm considering optimal reactive power dispatch problem. *IEEE Access* **2021**, *9*, 49249–49266. [CrossRef]
21. Areekkara, S.; Kumar, R.; Bansal, R.C. An Intelligent Multi Agent based Approach for Autonomous Energy Management in a Microgrid. *Electr. Power Components Syst.* **2021**, *49*, 18–31. [CrossRef]
22. Mahela, O.P.; Khosravy, M.; Gupta, N.; Khan, B.; Alhelou, H.H.; Mahla, R.; Patel, N.; Siano, P. Comprehensive overview of multi-agent systems for controlling smart grids. *CSEE J. Power Energy Syst.* **2022**, *8*, 115–131. [CrossRef]
23. Shahbazi, H.; Karbalaei, F. Decentralized Voltage Control of Power Systems Using Multi-agent Systems. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 249–259. [CrossRef]
24. Afandi, I.; Ciufo, P.; Agalgaonkar, A.; Perera, S. A holistic approach for integrated volt/var control in MV and LV networks. *Electr. Power Syst. Res.* **2018**, *165*, 9–17. [CrossRef]
25. Chen, Z.; Du, Z.; Zhan, H. An optimal volt/var control strategy for an islanded microgrid considering the volt/var control capability. *IET Conf. Publ.* **2019**, *2019*, 1–6. [CrossRef]
26. Wu, M.; Hong, L.; Wang, Y.; Yan, Z.; Chen, Z. Volt-VAR control for distribution networks with high penetration of DGs: An overview. *Electr. J.* **2022**, *35*, 107130. [CrossRef]
27. Gao, Y.; Wang, W.; Yu, N. Consensus Multi-Agent Reinforcement Learning for Volt-VAR Control in Power Distribution Networks. *IEEE Trans. Smart Grid* **2021**, *12*, 3594–3604. [CrossRef]
28. Afandi, I.; Agalgaonkar, A.P.; Perera, S. Integrated Volt/Var Control Method for Voltage Regulation and Voltage Unbalance Reduction in Active Distribution Networks. *Energies* **2022**, *15*, 2225. [CrossRef]
29. Asano, M.; Hirayama, A.; Wong, F.; Rahimi, K.; Chun, H.; Moghe, R.; Tholomier, D. Dynamic Control of Volt-VAr Control Devices: An Effective Approach to Overcome Associated Issues with High Penetration of Solar Photovoltaic Resources. In Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference, Chicago, IL, USA, 12–15 October 2020; pp. 1–5. [CrossRef]

30. Ellahi, M.; Abbas, G.; Satrya, G.B.; Usman, M.R.; Gu, J. A Modified Hybrid Particle Swarm Optimization with Bat Algorithm Parameter Inspired Acceleration Coefficients for Solving Eco-Friendly and Economic Dispatch Problems. *IEEE Access* **2021**, *9*, 82169–82187. [CrossRef]
31. Nagra, A.A.; Han, F.; Ling, Q.H. An improved hybrid self-inertia weight adaptive particle swarm optimization algorithm with local search. *Eng. Optim.* **2019**, *51*, 1115–1132. [CrossRef]
32. Jiang, J.J.; Wei, W.X.; Shao, W.L.; Liang, Y.F.; Qu, Y.Y. Research on Large-Scale Bi-Level Particle Swarm Optimization Algorithm. *IEEE Access* **2021**, *9*, 56364–56375. [CrossRef]
33. Fisli, S.; Djendi, M. Hybrid PSO-NLMS (HPSO-NLMS) algorithm for blind speech quality enhancement in time domain. *Appl. Acoust.* **2021**, *177*, 107936. [CrossRef]
34. Rocha, M.C.D.; Saraiva, J.T. A multiyear dynamic transmission expansion planning model using a discrete based EPSO approach. *Electr. Power Syst. Res.* **2012**, *93*, 83–92. [CrossRef]
35. Zhao, Q.; Li, C. Two-Stage Multi-Swarm Particle Swarm Optimizer for Unconstrained and Constrained Global Optimization. *IEEE Access* **2020**, *8*, 124905–124927. [CrossRef]
36. Sidea, D.O.; Picioroaga, I.I.; Tudose, A.M.; Bulac, C.; Tristiu, I. Multi-Objective Particle Swarm optimization Applied on the Optimal Reactive Power Dispatch in Electrical Distribution Systems. In Proceedings of the 2020 11th International Conference and Exposition on Electrical And Power Engineering, Iaşi, Romania, 22–23 October 2020; pp. 413–418. [CrossRef]

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