An Assessment of Optimal Allocation of FACTS Devices in Power Systems Using Metaheuristics

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Abstract

The increasing power demand, the optimal use of grids, the need for economic efficiency, and the high costs associated with building new grids have created unavoidable challenges such as power line overload and excessive power transmission, voltage instability, high losses, low power quality, voltage profile problems, and reliability issues. Flexible alternating current transmission systems (FACTS) devices have proven to be highly effective and viable in mitigating the above challenges in transmission systems. However, the type, location, and capacity of FACTS devices should be properly optimized to maximise their resulting benefits. The problem of knowing the optimal type, size, and position of FACTS controllers in power systems, known as FACTS allocation problem, has attracted the attention of many electrical engineering researchers. Analytical techniques have insufficient computation precision in determining the optimal allocation of FACTS devices, also, arithmetic programming methods are often not effective in managing constrained optimization problems. On the other hand, metaheuristics approaches are random population-based optimization algorithms that are highly effective in dealing with multimodal high constraints, multi-objectives, and discrete systems. Metaheuristics are known to be the most commonly used methods to determine the optimal allocation of FACTS devices. In this paper, applications of different metaheuristics for solving FACTS devices allocation problem are deeply assessed. The assessment is limited to FACTS devices and the optimal allocation of these devices using metaheuristics.

Keywords: Algorithm; FACTS Devices; Metaheuristics; Optimal Allocation; Optimization.

1. Introduction

Optimizing the allocation of FACTS controllers for power system networks can benefit grid transfer capability without the need of costly new transmission system (Shehata et al., 2021; B. Singh & Kumar, 2020; Sreedharan et al., 2020). Based on high-speed power electronics equipment, FACTS devices are coupled to electrical networks to improve controllability and enhance the capacity of the transmitted power with a quick time response while taking power system constraints into account (AL Ahmad & Sirjani, 2019; Pruski & Paszek, 2020). In order to obtain maximum benefits through the implementation of FACTS devices, the appropriate evaluation devices must be located in optimal locations. Several optimization techniques have been applied for the assignment of FACTS controllers.

Analytic approaches, metaheuristic optimisation methods, arithmetic programming methods or traditional optimisation methods, and hybrid methods were the approaches and techniques employed in prior literature research to determine the best placements and settings of FACTS devices. The ability of FACTS controllers to accept control algorithms that are built to fulfill various objectives distinguishes them (Lashkar Ara et al., 2012). Heuristic research methods are the fastest, most reliable, and effective techniques for these problems (Kavitha & Neela, 2018; Shehata & Korovkin, 2020). Because of their flexibility, metaheuristics are successfully used to solve several complex engineering optimization problems, including tuning FACTS devices (Alfi, 2011; Alfi et al., 2012; Dash et al., 2019; Jyotshna & Madhuri, 2015; Ravi & Rajaram, 2013; Saurav et al., 2018; Sirjani & Rezaee Jordehi, 2017; Yildiz & Saitou, 2011; Yildiz & Solanki, 2012). This multi-objective optimization problem, called the optimal allocation of FACTS devices, is solved by taking into account the multi-equality and unevenness of static and dynamic constraints in a transmission/distribution system, such as the power balance equation, the active and reactive power of the generator, the bus voltage, the nominal values of the FACTS devices, the thermal limits of the transmission line, the power loss equation, the power flow equations and the demand limits (Alabduljabbar & Milanović, 2010).

Glover and Kochenberger (Glover & Kochenberger, 2003) define metaheuristics as an iterative procedure that directs the operation of one or more subordinate heuristics (which might range from a local search process to a constructive process of random solutions) to create high-quality solutions to a problem. The establishment of two distinct levels for the resolution of metaheuristic problems makes this definition an interesting concept: the heuristic level, which is by definition highly dependent on the problem, and the metaheuristic level, which is based on the aforementioned level but expressed as a process independent of the problem.

Fundamentally, there have been three sources that impact the creation of problem-solving algorithms: the human brain (Russell & Norvik, 2010); Darwinian evolution (Zayed, 2015); and the social behaviour of insects and other creatures (James Kennedy et al., 2001). The first source led to the rise of artificial intelligence, the second to evolutionary computing and the third to swarm intelligence. In this article, we focus on swarm intelligence; more specifically, several metaheuristic algorithms are considered representative works of these algorithms.

Heuristic approaches have shown to be a complete tool for solving difficult optimization problems; they provide a balance between "good" solutions (relatively closer to the global optimum) and reasonable time and cost. Heuristics, on the other hand, are often dependent on unique qualities of the situation at hand, making their creation and development a difficult process. In order to solve this disadvantage, metaheuristics appear to be a significant advance; they are problem-independent algorithms that can be adapted to incorporate problem-specific knowledge (Glover, 1977). Metaheuristics have been remarkably developed in recent decades, becoming popular and applied to many problems in various field. However, when new ones are considered, metaheuristics need to be implemented and tested, which involves costs and risks.

2. Classification of FACTS Devices

FACTS technology comprises of a range of controllers and is a power electronics based electronical technology.

Applications for FACTS devices in power system networks encompass voltage stability improvement, dynamic and transient stability enhancement, an increase in the transmission line's power transfer capability, power factor correction, power profile improvement, voltage regulation and power loss alleviation (Chirantan et al., 2018). There are different types of FACTS devices, however, they are classified based on their mode of connection as illustrated in Figure1 below (Prashant & Siddiquit, 2021).

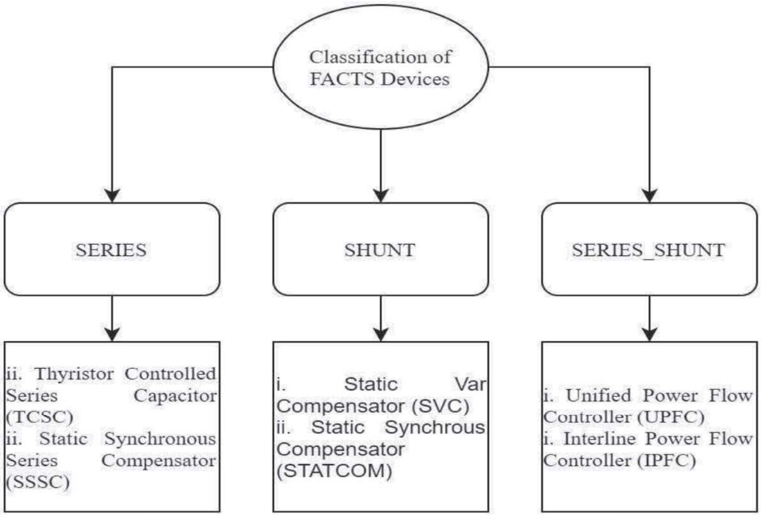

Figure 1: Classification of FACTS devices

2.1 Series Compensation

To transfer actual power at a certain voltage in the transmission system, series compensation is utilized. System losses are decreased and network power flow capacity is increased by strategically placing these devices. The voltage is added in series with the network by these controllers, which improves the voltage profile. It's a type of transmission line that's utilized over vast distances. Some of the examples of Series FACTS devices are SSSC (Static Synchronous Series Compensator), TCSC (Thyristor Controlled Series Capacitor), IPC (Interphase power controller), TSSC (Thyristor switched series Capacitor), TCSC (Thyristor controlled series capacitor), TCSR (Thyristor controlled series reactor), TSSR (Thyristor switched series reactor), and TCVR (Thyristor controlled voltage regulator).

2.2 Shunt Compensation Devices

These are the FACTS tools that are used to manage the stress level, reducing the losses by optimally positioning FACTS devices in the network. Static Var Compensator (SVC), Static Synchronous Compensator (STATCOM), Thyristor controlled reactor (TCR), Thyristor switched capacitor (TSC), Thyristor switched reactance (TSR) are some of the examples of shunt compensators.

2.3 Combined Series Shunt Compensator

It is a combination of shunt and series connected FACTS devices. So, they have the characteristics of all types of controllers and they are very helpful regarding improving the power flow capacity of system. Some of the examples of combined series-shunt compensators are Unified Power Flow Compensator (UPFC), Thyristor controlled phase shift transformer (TCPST) Interlink power flow Controller (IPFC) Generalized unified power flow controller (GUPFC).

3. Application and Comparison of FACTS Devices

Table 1 summarises the application of different FACTS devices to solve different power utility problems. Table 2 shoes the capability comparison of Series, Shunt and Combined Series-Shunt FACTS devices.

Table 1: Application of different FACTS devices

No	Issues	Device(s)	Solutions
1.	Minimum loads with high voltage	STATCOM, SVC	Absorbing reactive power
2.	Transmission overloading circuit	UPFC, TCSC, SSSC	Reducing overload
3.	Parallel line loading	TCSC, UPFC	Series line reactance is modified
4.	Fault after power run communion	SSSC, UPFC	Reorganize the system
5.	Parallel line fluctuation	TCSC, SSSC, UPFC	Circuit loading is minimised
6.	Flow of power in opposite direction	SSSC, UPFC	Modified Phase angle
7.	Weak voltage after failure	SVC, STATCOM	Sending reactive power and preclude overloading
8.	High voltage after failure	STATCOM, SVC	Absorbing reactive power
9.	High loads and low voltage	STATCOM	Sending reactive power
10.	High/Low reactive power	STATCOM	Injection of reactive current

Table 2: Capability comparison of Series, Shunt and Combined Series-Shunt FACTS devices

No.	Attributes	FACTS Devices				
		Series		Shunt		Series-Shunt
		SSSC	TCSC	SVC	STATCOM	UPFC
1.	Voltage Controlling	✓	✓	✓	✓	✓
2.	Voltage level Enhancement			✓	✓	✓
3.	Power back up Control	✓	✓			✓
4.	Voltage Source Control	✓	✓		✓	✓
5.	Limiting Fault Current		✓			✓
6.	Forced Response Commutated	✓			✓	✓
7.	Dynamic Inverter	✓	✓			✓
8.	Forced Commutated				✓	✓
9.	Damping Fluctuation	✓	✓	✓	✓	✓
10.	Current Inverter	✓	✓	✓		

4. Operational Advantages of Facts Devices

Apart from the technical capabilities of FACTS devices mentioned in Table 1 and Table 2 and among others, below is a summary of FACTS devices operational merits.

- System losses are reduced.
- System stability is increased.
- Voltage flicker is controlled by using STATCOM most effectively.
- Power flow in transmission line is enhanced.
- Better stability.

5. Optimal Allocation of Facts Devices Using Various Techniques

The challenge of optimal placement of FACTS devices has been addressed by a number of power system optimization approaches described in the literature. In this section, citations are organized by the most prevalent approaches, with the goal of discovering which methodology has been used the most frequently, and hence which one is most suited for a specific power system research incorporating FACTS optimum placement.

The optimal location and power ratings of various FACTS controllers/devices can be thought of as multimodal, highly restricted, and complicated optimization issues. As a result, the approaches are divided into four groups as listed below (AL Ahmad & Sirjani, 2019; Kang et al., 2017a).

- Conventional optimisation Methods or Arithmetic Programming Methods

- Analytic Techniques
- Meta-heuristic Optimisation Techniques
- Hybrid Approaches

These categories are explored in this section, as well as a more in-depth look at metaheuristic optimisation approaches.

5.1 Arithmetic Programming Approaches

Although traditional optimisation techniques have good convergence properties, dealing with restricted optimisation issues is problematic (Kang et al., 2017b). Previous research has used the Newton Raphson (NR) optimum power flow method for the optimal placement of SVCs to preserve system security by progressively lowering the security index (Padmavathi et al., 2013). In (Zhang et al., 2018), a customized reformulation and decomposition algorithm CRDA is devised and applied to solve a suggested MILP bi-level optimization model to best distribute variable series reactors VSR such as TCSC and phase shifting transformer (PST) in the face of significant wind penetration. The cost of FACTS devices, the cost of wind power curtailment, and the possibility of load shedding are all upper-level objective functions. Market clearing is investigated using lower-level goal functions under 20 distinct load-wind situations. The suggested approach and the function of series FACTs devices in aiding wind power integration were tested using the IEEE118 bus system. The TCSC's ideal location and size have been proposed using MINLP based on the line flow LF equations (Etemad et al., 2010). The MILP (Lima et al., 2003) determines the best position for TCPSTs to maximize system loadability. To enhance system loadability, the MILP and MINLP have been suggested to find the best placements of various types of FACTS devices (A. Sharma et al., 2005; A. K. Sharma, 2006). For congestion management in a restructured market context, the MIP optimisation approach has been suggested in (Yousefi et al., 2012) for optimal coordinative operation between demand, VSC, TCSC, and generators.

5.2 Analytic Techniques

Computing efficiency is a benefit of analytical or sensitivity-based techniques; nevertheless, failure to account for the nonlinearity of the power flow model might have a detrimental impact on computation accuracy (Kang et al., 2017b). Furthermore, analytical techniques are unable to cope with the appropriate positioning and configuration of FACTS devices at the same time.

Previous research has found that using a sensitivity-based method to increase system security, the optimal allocation of both the TCSC and the UPFC may be determined (Shaheen et al., 2018). To evaluate whether line is ideal for installing TCSC to accomplish power system security in normal and fault situations, the Thermal Capacity Index (TCI) and Contingency Capacity Index (CCI) have been suggested (Shanmukha Sundar & Ravikumar, 2012). For establishing both the TCSC's and the SSSC's ideal placements and settings for power system security enhancement, the actual power flow performance index (PI) sensitivity-based method and the notion of the line outage distribution factor are proposed (Vaidya & Rajderkar, 2011). To determine the TCSC's best placement to alleviate congestion, a sensitivity method based on the relief of the system's total reactive power and real power performance index is used (Besharat & Taher, 2008).To accomplish power system security, the line loading security performance sensitivity index variables are used to determine the best position of UPFCs (J. G. Singh et al., 2010).

Rao and Rao (Rao & Rao, 2017) used a two-stage strategy to reduce system power loss by placing a STATCOM in the appropriate position and calculating its ideal power rating. The Newton Raphson technique identified the appropriate capacity of the STATCOM, whereas the generalised approach based on a sensitivity analysis indicated the best placement of the STATCOM. The IEEE 14 bus system was used to evaluate the performance of the suggested approach. When STATCOM FACTS devices were used, the system exhibited reduced power loss and a better voltage profile than when the devices were not used. To minimize overloads in transmission lines, the single contingency sensitivity index is used to identify the best position of TCSCs for power system static security under single fault or contingency situations (Lu & Abur, 2002).

5.3 Metaheuristic Optimisation Techniques

The most popular approaches for determining the best allocation of FACTS devices are metaheuristic optimisation techniques (Jordehi & Jasni, 2013). They are stochastic, population-based optimisation algorithms that are very good at dealing with multimodal, highly restricted, multi-objective, discrete systems. There are three types of metaheuristic optimization approaches; swarm-based algorithms, evolution-based algorithms, and hybrid metaheuristic optimisation algorithms.

The immune algorithm, ant colony optimisation algorithm, artificial bee colony, particle swarm optimisation, harmony search method, gravitational search algorithm, teaching learning algorithm, firefly algorithm, and chemical reaction optimisation are all examples of swarm-based algorithms. The differential algorithm, genetic algorithm evolutionary programming and evolutionary strategy algorithms, and differential search algorithm are examples of evolution-based algorithms. The IPSO and IGA, FA and CS, PSO and SQP, and ABC and GSA are examples of hybrid metaheuristic optimisation algorithms. Metaheuristic optimisation approaches may be used to concurrently identify the best location and size for several types of FACTS devices.

5.4 Hybrid Approaches of Metaheuristic Techniques and Conventional Optimization Methods and Analytic Methods

Metaheuristic and analytical techniques, as well as metaheuristic and traditional optimisation methods, are examples of hybrid approaches. The use of analytic methods or traditional optimisation approaches in conjunction with metaheuristic optimisation techniques helps to reduce the search space of the proposed metaheuristic optimisation methodology. As a consequence, the structure is simpler, and the computing time is reduced.

(Elmitwally & Eladl, 2016) proposes a hybrid PSO-sequential quadratic programming (SQP) technique for increasing the social welfare of a deregulated electricity system while taking wind energy and demand growth into account. The suggested approach was validated using the IEEE 14 bus and IEEE 118 bus systems. Three distinct FACTS devices (TCSC, SVC, and UPFC) were determined to have the best placement and capability for improving social welfare and reducing compensation given to market players owing to generation rescheduling and load shedding. In comparison to the scenario without FACTS, this technique led to increase in social welfare and a reduction in generation rescheduling and load shedding expenses. (Mishra & G., 2017) proposes the Disparity Line Utilization Factor (DLUF) and GSA for deregulated power system congestion management by estimating the best location and size of IPFCs under various load growth percentages. The GSA calculated the appropriate power ratings and tuning of IPFCs to control congestion in transmission lines, and the IPFCs were put at the lines with the highest LUF. The multi-objective optimisation function was utilized to tune the IPFC for the best performance, including active power loss mitigation, overall voltage deviation reduction, security margin promotion, and IPFC device alleviation capacity. The proposed approach was put to the test using the IEEE 30 bus network. The appropriate positioning and adjustment of IPFC devices under various loading circumstances resulted in better values for the objective function.

6. Comprehensive Summary of Metaheuristic Optimization Algorithms

Many types of metaheuristics algorithms have been used to determine the optimal allocation of FACTS and other devices in electrical power systems. The frequently used metaheuristic algorithms are listed and detailed below.

6.1 Ant Colony Optimization

M. Dorigo and his colleagues were the first to develop the ant colony optimization (ACO) as a nature-inspired metaheuristic for solving challenging combinatorial optimization problems (Dwivedi & Vadhera, 2019). The foraging activity of actual ants is the inspiration for ACO. When looking for food, these ants take a randomized stroll around the region surrounding their colony to see what they can find. Ants leave a chemical pheromone trail on the ground along their journey between food source and nest in order to designate a desirable path that will direct other ants to the food source (Jamnani & Pandya, 2019). After a period of time, the shortest path between the nest and the food supply has a larger concentration of pheromone, attracting additional ants. Artificial ant colonies took advantage of this feature of actual ant colonies to create solutions to an optimization issue and communicate quality information using a communication system similar to that used by real ants (Rezaeian Marjani et al., 2019).

6.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) was first presented as a global optimization approach by James Kennedy and Russell Eberhart in 1995 (J. Kennedy & Eberhart, 1995). It solves optimization issues using the concept of bird flocking behavior. PSO and evolutionary optimization differ in a variety of ways, as shown in [7], which explores some of the conceptual and performance differences.

Many autonomous entities (particles) are produced stochastically in the search space using the PSO method. Each particle represents a potential solution to the issue, with a velocity, a position in the search space, and a memory that allows it to recall its prior best position. Certain number (N) of particles move about in a dimensional (D) search space to form a swarm. Furthermore, every particle swarm has a topology that describes the relationships between the particles. The neighborhood of a particle ‘i’ is the set of particles to which it is topologically linked. The term "neighborhood" can refer to the entire population or a portion of it. To find “some other particles” that can impact the individual, several topologies have been utilized. gbest (for "global best") and lbest (for "local best") are the two most often utilized. The gbest particle swarm topology is usually the one which the target particle impacts by the best neighbor in the whole population. While it is possible to think of this as a completely linked graph. The lbest topology in (Alfi et al., 2012) is a basic ring lattice with toroidal wrapping in which each individual is connected to two neighboring members in the population array (naturally, this may be expanded to more than two). The gbest topology, according to Kennedy et al (James Kennedy et al., 2001) has a propensity to converge fast, with a larger probability of being trapped in local optima. The best topology, on the other hand, was slower but more thoroughly investigated, and it usually resulted in a superior optimum.

6.3 Genetic Algorithm

The Genetic Algorithm (GA) is a very well and widely utilized evolutionary computation method. It was created at the University of Michigan in the early 1970s by John Holland and his students, who were interested in the study of adaptive systems (Sood et al., 2002). The fundamental GA is extremely general, and many elements may be handled differently depending on the problem: solution representation (chromosomes), selection method, crossover type (the recombination operator of GAs), mutation operators, and so on. A fixed-length binary string is the most frequent chromosomal format used in GAs. Crossover and mutation procedures can be implemented using simple bit manipulation methods. The GA as a problem-solving approach is incomplete without these genetic operators. The focus is mostly on crossover as the primary variation operator, which mixes several (typically two) people who have been chosen together by swapping some of their components.

6.4 Simulated Annealing (SA)

The simulated annealing technique (SA) has its roots in statistical mechanics (Metropolis algorithm (Martin et al., 1991). Kirkpatrick et al. (Kirkpatrick et al., 1983) were the first to propose it, followed by Cerny. SA is based on the metallurgists' annealing process for obtaining a “well ordered” stable state with low energy (while preventing the “metastable” structures found in local energy minima). This method entails transporting a substance at a high temp and afterwards gradually reducing it. SA converts the annealing process into an optimization problem: the problem's objective function, which is comparable to a material's energy, is then reduced by introducing a fake temperature, T, which is a simple adjustable parameter of the algorithm.

6.5 Tabu Search

Glover formalised Tabu Search (TS) in 1986 (Glover, 1986). TS was created to handle a local search algorithm that was incorporated in the application. It makes explicit use of the search history, both to get out of local minima and to apply an exploratory strategy. Its most distinguishing feature is the utilization of processes inspired by human memory. It follows a path that is diametrically opposed to SA's, which does not employ memory and so is unable to learn from the past.

6.6 Evolutionary Programming

L. J. Fogel initially proposed evolutionary programming (EP) as an evolutionary approach to artificial intelligence in the 1960s (L. J. Fogel et al., 1966). D. Fogel reintroduced EP in the early 1990s to address more broad issues such as prediction problems, numerical and combinatorial optimization, and machine learning (D. B. Fogel, 1995.). In EP, the representations are usually customized to the issue domain. The coding will be treated as a string of real values in real-valued vector optimization. The beginning population is chosen at random according to a density function and scored according to the stated goal.

6.7 Bacterial Foraging Optimization Algorithm

The Bacterial Foraging Optimization Algorithm (BFOA), first proposed in 2002 by Passino (Kevin M. Passino, 2002), is a relatively recent paradigm for addressing optimization issues, inspired by the sociable foraging behavior of a bacteria called Escherichia Coli (E. Coli) which is found in human intestines. For many species, foraging is a survival-critical activity that includes groups of organisms seeking to acquire and consume resources in a way that optimizes energy gained from food sources per unit time spent foraging while limiting exposure to predatory dangers (K.M. Passino, 2010). Social foraging, or foraging in groups, is an important part of avoiding predators and improving the chances of obtaining food. Several motile bacteria species, notably E. Coli bacteria, have been shown in many researches to have a particularly intriguing group foraging behavior.

6.8 Bat Algorithm (BA)

The BA was first proposed in 2010 by a British academic X. S. Yang, who was motivated by bat hunting echolocation behavior. Bats produce ultrasound through their mouths and then use the ultrasonic response to determine their orientation. X. S. Yang was also the first to develop the cuckoo search (CS) algorithm in 2009. The CS algorithm is based on a long-term study of the behaviors of cuckoos. Cuckoos deposit eggs instead of nesting, according to Yong, and they usually lay their eggs in the nests of other birds.

7. Discussion and Suggestions for Future Studies

Based on the available literature of FACTS devices optimal allocation and the use of metaheuristics, the following recommendations for further study in the subject of optimal allocation of FACTS devices are arrived at:

The optimal allocation of FACTs devices optimisation challenge was centered on a balanced power transmission network in all of the examined research investigations. As a result, the optimal placements and sizing of FACTs devices may be studied for an imbalanced transmission network.

Metaheuristic optimisation technique was used in most recent studies to optimal placement and size of FACTs devices; nevertheless, several studies did not compare the effectiveness of the proposed technique to other metaheuristic optimisation methods in terms of computational time, convergence characteristics, simulation results, and result accuracy.

When examining optimal allocation of FACTS devices, most previous research papers did not take into account the stochastic character of power systems. Future study should integrate power system predictability in problem-based optimum allocation of FACTS devices.

Total harmonic distortion (THD) reduction is one of the most significant concerns linked to power quality enhancement; yet, the optimal placements and size of the FACTs devices optimisation problem in power transmission networks lacks this aspect as an objective function. As a result, THD might be regarded as a new objective function in future study.

8. Conclusion

In this paper, a detailed discussion of FACTS devices with their comparison and corresponding benefits has been presented. FACTS devices provide many benefits like voltage enhancement, appropriate reactive power injection, voltage profile consistency at light, medium and heavy loads conditions however, optimal allocation of these devices is a key in achieving their capabilities. This issue of FACTS optimal allocation has been described in this study in detail using metaheuristics optimization techniques. Also, in this paper, a weighted discussion of various algorithms that are based on metaheuristic optimisation techniques has been provided. Furthermore, an overview of contemporary research work, including metaheuristics and optimization approaches, has been presented and thoroughly addressed. Finally, some recommendations for future developments in the research field based on the optimal allocation of FACTS devices using metaheuristics optimisation techniques have been suggested.

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