# A Novel Optimal Allocation of STATCOM to Enhance Voltage Stability in Power Networks

**Abstract**

Utilizing a static synchronous compensator (STATCOM) in the electrical power grid greatly improves the grid's voltage profile by enhancing voltage stability. This article proposes a novel approach based on Mixed Integer Distributed Ant Colony Optimization (MIDACO) to determine the optimal STATCOM installation in the electrical power grid. This approach has two control variables to optimize: the STATCOM size and location. This optimization aims to enhance voltage stability with minimum cost by minimizing two objectives: the voltage deviation index and the STATCOM cost. Also, this article presents a sensitivity analysis to show the stochastic nature of MIDACO and to explain the effect of MIDACO parameters on the optimization approach and the process of reaching the optimal solution. The proposed method has been evaluated on three standard test systems: IEEE 14-bus, IEEE 57-bus, and IEEE 118-bus. In addition, the MIDACO results are compared to those of the artificial bee colony algorithm, the genetic algorithm, and particle swarm optimization.

***Keywords*—** Voltage Stability; STATCOM; FACTS Devices; MIDACO; Optimisation.

## Nomenclature

| | |
|---|---|
| $Q_{STATCOM}$ | Reactive power support from STATCOM |
| $B_{STAT}$ | Susceptance of STATCOM |
| $V_x$ | Voltage magnitude at bus x |
| $V_{STAT}$ | STATCOM voltage |
| $Y_{STAT}$ | Admittance of STATCOM |
| $\theta_{STAT}$ | Admittance angle of STATCOM |
| $\delta_{STAT}$ | STATCOM voltage angle |
| $\delta_x$ | Voltage angle at bus x |
| $P_i$ | Active power at bus i |
| $Q_i$ | Reactive power at bus i |
| $V_i$ | Voltage magnitude at bus i |
| $I_i$ | Current at bus i |
| $\delta_i$ | Voltage angle at bus i |
| $V_j$ | Voltage magnitude at bus j |
| $\delta_j$ | Voltage angle at bus j |
| $Y_{ij}$ | Line admittance between bus i and bus j |
| $\theta_{ij}$ | Line admittance angle between bus i and bus j |
| $P_x$ | Active power equation at STATCOM bus |
| $Q_x$ | Reactive power equation at STATCOM bus |
| $P_{STATCOM}$ | Active power support from STATCOM |
| $Y_{xj}$ | Line admittance between STATCOM bus and bus j |
| $\theta_{xj}$ | Line admittance angle between STATCOM bus and bus j |
| $\Delta P$ | Active power mismatch |
| $\Delta Q$ | Reactive power mismatch |
| $\Delta V$ | Voltage magnitude increment |
| $\Delta\delta$ | Voltage angle increment |
| $P_i^{sch}$ | Scheduled active power at bus i |
| $Q_i^{sch}$ | Scheduled reactive power at bus i |
| $f_1$ | First objective (STATCOM installation cost) |
| $f_2$ | Second objective (voltage deviation index) |
| $C_{STATCOM}$ | STATCOM investment cost US dollars per KVAr |
| $D$ | STATCOM size MVAr |
| $V_{\mathrm{ref}}$ | The reference voltage at each bus |
| $n$ | Number of buses |
| $V_{min}$ | Minimum voltage |
| $V_{\max}$ | Maximum voltage |

| | |
|---|---|
| $\mathcal{P}(x)$ | Pprobability density functions for the continuous domain |
| $\mathcal{Q}(d)$ | Pprobability density functions for the discrete domain |
| $\mathcal{K}$ | Size of solution archive |
| $\mathfrak{C}$ | Evolutionary operator |
| $\omega$ | Weight of each individual |
| $\mu$ | Mean of each individual |
| $h$ | Number of integers |

## 1. Introduction

The electrical grid is a complex system that connects electrical power plants and generators with consumption loads via a network of transmission lines and transformers. Due to the rapid growth in demand and industrialization in recent years, the electrical power grid is required to operate at a high capacity near critical power angles and voltage limits. This situation increases the risk of affecting the electrical grid's voltage stability and raising the potential for voltage collapses, which cause generator outages and line outages, causing a blackout in the power system [1]. This being the case, enhancing voltage stability is considered one of the most critical issues regarding the planning and operation of electrical power grids.

In order to satisfy the growing demand and solve the voltage stability issues, more transmission lines must be installed, as well as new power sources. However, it is currently challenging to establish additional transmission lines to relieve congestion due to a convergence of economic, environmental, and geographic concerns. Increasing the effectiveness of the use of the transmission lines that are currently in operation is the only option that is now available. To make this possible, Flexible AC Transmission System devices, often known as FACTS devices, are the answer [2].

In voltage support, shunt FACTS devices like the static synchronous compensator STATCOM are used to compensate for reactive power and make the power system's voltage more stable. STATCOM is a power electronics-based instrument that was created to reinforce the voltage stability of the electrical power grid [3–5]. However, to get the greatest results out of STATCOM, it must be installed in the electrical power grid at the ideal size and placement to fulfill the purpose for which it is intended.

Several investigations have employed a variety of metaheuristic optimization-based strategies to improve the voltage profile of the electrical grid by providing the optimal STATCOM installation [6–9]. Optimal installation of STATCOM via Particle Swarm Optimization (PSO) was introduced in [10–11] to enhance voltage stability by minimizing voltage stability indices. In [12], a mutation-based PSO technique was utilized to modulate the stability of the system by analyzing the Unification Index (UI), while authors in [13] introduced a hybrid PSO to figure out the optimal installation of both STATCOM and Distribution Generators (DG). However, PSO lacks guaranteed convergence, which will lead it, in some cases, to be trapped in local optima. Moreover, the computational cost of PSO can be high, especially for large-scale optimization problems, which may require a huge number of particles and iterations to find the optimal solution.

The optimal installation of STATCOM via Genetic Algorithm (GA) to increase the demand limit and promote the stability of the electrical power grid is illustrated in [14]. In addition to that, different voltage stability indices have been minimized or maximized to enhance the voltage stability in several optimization approaches based on GA that have been performed [15–17], but GA can converge prematurely to a suboptimal solution, especially when the genetic operators are not properly tuned. Application of the Artificial Bee Colony algorithm (ABC) to find the best location and rating of STATCOM has been reported in [18–19]. Even though ABC is good in performance, it suffers from incompatible processes of exploration and exploitation, which will limit the scalability of ABC in large-scale optimization problems such as large power systems [20].

In contrast to traditional evolutionary algorithms, mixed integer techniques, which precisely address the combination of discrete and continuous variables, could offer significant advantages for optimizing STATCOM placement and sizing. Evolutionary algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Artificial Bee Colony (ABC) have shown promise in this domain. However, they often lack the inherent capability to efficiently handle the intricate blend of discrete (location) and continuous (size) optimization variables inherent in STATCOM problems. This limitation can lead to increased computational costs, risk of convergence to local optima, and scalability issues, particularly in large power systems. Recent studies have attempted to bridge this gap. For instance, a paper employing a mixed-integer convex approximation for PV-STATCOM integration simplifies the complex MINLP problem but may overlook solutions in non-convex regions [21], while another study using a Discrete-Continuous Chu–Beasley Genetic Algorithm (DC-CBGA) maintains the problem's original complexity, offering a unified approach to discrete and continuous variables [22]. However, these methods still face challenges in terms of computational efficiency and handling non-linear, non-convex optimization landscapes.

In this context, MIDACO emerges as a potentially superior alternative. Unlike the mentioned approaches, MIDACO, based on Mixed Integer Distributed Ant Colony Optimization, directly tackles the intrinsic complexities of MINLP without the need for problem simplification. Its heuristic nature, inspired by the foraging behavior of ants, allows for a probabilistic and diverse exploration of the solution space, making it particularly adept at navigating complex, non-linear, and non-convex problems [23]. Furthermore, MIDACO's flexibility in handling different types of objective functions and constraints, combined with its global optimization capabilities and CPU runtime efficiency, positions it as a more robust and adaptable solution for the large-scale, mixed-variable optimization challenges presented by STATCOM installation in electrical grids. This paper aims to fill the gap in the existing literature by demonstrating MIDACO's effectiveness in this context, comparing its performance against other evolutionary algorithms, and addressing the limitations they present in large-scale, mixed-integer optimization scenarios. In addition to that, a sensitivity analysis of MIDACO has been discussed in this paper to show the stochastic nature of MIDACO and explain the effect of MIDACO parameters on the optimization approach and the optimal solution.

## 2. STATCOM

The stability of the power system was improved by using a shunt FACTS device called STATCOM. The STATCOM system, which is based on the reactive power adjustment principle, allows for modifications to both the magnitude of the voltage at the buses and the amount of reactive power in the overall electrical system.

In general, STATCOM can be used as a voltage source capable of converting direct current to alternating current to regulate voltage at its terminal. STATCOM has two modes of operation: capacitive and inductive. Depending on the voltage profile on the network, STATCOM chooses the mode of operation. In cases of undervoltage, STATCOM operates in a capacitive function and generates reactive power. In overvoltage situations, STATCOM transitions to inductive mode and receives reactive power [24]. In this paper, STATCOM is operated as a synchronous generator, ignoring its zero-power output and the reference voltage, whereas the reactive power support is shown in Eq. (1) [25].

$$Q_{STATCOM} = B_{STAT}V_x^2 - V_xV_{STAT}Y_{STAT}\sin\left(\theta_{STAT} - \delta_{STAT} + \delta_x\right) \quad (1)$$

However, the aim of the proposed optimization approach is to optimize the STATCOM installation, not the design of STATCOM itself. To observe the impact of STATCOM integration on the voltage profile of the electrical grid, a load flow analysis with STATCOM integration was used.

Among the several load flow analysis solution approaches known, the Newton-Raphson method is widely regarded as the most complex and significant. Because of its accuracy and dependability, the Newton-Raphson (NR) technique has many advantages. Furthermore, the number of iterations is independent of system size, allowing larger power systems to achieve convergence in two to three iterations [26].

In general, the aim of the load flow analysis is to calculate the active power, reactive power, voltage magnitude, and voltage phase angle at each bus. Then, it calculates the power flow in the branches between buses. The unknown parameters at each bus that need to be determined depend on the type of bus; for the load buses, the unknown parameters are the voltage magnitude and the voltage phase angle, whereas, for the generator buses, the unknown parameters are the reactive power and the voltage phase angle. However, there is one bus in the power system known as the slack bus, which is considered a reference bus.

To calculate the unknown parameters at each bus, a set of equations known as power balance equations is needed. These equations are the results of analyzing the complex power at each bus [27]. Considering a typical bus (i), the complex power equation at bus (i) is shown in Eq. (2).

$$P_i - jQ_i = V_i^* I_i \quad (2)$$

At bus (i), the entering current is the sum of the multiplication of the impedance and the voltage for the (j) number of buses, as shown in Eq. (3).

$$I_i = \sum_{j=1}^{n} Y_{ij} V_j \tag{3}$$

From Eq. (4), the polar form is

$$I_i = \sum_{j=1}^{n} |Y_{ij}||V_j| < \theta_{ij} + \delta_j \tag{4}$$

After substituting Eq. (4) in Eq. (2), the complex power equation at bus (i) is

$$P_i - jQ_i = |V_i| \angle - \delta_i \sum_{j=1}^{n} |Y_{ij}||V_j| \angle \theta_{ij} + \delta_j \tag{5}$$

In the above equation, the real part represents the active power, and the imaginary part represents the reactive power. Thus, the power balance equations are shown in Eq. (6) and Eq. (7), respectively.

$$P_i = \sum_{j=1}^{n} |V_i \| V_j \| Y_{ij}| \cos\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{6}$$

$$Q_i = -\sum_{j=1}^{n} |V_i \| V_j \| Y_{ij}| \sin\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{7}$$

However, at the bus (x) where the STATCOM has been installed, the power flow equations are shown in Eq. (8) and Eq. (9) [28].

$$P_x = P_{STATCOM} + \sum_{j=1}^{n} |V_x \| V_j \| Y_{xj}| \cos\left(\theta_{xj} - \delta_x + \delta_j\right) \tag{8}$$

$$Q_x = Q_{STATCOM} - \sum_{j=1}^{n} |V_x \| V_j \| Y_{xj}| \sin\left(\theta_{xj} - \delta_x + \delta_j\right) \tag{9}$$

In this paper, the active power exchange between the STATCOM and the grid is zero, while the reactive power supplied or absorbed from the STATCOM is shown in Eq. (1). For each load bus, the two power balance equations are available since the active power and the reactive power are known, whereas, for the generator buses, only the active power equation is available because the reactive power is an unknown parameter.

Although the power balance equations are nonlinear, to linearize them, the N-R method expands them using Taylor's series, which creates a matrix of first-order partial derivatives of P and Q with respect to the voltage magnitude and voltage phase angle as shown in Eq. (10) [27].

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial V} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial V} \end{bmatrix} \cdot \begin{bmatrix} \Delta \delta \\ \Delta V \end{bmatrix} \quad (10)$$

In the above equation, $\Delta P$ and $\Delta Q$ are the mismatches which represent the difference between the calculated values ($P_i$ and $Q_i$) and the schedule values at iteration (m) as shown in Eq. (11) and Eq. (12).

$$\Delta P_i^{(m)} = P_i^{sch} - P_i^{(m)} \quad (11)$$

$$\Delta Q_i^{(m)} = Q_i^{sch} - Q_i^{(m)} \quad (12)$$

After each iteration, the phase angle and voltage magnitude increase by $\Delta\delta$ and $\Delta V$, as shown in Eq. (13) and Eq. (14), respectively. This process continues until the power mismatch in Eq. (11) and Eq. (12) becomes within the accuracy limit, which is 0.00001 in this paper.

$$\delta_i^{(m+1)} = \delta_i^{(m)} + \Delta\delta_i^{(m)} \quad (13)$$

$$\left|V_i^{(m+1)}\right| = \left|V_i^{(m)}\right| + \Delta \left|V_i^{(m)}\right| \quad (14)$$

## 3. Optimization Problem

Optimization approach in this study considers a multi-objective function (F) shown in Eq. (15) that is subject to inequality constraints whose purpose is to minimize two objectives, which are STATCOM installation cost ($f_1$) and voltage deviation index ($f_2$). These objectives are functions of a set of control variables, which are the STATCOM size and location.

$$\text{Min } F(x) = f_1(x) + f_2(x) \quad (15)$$

Due to the high STATCOM investment cost, minimizing the size of STATCOM is considered the first objective in this optimization approach. Fig. 1 shows the STATCOM investment cost based on the Siemens AG database [29].

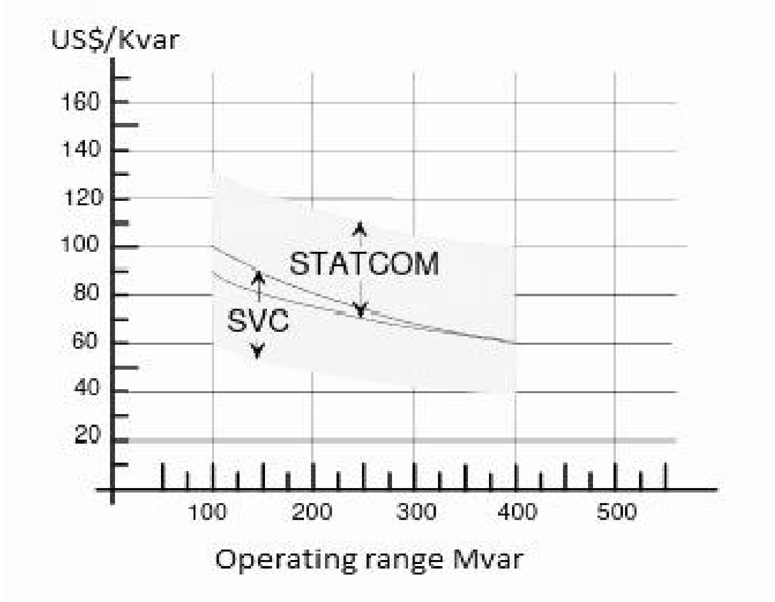


Fig. 1. STATCOM Investment Cost [29]

According to Fig. 1, Eq. (16) represents the mathematical expression for the STATCOM investment cost in the form of US dollars per Kvar [29], while Eq. (17) shows the STATCOM installation cost in US million dollars.

$$C_{STATCOM} = 0.000375D^2 - 0.3041D + 162.4\ (\$/\mathrm{Kvar}) \tag{16}$$

$$f_1 = C_{STATCOM} * D * 1000 \tag{17}$$

However, to observe the voltage stability of the electrical power grid, a voltage stability index is usually used. In this optimization approach, the voltage deviation index (VDI) was used to indicate the voltage stability enhancement after installing STATCOM in the electrical power grid. In this optimization approach, VDI is considered the second objective ( ), as shown in Eq. (18).

$$f_2 = \sum_{i=1}^{n} \left(\frac{V_{ref} - V_i}{V_{ref}}\right)^2 .100\% \tag{18}$$

This index measures the total difference between the actual voltage ($V_i$) and the rated voltage ($V_{ref}$) at each bus in the electrical power grid. Minimizing this index means a better voltage profile since the voltages at buses will be closer to the rated voltage. The deviation in this index is a function of per-unit values, where the rated voltage is 1 per unit as a reference value for all n-number of buses.

Inequality constraints, in the form of the bus voltage limit at load buses, regulate the two objectives in this optimization approach. However, the minimum voltage at each load bus is 0.95 per unit, whereas the maximum voltage is 1.05 per unit, as shown in Eq. (19).

$$V_{min} \leqslant V_i \leqslant V_{max} \tag{19}$$

However, the power balance constraints that are related to the load flow analysis are discussed in section 2.

## 4. Optimization Technique

The MIDACO solver is used as the optimization technique in this particular study. The Oracle Penalty Method and the Ant Colony Optimization (ACO) Method were merged to produce the MIDACO algorithm, a new expansion of the ACO algorithm. In the 1990s, Marco Dorigo originally discussed ACO in his doctoral thesis [30]. The way ants use pheromones to locate a path between their habitation and a food head is the basis for this algorithm. It was first used to settle the famed travelling salesman puzzle. Now, it is used for numerous difficult optimization problems.

Ants are social insects. They are animals in colonies. Finding food is the ant's main driving force, and this drives its behavior's. Ants are searching while swarming about their habitations. An ant will continually zigzag over a surface in its pursuit of food. As it travels through the ground, it leaves behind a natural substance that acts like a pheromone. Ants create pheromone trails to convey messages to one another. An ant will attempt to take as much food as it can when it discovers food. When it returns, it releases pheromones along the pathways based on the amount and caliber of the food. Ants can detect pheromones. As a result, more ants smell the path, and they follow it. The greater the concentration of pheromones along a certain route, the more likely it is that travelers will follow it [31].

At MIDACO, an innovative version of the Ant Colony Optimization was developed for mixed-integer search fields. The value of this modification can be determined by observing how well it maintains the integrity of its fundamental functional components. Instead of employing a pheromone table, the method utilized the concept of a pheromone-controlled Probability Density Function (PDF) [32]. Because the search domain here is a mixed integer search domain, MIDACO has two sorts of probability density functions: one for the continuous domain P(x) and the other for the discrete domain Q(d). These probability density functions create the probability distribution functions for the continuous domain and discrete domain, which are defined in Eq. (20) and Eq. (21), respectively.

$$\int_{-\infty}^{\infty} \mathcal{P}(x)dx = 1 \tag{20}$$

$$\sum_{d=-\infty}^{\infty} \mathcal{Q}(d) = 1 \tag{21}$$

In MIDACO, 'ants' act as individual agents exploring the optimization problem's search space, similar to entities in other evolutionary algorithms. These ants, representing different generations, are integral to each significant iteration of the algorithm. The position and potential solutions of these ants in the search space are depicted through Gaussian Probability Density Functions (PDFs), each characterized by a specific mean value (as illustrated in Fig. 2). These Gaussian PDFs collectively form a multi-kernel PDF. After each generation, the most promising solutions (those with the highest density means in this multi-kernel PDF) are identified and retained in a solution archive. Subsequent generations then stochastically produce new individuals based on these archived solutions, continually evolving towards optimal solutions [33].

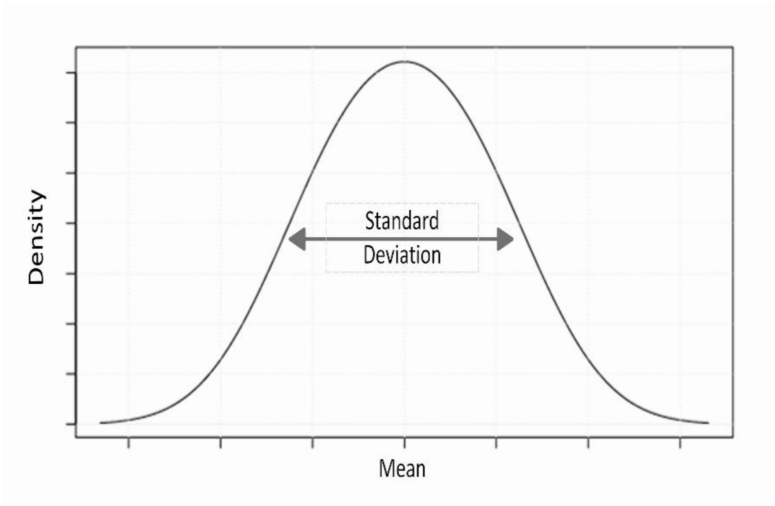


Fig. 2. Individual Gaussian PDF

In MIDACO, the very first generation of individuals is a uniform distribution of random samples. However, the next generations of individuals are done by the general evolutionary operator, which uses the information that has been saved in the solution archive after each generation for this purpose. The operator is a set of multi-kernel Gauss probability density functions, as shown in Eq. (22) [33].

$$\mathfrak{C}^h(x, \omega, \mu, \sigma) = \sum_{k=1}^{\mathcal{K}} \omega_k^h \frac{1}{\sigma^h\sqrt{2\pi}} e^{-\frac{\left(x-\mu_k^h\right)^2}{2\sigma^{h}2}} (h = 1, \dots, n_{con} + n_{int}) \quad (22)$$

This operator has three main parameters that determine how MIDACO's search procedure will proceed. The first parameter represents the weights of individual Gauss PDFs by giving the probability ranking of each kernel within each individual Gauss PDF. The second parameter is the mean for individual Gauss PDFs, and the third parameter is the standard deviation for every number of integers, as shown in Fig 3.

Among the all-triplet parameters $(\omega, \mu, \sigma)$, the $\sigma$ is the only parametre that can be controlled by tuning the FOCUS parameter in MIDACO directly by the user. Increasing the FOCUS parameter will reduce the upper bound of the standard deviation Gauss PDF. This will make the search process of MIDACO more local or greedy. Varying the FOCUS parameter inversely affects the upper bounds of the standard deviation of the individual's Gaussian PDF (the bandwidth), as shown in Fig. 3. A small value of FOCUS leads to an increase in the bandwidth of individual PDF. This wider individual PDF increases the influence of each individual on neighboring individuals when creating the multi-kernel PDF. This higher influence makes the multi-kernel PDF smoother. In this case, the density of each individual in this multi-kernel PDF represents the individual weight itself and the influence of the neighboring individuals' weights on it. However, with higher FOCUS values, the opposite will occur, and the density of each individual in the multi-kernel PDF will be more based on its weight than its neighbors' weights.

In addition to $\sigma$, the user can control the evolutionary operator $\mathfrak{C}$ by tuning the KERNEL parametre of MIDACO to control the size of the solution archive. Moreover, the user can change the number of individuals from each generation by tuning the ANTS parameter in MIDACO. In addition to that, MIDACO provides users the option to vary the series of pseudo-random numbers from the pseudo-random number generator by varying the SEED. At each setting of the SEED parameter, the randomly generated number around each $\mu$ when creating a new ant will change.

For the purpose of resolving multi-objective optimization, MIDACO offers further parameters. MIDACO algorithm uses the concept of utopia-nadir balancing to provide the best solutions for multi-objective problems. That's why MIDACO has the BALANCE option; setting it to its default value (zero) causes it to reflect the center of the Pareto front, which provides the best compromise among the many objectives' factors. The MIDACO method is able to focus on a specific region of the Pareto front due to the utopia-nadir tradeoff, which eliminates the need to initially determine the scale of the problem [34].

However, MIDACO has different stopping criteria that can be categorized into hard limit criteria and algorithm criteria. In this optimization approach, the stopping criteria is the number of function evaluations, which belongs to the hard limit criteria.

In this research, MIDACO was utilized to provide the optimal rating and position of STATCOM to enhance the voltage stability of the electrical power grid with minimum installation cost. Fig. 3 depicts the flowchart of the MIDACO-based optimization approach utilized in this study, while the flowchart in Fig. 4 shows the Newton-Raphson load flow analysis with STATCOM integration.

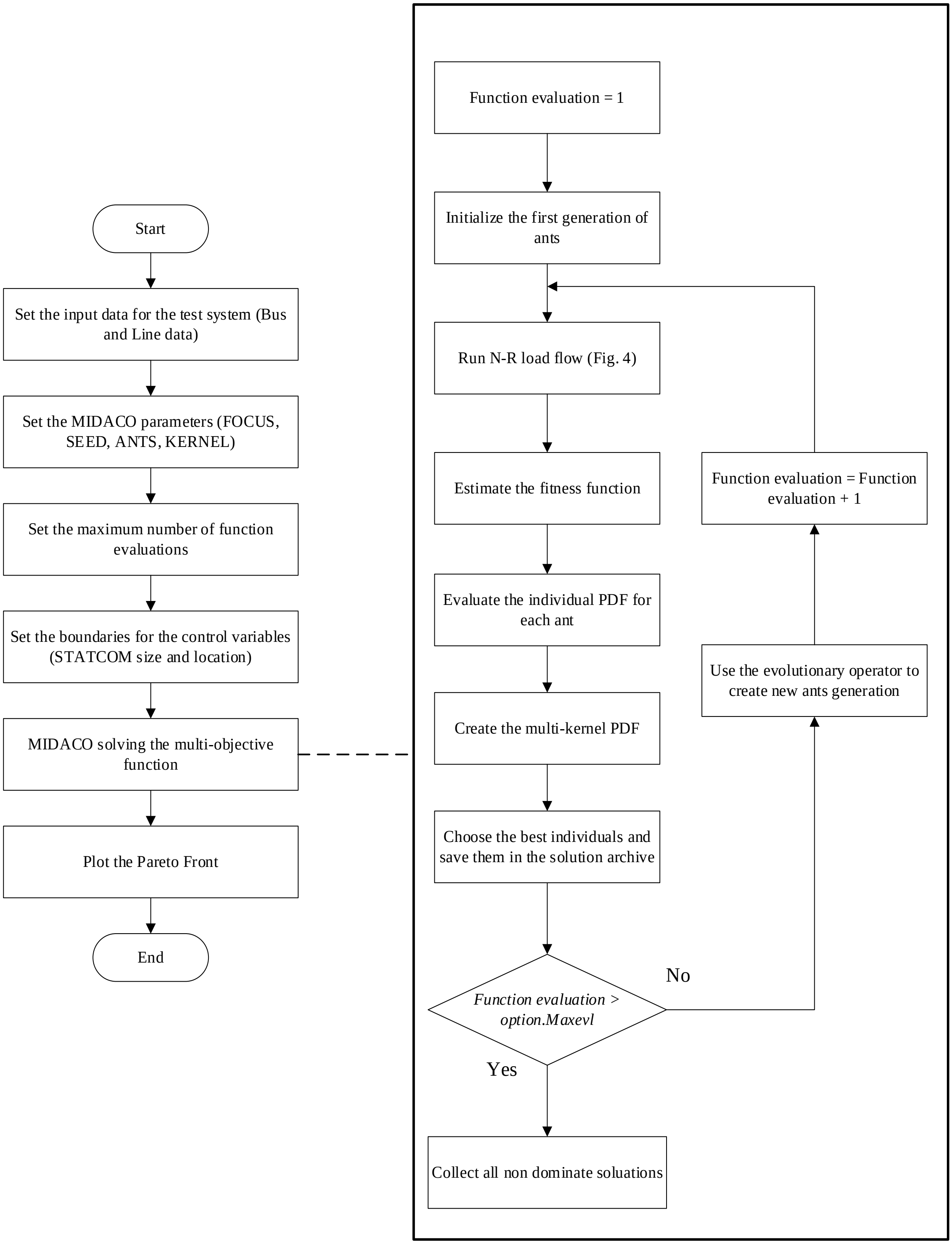


Fig.3. Flow Chart for the Optimisation Approach and MIDACO

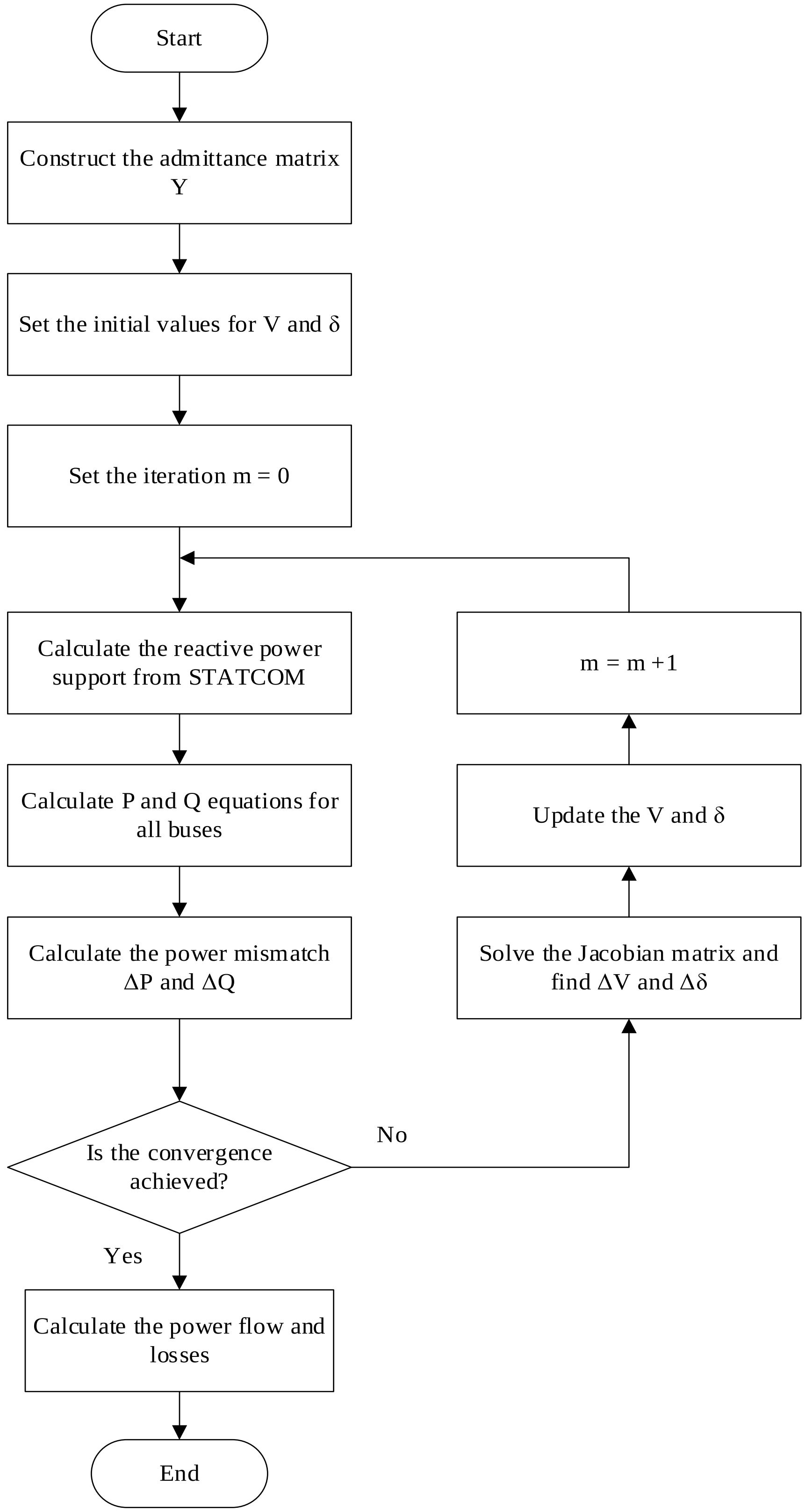


Fig. 4. Newton Raphson Load Flow Analysis Chart

## 5. Case Study

The proposed optimisation approach in this paper has been demonstrated on the standard IEEE 118-bus system as a main test system. This IEEE test system shown in Fig. 5 represents a simple approximation of the American electric power system in 1962 [35].

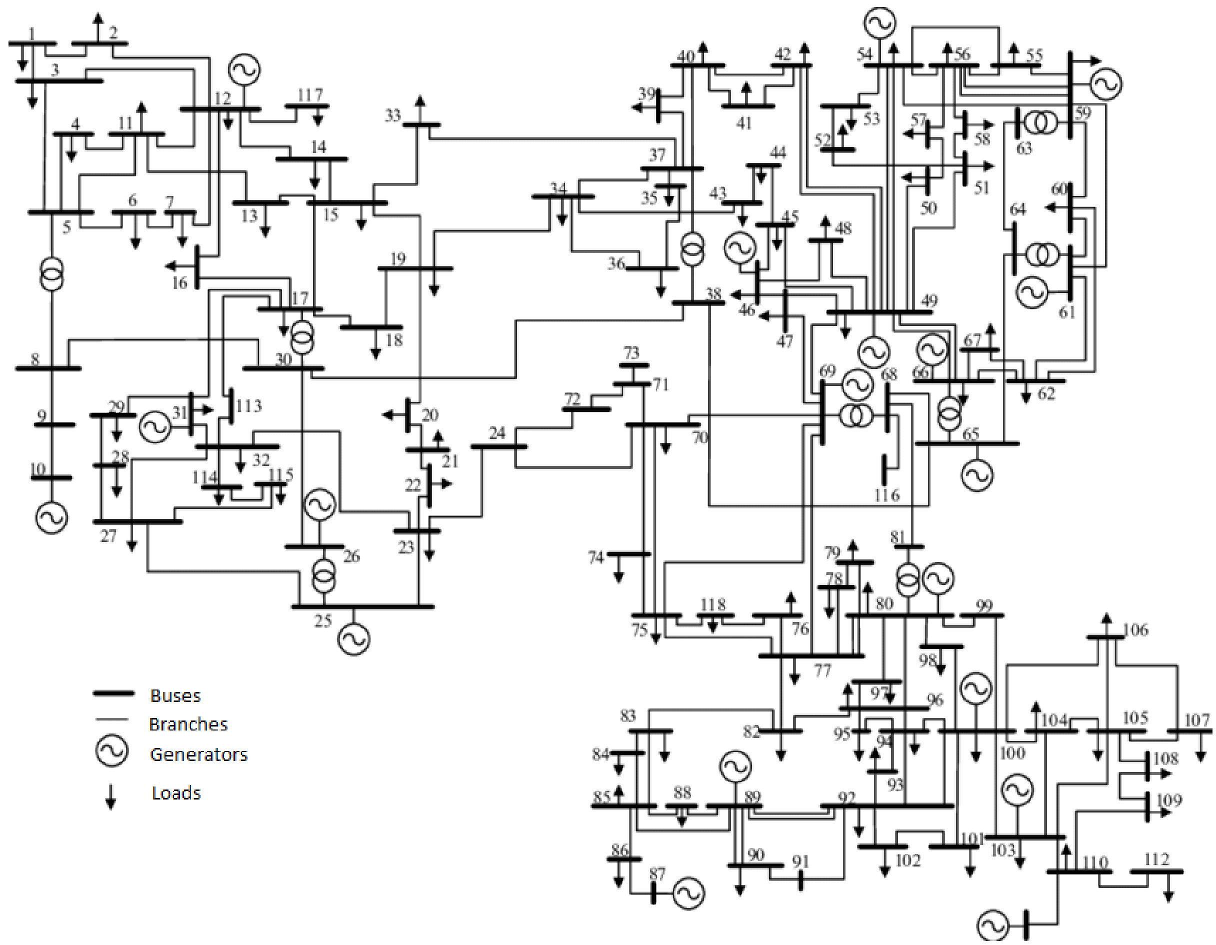


Fig. 5. Single Line Diagram of the IEEE 118-bus System [35]

This 118-bus test system has 91 loads, 9 transformers, 177 lines, and 19 generators. However, to estimate the voltage profile of the test system, the Newton-Raphson load flow analysis will be performed.

## 6. Results and Discussion

The proposed optimisation approach has been implemented on the standard IEEE 118-bus system to enhance voltage stability with minimum STATCOM installation cost. Table 1 shows the optimal solution from MIDACO for the STATCOM installation after 10,000 function evaluations. MIDACO optimal solution in this paper is the solution when the SEED number has varied from 0 to 99 while all other parametres are set to the default value (zero).

Table 1

Optimal Solution at MIDACO Default Settings

| STATCOM Size (MVAr) | STATCOM Location (Bus Number) | VDI % | Installation Cost (US Million Dollars) | VDI Reductiom% |
|---|---|---|---|---|
| 33 | 20 | 7.96 | 5.041 | 7.65 |

According to Table 1, the optimal location of STATCOM is at bus number 20, and the optimal STATCOM size is 33 MVAr. This optimal STATCOM installation by MIDACO has reduced the VDI to 7.97% with a reduction of 7.65%. However, the STATCOM installation cost is 5.041 million US dollars.

Figure 6 shows the impact of SEED analysis on the optimal STATCOM size. In this analysis, the sequence of a pseudo-random number from the pseudo-random number generator has been changed stochastically by varying the SEED parametre from 0 to 99, and the effect of this varying on the optimal STATCOM size has been shown in Fig. 6.

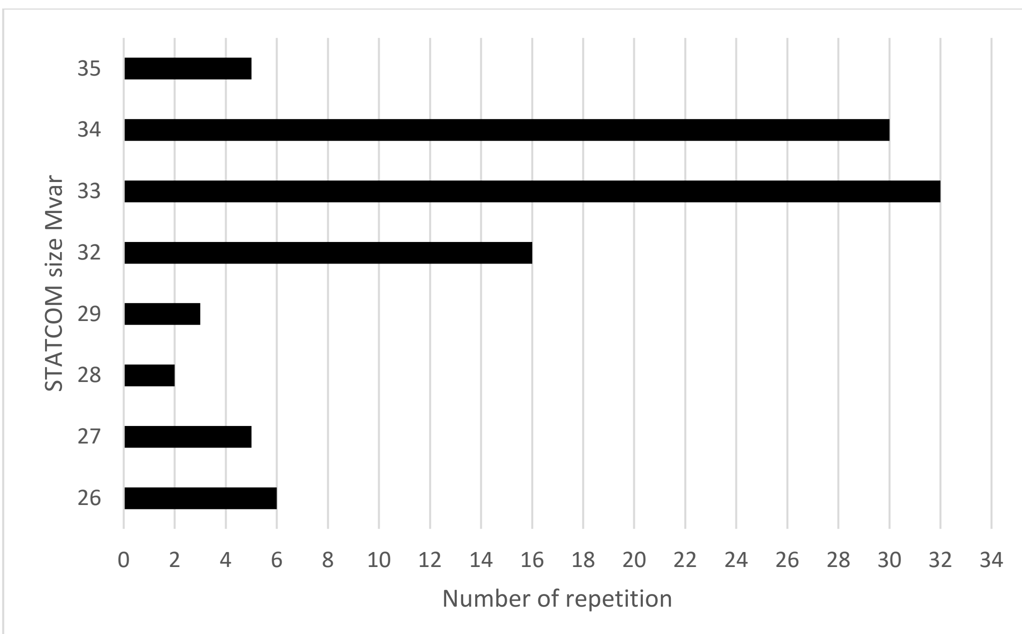


Fig.6. The Impact of SEED Analysis on the Optimal STATCOM Size

From Fig. 6, results show that the optimal location of STATCOM hasn’t changed, whereas the optimal STATCOM size has varied from 26 MVAr to 35 MVAr. Table 2 shows the optimal STATCOM installation regarding each objective and the number of repetitions in the SEED analysis for each of them.

Table 2

Optimal Control Variables Regarding Each Objective in the SEED Analysis

| Objective | STATCOM Size (MVAr) | STATCOM Location (Bus Number) | VDI % | Installation Cost (US Million Dollars) | VDI Reductiom% | Number of Repetitions |
|---|---|---|---|---|---|---|
| Installation cost | 26 | 20 | 7.98 | 4.023 | 7.53 | 6 |
| VDI | 35 | 20 | 7.95 | 5.327 | 7.87 | 5 |

According to the results, the optimal control variable regarding the first objective (STATCOM installation) has been repeated six times in the SEED analysis, which is more than the number of repetitions for the optimal control variable regarding the second objective (VDI).

Even though the optimal sizing has varied between 26 MVAr and 35 MVAr, the VDI has only varied within a range of 0.03, whereas the range of variance for the STATCOM installation cost is more noticeable, with a range of 1.304 US million dollars.

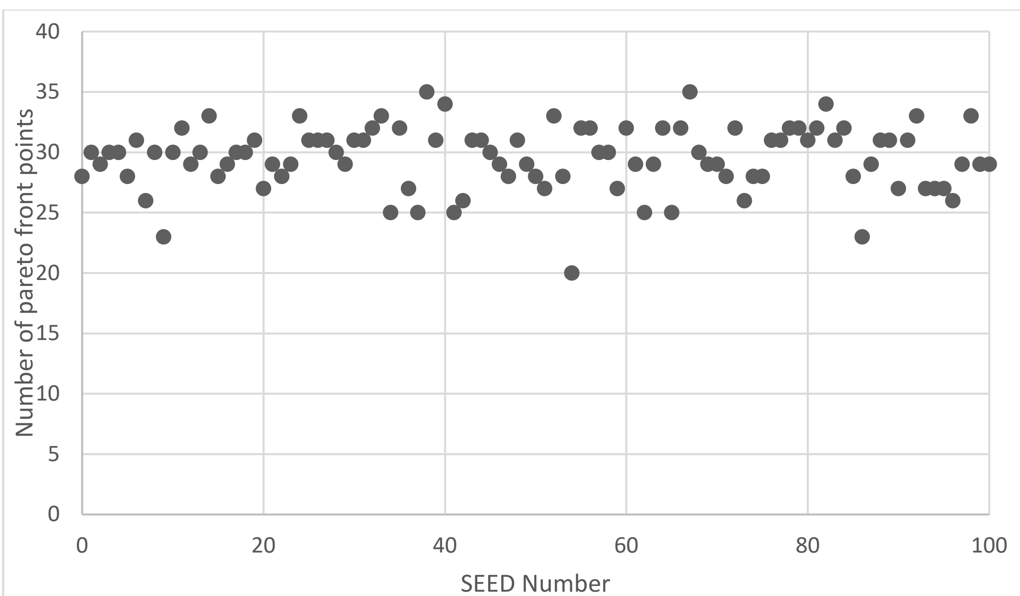


Fig. 7 The Impact of SEED Analysis on the Number of Pareto Front Points

The stochastic procedure for generating the random numbers around each ant when creating new ants has the responsibility to provide different Pareto fronts after the last end function evaluation, as shown in Fig. 6. However, not only the number of Pareto points has changed, but also the location of the non-dominated solutions on the Pareto front itself. Thus, the solution that represents the most equitable compromise among all of the objective functions in the middle of the Pareto front will change, and the MIDACO choice for the optimal solution will also change, as shown in Fig. 5.

Results in Table 3 illustrate the effect of the BALANCE parametre on the MIDACO choice for the optimal solution.

Table 3

The Impact of BALANCE Parametre on the MIDACO Optimal Solution (SEED=0, ANTS=0, KERNEL=0, FOUCS=0)

| Settings Number | BALANCE | STATCOM Size (Mvar) | STATCOM Location (Bus Number) | Installation Cost (US Million Dollars) | VDI % |
|---|---|---|---|---|---|
| 1 | 0.11 | 34 | 20 | 5.041 | 7.96 |
| 2 | 0.31 | 19 | 20 | 2.978 | 8.15 |
| 3 | 0.71 | 5 | 115 | 0.804 | 8.29 |
| 4 | 0.13 | 47 | 19 | 7.000 | 7.83 |
| 5 | 0.17 | 77 | 19 | 10.871 | 7.77 |

Table 2 shows 5 settings for the BALANCE parametre. The first one is for the equal balance between the two objectives, where the MIDACO solution represents the most equitable compromise among the two objectives and is located in the middle of the Pareto front. However, in settings 2 and 3, the search space for optimal solutions from MIDACO was more focused on the first objective (STATCOM installation cost), whereas the opposite occurs in settings 4 and 5, when MIDACO gives more priority to the second objective (VDI). Fig. 7 shows the Pareto front points for each setting of the BALANCE parametre in Table 3.

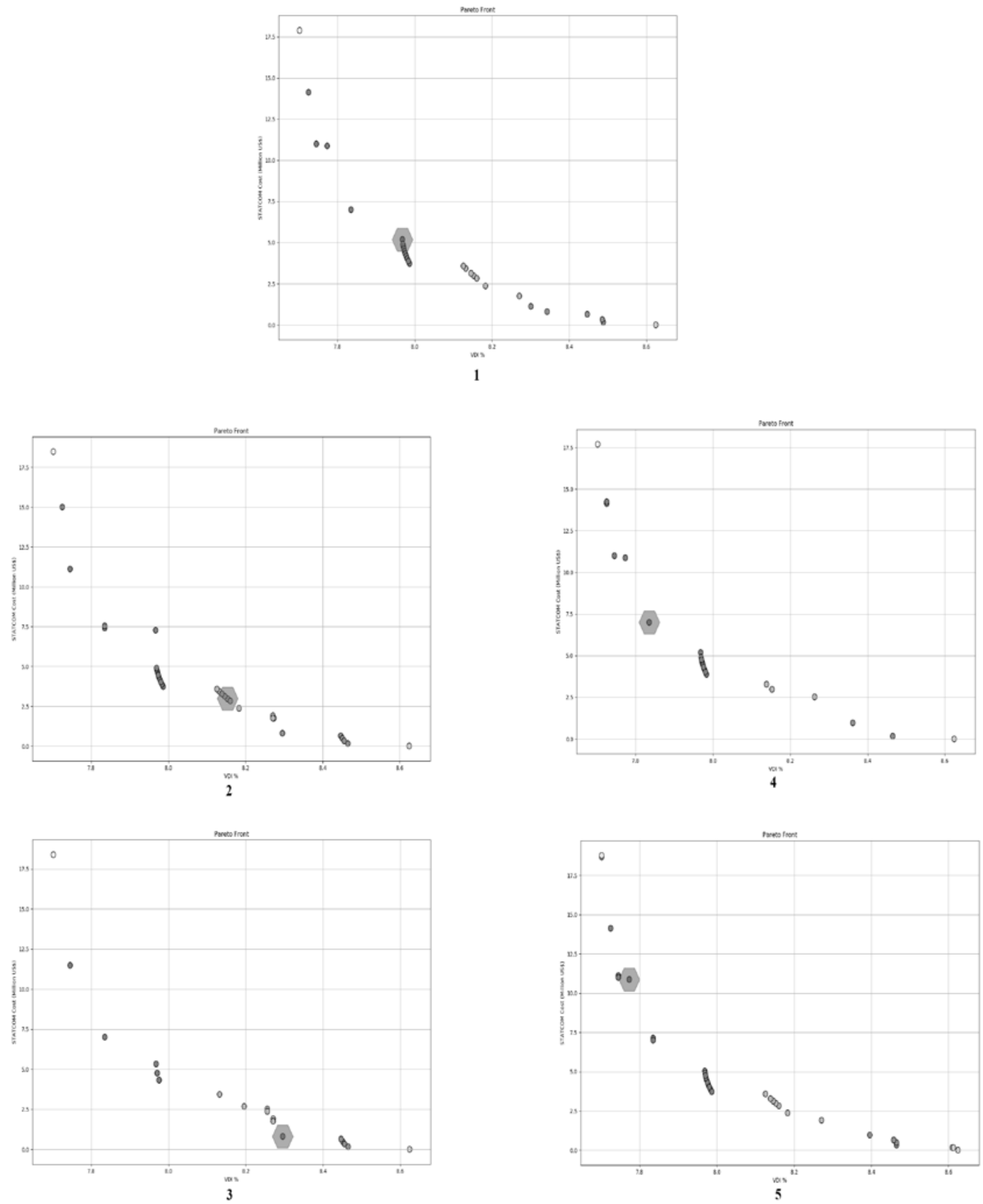


Fig. 8 The Impact of the BALANCE Parametre on the Optimal Solution

In order to explain the effect of the standard deviation on the optimal solution, a FOCUS analysis has been carried out in Table 4. The aim of this analysis is to figure out which solution has a mean with the highest weight. Table 4 shows 5 different FOCUS settings; the FOCUS parametre has been increased from zero (the default FOCUS value) to 1000.

Table 4

The Impact of FOCUS Analysis on the MIDACO Optimal Solution (SEED=0, ANTS=0, KERNEL=0, BALANCE=0)

| FOCUS | STATCOM Size (Mvar) | STATCOM Location (Bus Number) | VDI % | Installation Cost (US Million Dollars) |
|---|---|---|---|---|
| 0 | 34 | 20 | 7.96 | 5.184 |
| 10 | 33 | 20 | 7.96 | 5.041 |
| 100 | 27 | 20 | 7.97 | 4.170 |
| 1000 | 26 | 20 | 7.98 | 4.023 |

Even though the SEED number was fixed in this analysis, the results show that the optimal STATCOM size has changed by varying the FOCUS parametre. Table 5 shows the effect of varying the number of ants in each generation and the size of the solution archive on the deterministic optimal solution from MIDACO.

Table 5

The Impact of ANTS-KERENAL Analysis on the MIDACO Optimal Solution (SEED=0, BALANCE=0, FOUCS=0)

| Settings Number | KERNEL | ANTS | STATCOM Size (Mvar) | STATCOM Location (Bus Number) | VDI % | Installation Cost (US Million Dollars) |
|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 26 | 20 | 7.98 | 4.023 |
| 2 | 2 | 2 | 28 | 20 | 7.975 | 4.316 |
| 3 | 5 | 30 | 27 | 20 | 7.978 | 4.170 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 4 | 50 | 100 | 34 | 20 | 7.968 | 5.184 |
| 5 | 5 | 500 | 33 | 20 | 7.968 | 5.041 |

In Table 5, different ANTS and KERNEL combinations give five different deterministic solutions. However, as can be seen in settings 4 and 5, the large number of ants in each generation helps to reach a deterministic solution that is close to the probabilistic given by MIDACO, as shown in Table 1. On the other hand, the size of the solution archive has a minor effect on the solution compared with the number of ants in each generation.

In order to figure out when MIDACO converges, a function evaluation analysis has been carried out in Table 6 until MIDACO converges.

Table 6

The Impact of Increasing the Maximum Number of Function Evaluations

| Function Evaluations | STATCOM Size (Mvar) | STATCOM Location (Bus Number) | VDI % | Installation Cost (US Million Dollars) | Computational Time (sec) |
|---|---|---|---|---|---|
| 10 | 42 | 48 | 8.604 | 6.311 | 1 |
| 20 | 116 | 35 | 8.443 | 15.323 | 1 |
| 30 | 47 | 17 | 8.302 | 6.999 | 1 |
| 40 | 88 | 1 | 8.249 | 12.188 | 1 |
| 70 | 72 | 17 | 8.22 | 10.254 | 2 |
| 120 | 31 | 20 | 7.970 | 4.753 | 3 |
| 130 | 32 | 20 | 7.969 | 4.897 | 3 |
| 210 | 37 | 20 | 7.968 | 5.611 | 5 |
| 220 | 36 | 20 | 7.968 | 5.469 | 5 |

| | | | | | |
|---|---|---|---|---|---|
| 290 | 35 | 20 | 7.968 | 5.327 | 5 |
| 450 | 33 | 20 | 7.968 | 5.041 | 7 |

According to the results, MIDACO needed 7 seconds to converge after 450 function evaluations. However, MIDACO reached the optimal STATCOM location after 120 function evaluations and then optimised the STATCOM size until it reached the optimal STATCOM installation.

A comparison analysis of MIDACO's performance with three popular optimisation techniques—GA, PSO, and ABC—is presented in Table 7 to demonstrate the efficacy of the suggested optimisation approach. For the GA in this analysis, the mutation probability, crossover rate, and population size are set to 0.01, 0.8, and 100, respectively. For the PSO, the swarm size is 200, and the inertia weight is 1, with a damping ratio of 0.99, where the learning coefficient was set to 1.5, and the global learning coefficient was 2. And for the ABC, the number of foods and the number of bees are 10 and 20, respectively. However, the number of function evaluations is 10,000 for each solver in this comparison.

Table 7

Comparsion of MIDACO, PSO, GA, and ABC

| Solver | STATCOM Size (Mvar) | STATCOM Location (Bus Number) | VDI % | Installation Cost (US Million Dollars) | VDI Reductiom% | Convergence Time (sec) |
|---|---|---|---|---|---|---|
| MIDACO | 33 | 20 | 7.96 | 5.041 | 7.6 | 7 |
| PSO | 47 | 19 | 7.83 | 6.995 | 9.1 | 121 |
| GA | 51 | 51 | 7.95 | 7.959 | 7.7 | 92 |
| ABC | 47 | 19 | 7.83 | 6.995 | 9.1 | 44 |

The results in Table 7 show that PSO and ABC have similar results regarding the optimal location size for STATCOM. Even though the results are similar, ABC converges much faster compared with PSO. Although the results from GA are different from PSO and ABC, the optimal STATCOM installation is at bus number 51, with a STATCOM size of 51 Mvar. According to these results, the larger STATCOM sizes from PSO, GA, and ABC have more impact on VDI compared with the smaller STATCOM sizes from MIDACO. However, MIDACO has the best results for minizine VDI with the lowest installation cost, as shown in Table 7. Moreover, MIDACO is significantly faster and needs less computational time to converge compared with the other solvers.

However, the proposed methodology has been demonstrated on different test systems. Table 8 shows the results for the optimal STATCOM installation by MIDACO on the IEEE 14-bus system and the IEEE 57-bus system.

Table 8

Simulated Results for IEEE 14-bus System and IEEE 57-bus System

| Test System | STATCOM Size (Mvar) | STATCOM Location (Bus Number) | VDI % | Installation Cost (US Million Dollars) | VDI Reduction% | Convergence Time (sec) |
|---|---|---|---|---|---|---|
| IEEE 14 | 8 | 12 | 1.03 | 1.279 | 23.1 | 1 |
| IEEE 57 | 4 | 31 | 4.66 | 0.644 | 30.4 | 5 |

The results illustrate the ability of the proposed optimisation approach to provide the optimal STATCOM deployment to enhance the voltage stability on several test systems with the minimum STATCOM installation cost.

## 7. Conclusion

This paper presents a novel application of the Mixed Integer Distributed Ant Colony Optimization (MIDACO) solver for optimizing the installation of STATCOM in electrical power grids. The proposed optimization approach in this paper has been applied for different test systems, and the results showed the advantage of MIDACO mixed integer technique which is, unlike other evolutionary algorithms, efficiently managed the blend of discrete (location) and continuous (size) variables, overcoming common issues such as local optima entrapment and high computational costs. Also, the results showed that he MIDACO-based approach not only enhances voltage stability but also minimizes the installation costs of STATCOM more effectively compared to other optimization algorithms.

In addition to that, this paper contributes to the theoretical understanding of MIDACO's parameters and optimization behaviour, offering valuable guidelines for its application in real-world scenarios and that by providing an exploration into the sensitivity of various parameters within the MIDACO framework.

Future work could extend the application of MIDACO to such scenarios, including the exploration of its effectiveness in grids with high penetration of renewable energy sources. Investigating the interaction and optimization of multiple Flexible AC Transmission System (FACTS) devices within the grid could also provide a more comprehensive understanding of the potential of MIDACO in power system optimization,

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