Optimum Arrangement of Various Renewable Energy-Integrated Distribution Generation Systems

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DECLARATION OF CANDIDATE

We therefore solemnly affirm that the research described for this undergraduate thesis is unique to us which has on no occasion before been submitted to another university, institution, or organization for a degree or other academic credential.

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In the name of God, the Most Gracious, the Most Merciful.

The study would not have been possible without Allah, the Almighty, so the writers would like to first and foremost pay their honest appreciativeness to Him.

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ABSTRACT

Fossil fuel is the conventional source of energy. However, it is exhaustible and from multiple studies, it is well known about the ramifications they have on our environment. Therefore, incorporating renewable energy via Renewable Energy based Distributed Generation (RDG) is a topic which piques interest to ensure the most effective working of modern power networks. However, since renewable energy sources like sunlight and wind is neither continuous nor steady, getting the RDG units' optimal placement and size is a crucial task. On a further note, for agro-based countries or countries containing plenty of livestock, incorporating biogas units will also contribute to ensuring efficient generation of electricity. In this study, a novel method to find out the optimal allocation and sizing of RDG units has been proposed using latest optimization algorithms like the Pelican Optimizer Algorithm (POA) and the Dandelion Optimizer (DA), taking into account multi objective operational constraints like ensuring minimum voltage deviation and power loss. The IEEE-33-bus and IEEE-69-bus systems were used as test systems. It was also seen that the algorithms gave better results when compared to widely used algorithm like the Particle Swarm Optimization (PSO) and Equilibrium Optimizer in cases where RDG units were introduced in the test systems, instead of no RDG present. After running the optimization algorithms in the proposed models, it was observed that DA performed best for IEEE 69 bus system. Whereas, the POA was the better performing in case of IEEE 33 bus system. But both POA and DA outperform the previously used Particle Swarm Optimization (PSO) and Equilibrium Optimizer (EO). It can be said that the performance of the two proposed algorithms depend on the nature of the distribution system used.

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CHAPTER 1
INTRODUCTION

1.1 Background

A reliable and economical supply of electrical energy is crucial for industrial processes and the functionalities of society. [1]. However, the primary energy source's reliance on fossil fuels for power generation has generated questions due to their quick depletion, endangering the use of fossil fuels in the future. Since fossil fuels are readily depleted their consistent usage has raised questions, endangering their use for the future. Therefore, there is an upward trend towards using various renewable energy sources to produce power. A probable solution to the problems caused by the lack of conventional energy sources assimilation of Renewable Distributed Generation (RDG) unit's systems inside distribution networks.

Over the years, a lot of study has been done to examine the potential advantages, difficulties, and application areas of integrating RDG in distribution networks. The authors, for instance, address the main issues, opportunities, and limitations associated with integrating distributed generation into electric power networks. Distributed Generators (DGs) now have access to the most practical and profitable energy sources available. [2] presents the potential for the future and scientific developments in the exploitation of renewable energy sources. Many studies have probed into other alternative sources while considering their availability into electric power networks and smart grids, including [3-6]. As a practical way to fulfill the growing demand for electricity and lessen reliance on dwindling supplies existing fuel sources.

1.2 Motivation

Thorough checking and planning frameworks have been recommended in order to address the issues with grid- integrated DG planning [7]. Using some variables, [8] shows the effect of RDGs on the distribution grid. It is crucially important to remember that natural elements have an impact on the electricity produced from renewable energy sources [9]. While the environmental benefits of dispersed energy resources and their role in lowering greenhouse gas emissions are studied in [10], the financial, general economic, and sociological implications of distributed energy generation are discussed in [11]. Research studies have suggested exhibiting approaches for incorporating a degree of uncertainty [12], effective operational schedules for multi-grid distribution systems [13], [14] and in order to maximize the technological, economic and environmental benefits planning frameworks to increase the flexibility of power-water distribution networks. Algorithms and optimization approaches to enable the best imaginable unification of DGs in active distribution systems, have also been used [15].

1.3 Problem Statement:

Our system parameters may suffer from adversities for abnormal rate of incorporation of RDGs. Therefore, careful consideration and careful planning are compulsory when integrating RDG units into distribution networks in order to ensure that network performance requirements may be fulfilled. Additionally, external anomalies can largely influence the power produced by the RDG sources.

Installation of a variety of DGs of different types in distribution networks have been the subject of numerous research ideas that have used various optimization methodologies. The majority of these projects focus on enhancing the technical aspects of voltage stability and power loss reduction in the distribution network. In addition, previous research shows that choosing the right RDG location for distribution networks is a never-ending difficulty. It is impossible to overstate the importance of optimization approaches in this area of research since it would be desirable to gain significant improvements using a unique or improved optimization methodology.

CHAPTER 2
LITERATURE REVIEW

2.1 Existing Researches

Weather, temperature, site location, and time are just a few of the variables that have a big impact on the energy that RDG sources deliver. Dealing with random anomalies in networks of DG-integrated power system is the main research challenge in this area. Inadequate RDG unit penetration can have adverse effects on system performance. The point estimate method (PEM), scenario-based analysis (SBA), and Monte Carlo simulation (MCS) are three ways to handling uncertainty that have been explored in [16]. In [17], MCS-based probabilistic techniques were used to analyze the effects of wind and PV generation on distribution networks. Optimization techniques like MCS and (PSO) have been applied in [18]. To incorporate renewable energy sources into distribution networks, enhanced optimization methods, such as the improved Harris hawks based particle swarm optimizer (HHO-PSO), have been suggested [19]. Particle swarm optimization and gravitational search algorithm (PPSOGSA) are two examples of hybrid approach that have been proposed when integrating renewable energy sources into distribution networks if any case uncertainties are involved [20]. For the best DG sizing and placement, including the ant lion optimization algorithm (ALOA), backtrack search optimization algorithm (BSOA), artificial bee colony algorithm (ABC), hybrid grey wolf optimizer, bacterial foraging optimization algorithm (BFOA), intelligent water drop algorithm (IWD), stud krill herd algorithm (SKHA), and combined genetic algorithm-particle swarm optimization (GA-PSO) algorithm techniques have been applied [21-28]. For the best positioning and sizing of DGs to achieve loss minimization and other techno-economic advantages, other optimization techniques have been proposed [29–31]. These include mixed-integer nonlinear programming (MINLP), multi-objective opposition-based chaotic differential evolution (MOCDE), and evolutionary programming (EP).

Real-time data use in realistic distribution networks is another topic of research in this area. For instance, the whale optimization approach (WOA) algorithm has been tested on a number of distribution networks, including IEEE 15-bus, 33-bus, 69-bus, 85-bus, and 118-bus test systems [32]. Hybrid particle swarm optimization combined with gravitational search algorithm (PSOGSA) and MMFO has been proposed to find the ideal spot and RDG unit capacity while taking into account power losses, expenditures on operations, voltage characteristics, and consistency of voltage in practical applications for example to say about MEDN 15-bus and Moscow 111-bus systems. [33]. The power voltage sensitive constant (PVSC), which has been demonstrated on IEEE 33-bus and 130-bus power distribution systems, has been introduced as a solution to the RDG utilization problem. [34]. In [35], fuzzy expert rules based on bus voltage magnitudes and loss sensitivity factors were applied to direct distributed generator placement selections. On IEEE 30-bus and 57-bus systems, the SHADE-EC algorithm has been used for deterministic RDG placement while taking control mechanisms through consideration when resolving both types of objective random probability distribution or pattern situations [36]. In [37], when dealing with uncertainties, ideal arrangement of Various Renewable Energy-Integration using Artificial Hummingbird Algorithm was applied by Md. Shadman Abid et al.

In conclusion, studies examine a range of topics, including the advantages, difficulties, and scopes of implementing RDGs, addressing uncertainty, choosing the finest site and size for DGs, and utilizing optimization approaches. To evaluate the efficacy of suggested algorithms and solutions, realistic distribution networks and real-time data are also taken into consideration. Achieving effective, reliable, and sustainable energy generating and distribution networks is the ultimate goal.

2.2 Research Gaps:

These conclusions may be drawn from the aforementioned literature review:

- Very few studies on the optimum allocation of RDG units and the optimal size have been conducted.
- The integration of biogas as a unit of renewable energy source is completely a new concept along with other well-known RDG units.
- The overall loss of the system and the bus voltage deviation were not minimized together in most of the previous works.
- Latest swarm algorithms like Pelican Optimization algorithm (POA) and Dandelion Optimizer (DO) are yet to be investigated in the research area of RDG placement and sizing.

2.3 Research Contribution:

The primary aim of this research is to assess the placement and size of RDG units to reduce active power loss, and reduce voltage deviation. The core aids of the current work are listed as follows:

- The location and sizing of RDG units were determined as part of the optimization problem.
- Along with solar (PV) and wind (WT) RDG units, the biogas unit was taken into account and used as an additional RDG unit.
- An energy production mathematical model for biogas was designed in order to accommodate the electrical power created by the biogas RDG unit in the distribution system.
- The optimum solution is compared between two latest algorithms, Pelican Optimization algorithm (POA) and Dandelion Optimizer (DO) and also algorithms like Equilibrium Optimizer (EO) and widely used Particle Swarm Optimization (PSO).
- The power loss of the system, voltage deviation, DG dimension and DG bus positions were determined using each of the said optimization algorithms and the results were compared.

CHAPTER 3
MODELLING AND RESEARCH METHODOLOGY

3.1 Fitness Function

The main objective of this study is to maximize and optimize the technical benefits obtained by integrating Renewable Distributed Generations (RDGs) into conventional distribution networks. Simulated investigations are used to thoroughly evaluate and investigate many aspects in order to accomplish this goal. These features include minimizing active power loss, improving bus voltage. By combining these two evaluation criteria into a single objective function, the weighted sum approach is used to efficiently assess the system's performance. This method makes it possible to evaluate the RDGs' overall efficacy and efficiency within the distribution network in great detail.

$$fitness = \min(P_{loss} + V_D) \tag{1}$$

The P_{loss} and V_D of the fitness function can be expressed using the following equations:

$$P_{loss} = \sum_{b=1}^{N_{BR}} P_{loss,b} \tag{2}$$

$$V_D = \sum_{i=1}^{N_B} \left| V_i - V_i^{ref} \right| \tag{3}$$

The total voltage magnitude is denoted by V_i whereas the voltage deviation is shown by V_D at the i^{th} bus respectively in (p.u). V_i^{ref} represents 1 p.u in voltage magnitude.

3.2 Modelling of RDG units

Weather-related variables including solar radiation, wind speed, temperature, and more have significant effects on the generation of energy from renewable sources. Given renewable power generation is heavily reliant on the weather, it is crucial to carefully evaluate the jeopardy and unpredictability of this source of energy before thinking about incorporating Renewable Distributed Generation (RDG) units into electrical networks. The Monte Carlo simulation, which takes a probabilistic approach, is one often used technique for assessing power system concerns. Additionally, specialized functions are employed to model the uncertainty associated with each of these factors, such as the Weibull function for wind speed and the beta function for solar irradiation. In direction to do so, a daily weather data has been collected to analyze the random or random probability distribution nature of wind velocities and solar irradiance [39]. The biogas data [40] has been collected and analyzed to incorporate with the solar and wind generations

3.2.1 Modelling the Solar Panels (PV)

Solar irradiance is the primary component on which the power from PV units depend on.

$$P_{PV}(G) = \begin{cases} \dfrac{P_{PVR} * G^2}{G_{STC} * R}, for\ \ G < R_C \\ \dfrac{P_{PVR} * G}{R}, for\ \ G > R_C \end{cases} \tag{4}$$

However, in order to achieve a realistic solar model, we need to take into consideration random probability distribution nature of the solar irradiance. We do so by using the beta probability density function.

$$f(G) = \begin{cases} \left[\dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\right] * G^{\alpha+1} * (1-G)^{\beta-1}\,, \\ for\ 0 \le G \le 1, \alpha \ge 0, \beta \ge 0 \\ 0, \quad otherwise \end{cases} \tag{5}$$

We are to consider the shape factors of the density function by considering the standard deviation and the average deviation of the solar irradiances. The shape factors are denoted by $\alpha\ and\ \beta$ respectively as shown in the following set of equations:

$$\beta^t = (1-\mu_G^t) * [(1+\mu_G^t) * \frac{\mu_G^t}{\sigma_G^t t^2} - 1] \tag{6}$$

$$\alpha^t = (\mu_G^t * \beta^t)/(1-\mu_G^t) \tag{7}$$

By dividing the time span under consideration, t, into N_s states, beta PDF can be converted into a discrete form. And by rearranging, we get the following equation:

$$P_{PV} = [\sum_{g=1}^{N_s} P_{PVg} * f_s(S_G^t)]/[\sum_{g=1}^{N_s} f_s(S_G^t)] \tag{8}$$

At the time interval t and the state g, the probability is$f_s(S_G^t)$.

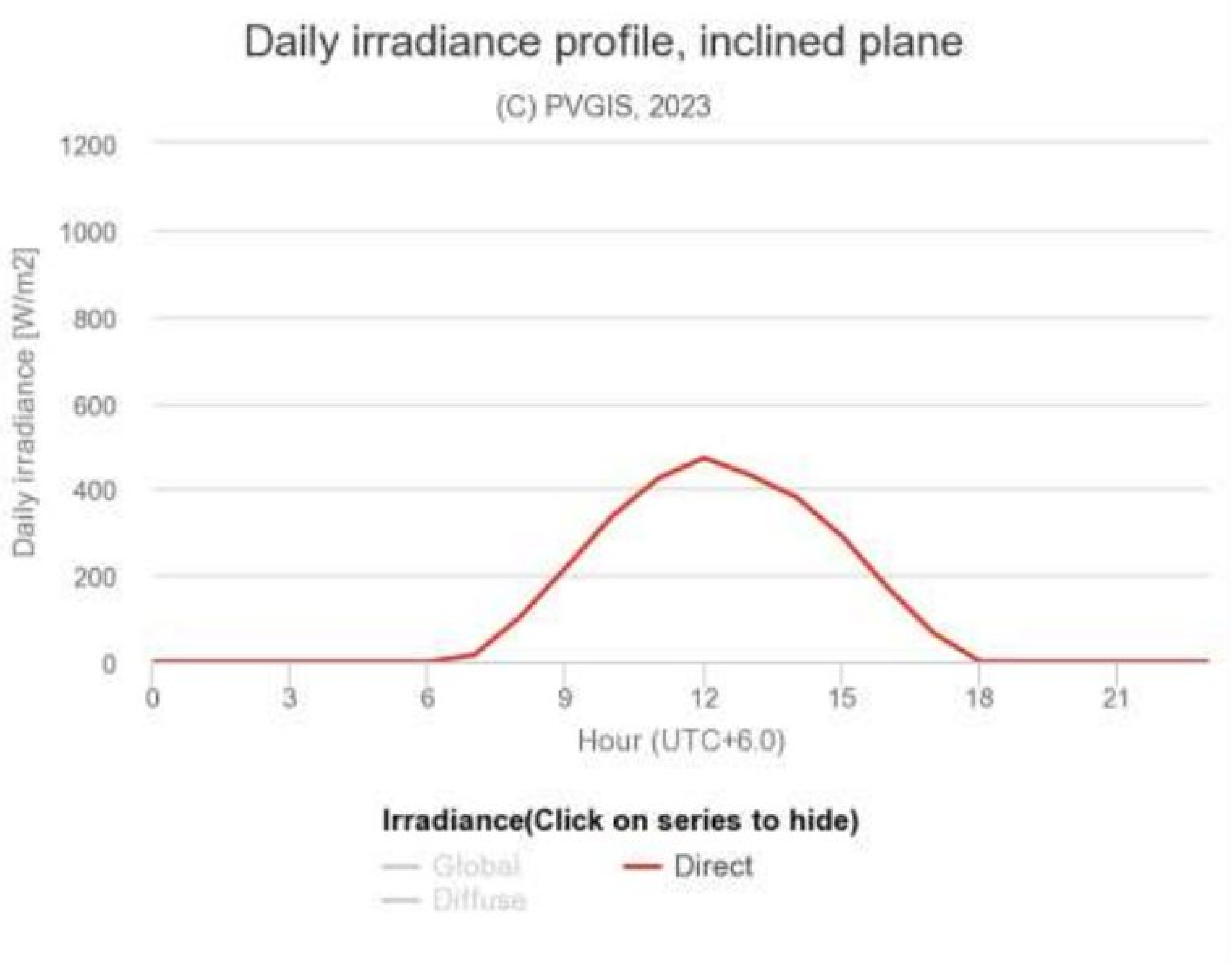

Fig. 3.1 Hourly solar Irradiance of 18th April, 2023

3.2.2 Modelling the Wind Turbine

The power generated by a wind turbine can be expresses as follows:

$$P_{WT}(v) = \begin{cases} 0 & for\ v \le v_{ci} \\ \dfrac{v - v_{ci}}{v_{n} - v_{ci}} * P_{WTR} & for\ v_{ci} \le v \le v_{n} \\ P_{WTR} & for\ v_{n} \le v \le v_{co} \\ 0 & for\ v \ge v_{co} \end{cases} \quad (9)$$

The following Weibull probability density function can be used to assess the stochastic nature of wind resources in a certain region:

$$f_v(v) = k / C * (v / C)^{k-1} * e^{-(v/C)^k} \quad (10)$$

The cumulative distribution function of the Weibull function can be expressed as following Eq. (11) and the inverse of it can determine the wind speed as in Eq. (12).

$$f_v(v) = 1 - e^{-(v/C)^k} \tag{11}$$

$$v = C * [-\ln(r)]^{(1/K)} \tag{12}$$

Where, k and C are the shape factors, can be used to calculate their predicted values using the average and standard deviation of the wind speed observations over a period of time.

$$K^t = (\sigma_v^t \,/\, \mu_v^t)^{-1.086} \tag{13}$$

$$C^t = \mu_v^t \,/\, \Gamma(1 + 1 \,/\, k^t) \tag{14}$$

By dividing the time span under consideration, t, into Nv states, Weibull probability density function can be stated in discrete form. Eq (13) and (14) can be revised to reflect g as the inverse of Nv, and Eq. (15) can be used to express the predicted wind turbine power.

$$P_{WT} = \left[\sum_{g=1}^{N_v} P_{WTg^*} f_v\left(v_g^t\right)\right] / \left[\sum_{g=1}^{N_v} f_v\left(v_g^t\right)\right] \tag{15}$$

Where, v=v_g^t and $f_v\left(v_g^t\right)$ is the probability of wind speed at t^{th} time interval for g^{th} state.

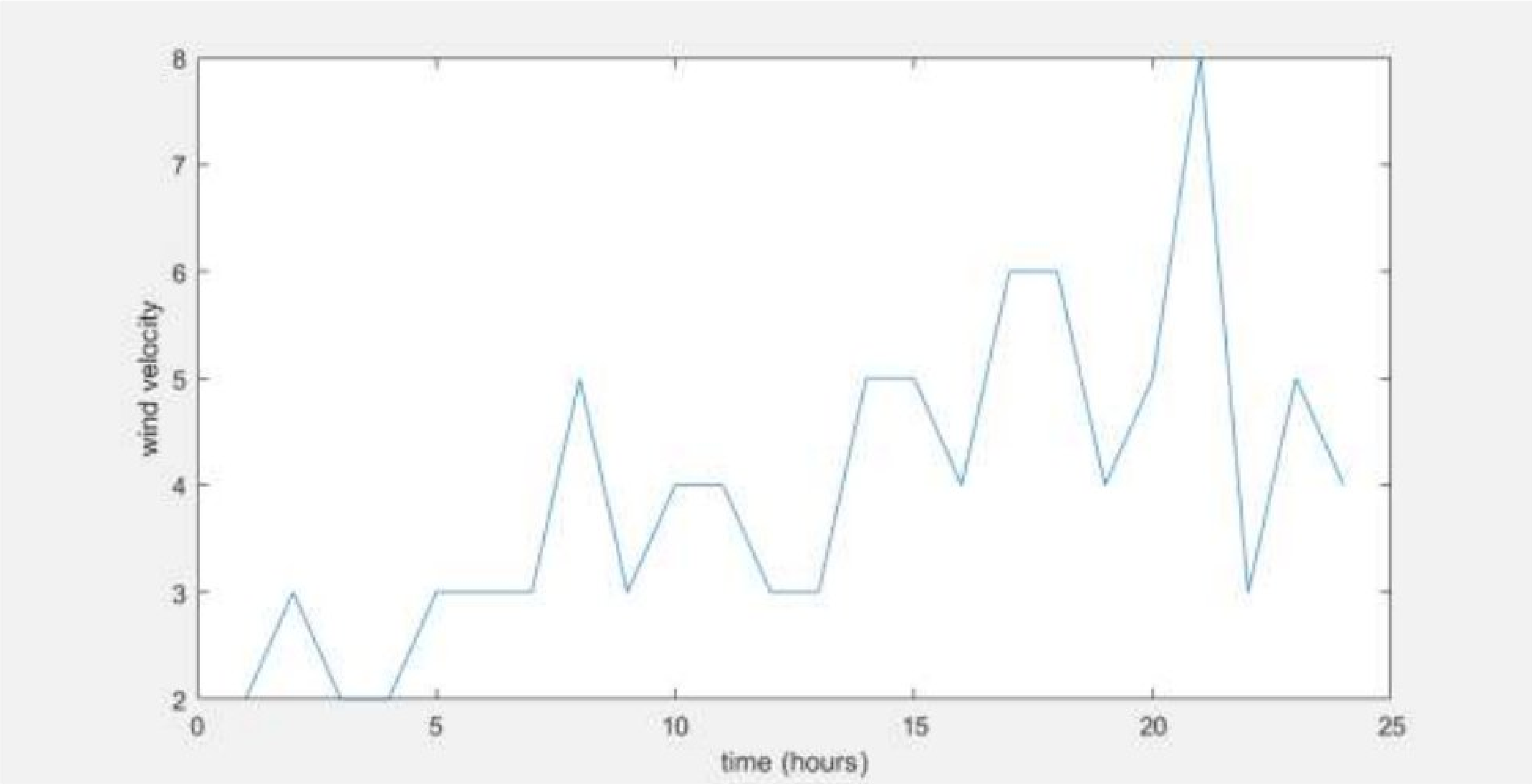

Fig. 3.2 Hourly wind velocity of 18th April, 2023

3.2.3 Modelling of Biogas units:

In a biogas plant, waste from the agricultural industry, green plants, animal manure, and byproducts from slaughterhouses can all be converted into combustible gas. More details on how biogas is produced and fermented by anaerobic process can be found out by reading [41].

Given that biogas produces energy per volume in the rate of 21-23.5 MJ/m3, 1 m3 of biogas corresponds to 0.5–0.6 l of diesel fuel. [46]. A dairy farm of Gazipur, Bangladesh, that produces sufficient cow dung has been selected, as primary source of fuel to produce biogas for our proposed model. Through investigation and the gathering of data from the dairy farm where the total no. of cows considered were 1500, it was speculated that the daily production of cow from the cows were 25 Kg. 25% of the daily collected cow dung was considered to be usable for biogas production.

If properly digested, one kilogram of cow waste produces 0.035 m3 of biogas [42]. For a biogas plant's digester to calculate the active slurry volume, the hydraulic retention time (HRT) must be known. It is believed that a digester would retain a particle or quantity of liquid waste for this length of time. The quantity is calculated by dividing the digester's volume by the daily slurry additions. The amount of a digester's tank that is actively involved in the anaerobic digestion process is known as the active slurry volume. It stands for the area of the tank that is home to the mixture of organic waste and the microorganisms necessary for the waste's digestion and decomposition. Active slurry is therefore given by:

$$Vs = \frac{2 \times W}{1000} \times HRT \tag{16}$$

for the animal waste W, HRT = 20 days [43]

So, for the proposed biogas model, the volume of its digester, when built, can easily be found out from the Eqs. (23). In general, 60% of biogas is produced as methane. [44] This is preferable because, in general, the production of electricity from biogas necessitates a minimum of 45% methane in the fuel. For this, we used a 24% biogas to electricity conversion efficiency. From [45], it is proved that, energy produced from per unit volume of biogas is 6 KWh.

Finally, incorporating all the above facts, it can be finally concluded that the actual electric power output as obtained from a biogas plant is represented by:

$$P_{bio} = n_{Bio} * Hm_{Bio} * \%_{usable-dung} * W_{dung\ per\ cow} * N_{cattle\ no.} \tag{17}$$

Where, P_{Bio} is the power produced by the biogas plants daily, Hm_{Bio} *is* the energy produced from per unit volume of biogas in kilowatt-hour/ m^3, Cb_{Bio} is the biogas yield in m^3/kg and η_{Bio} is the efficiency of the biogas plants and the corresponding conversion.

The daily power data derived from here is sample in 24-hour sample data using random Gaussian distribution.

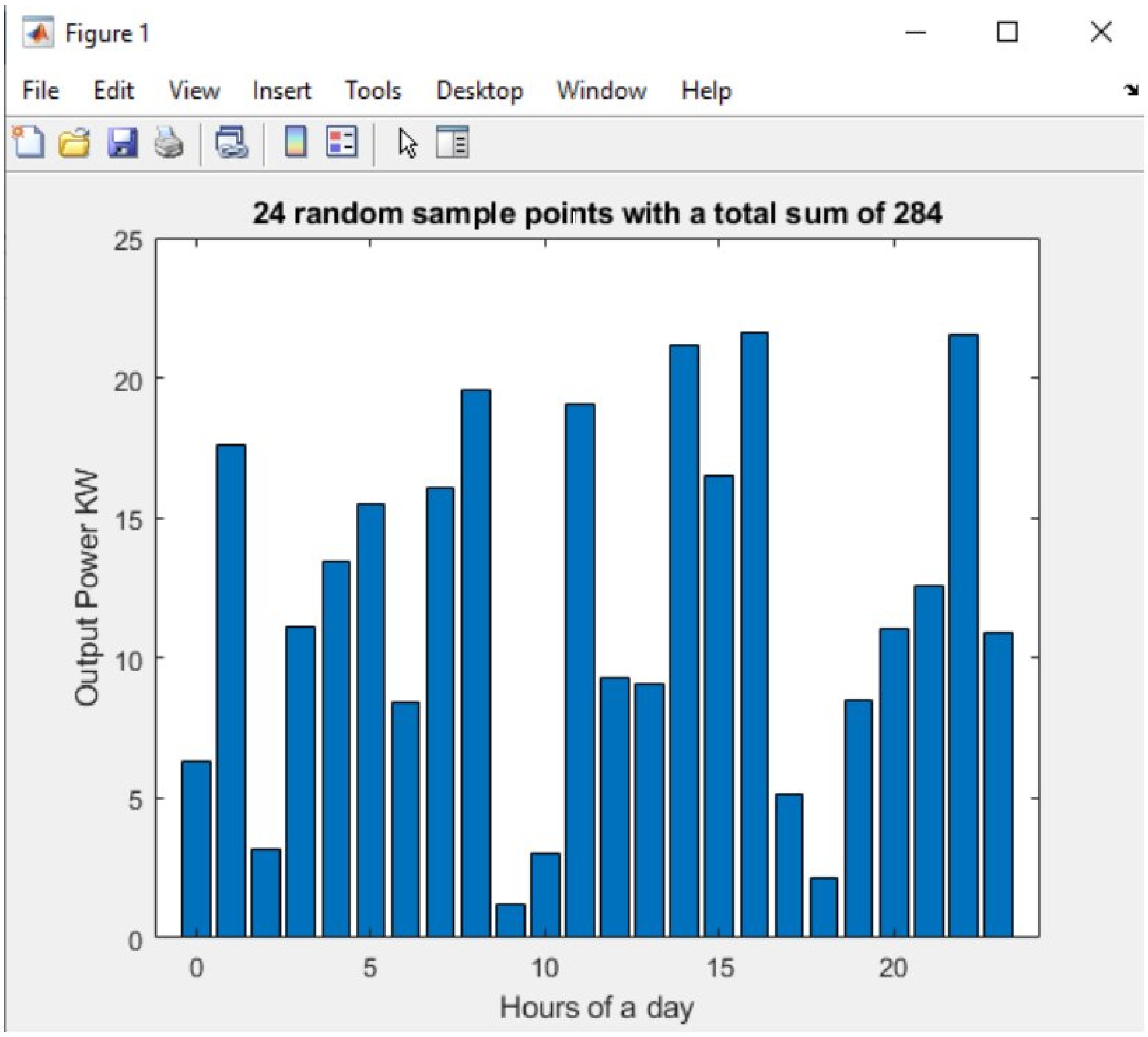

Fig. 3.3 Hourly biogas output

In this case, for the proposed model of biogas plant for our research, 30 KW rated capacity biogas generator has been used for simulation,

Genset Rating	30 KW
Brand	YANMAR
Model	30 KW
Fuel Consumption (at 100% Load)	200 GRAM/KW/HRS
Fuel Tank Capacity	6 LITTER
Phase	Three Phase

Fig. 3.4 Biogas plant specifications

3.3 Test System Description

We employed the IEEE 33 and IEEE 69 bus distribution system as the test system in this work.

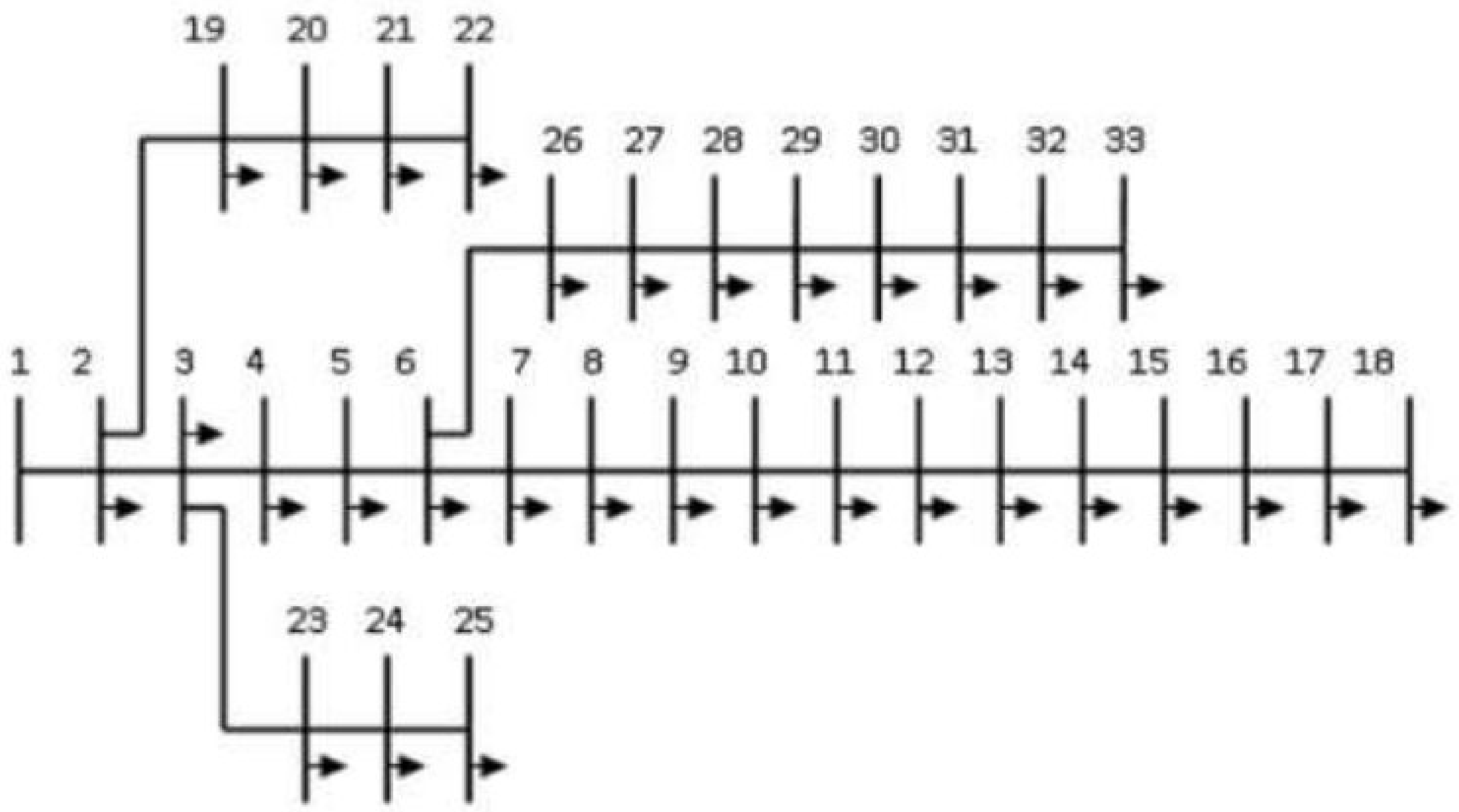

Fig. 3.5 IEEE 33 bus distribution system

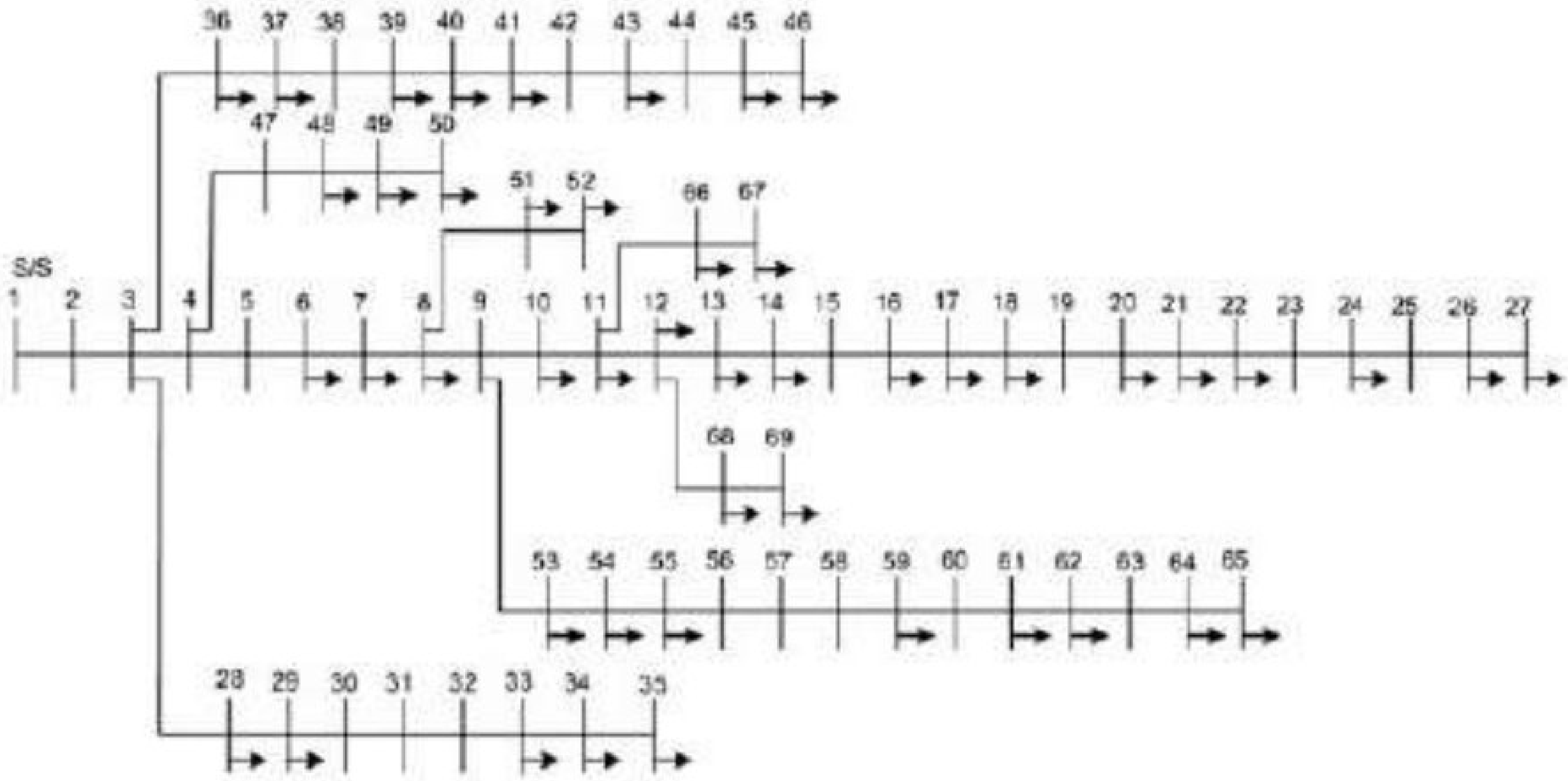

Fig. 3.6 IEEE 69 bus distribution system

In Figs. 3.8 and 3.9, the one-line schematics for the IEEE 33 and IEEE 69 buses, respectively, are exhibited. In comparison to the former bus system, which has a total load demand of 3.802 MW and 2.695 MVAr, the later bus system has a total load demand of 3.715 MW and 2.3 MVAr.

Table 3.1 System specifications of IEEE 33 and IEEE 69 bus systems

System Specifications	33 bus system	69 bus system
NB	33	69
Nbr	32	68
V_{sys} (KV)	11	12.66
Base MVA	100	100
Real power (MW)	3.715	3.802
Reactive Power (MVAr)	2.300	2.695
S_{load} (MVA)	3.715+j2.300	3.802+j2.694

3.4 Operational Constraints

The following requirements are implemented to guarantee that the optimization process maintains specific operational limitations:

Power Flow Balance

The sum of the real and reactive load demand (P_{load}, Q_{load}), as well as the real and reactive power losses (P_{loss}, Q_{loss}), should match the total both power generation (P_{gen}, Q_{gen}). This can be stated mathematically as:

$$\sum_{N=1}^{N_G} P_{gen} = \sum_{i=1}^{N_L} P_{Load} + \sum_{l=1}^{N_{Line}} P_{Loss} \tag{18}$$

$$\sum_{N=1}^{N_G} Q_{gen} = \sum_{i=1}^{N_L} Q_{Load} + \sum_{l=1}^{N_{Line}} Q_{Loss} \tag{19}$$

In this instance, , NL symbolizes the total load buses, N_G relates to the total number of generators and N_{line} for the total network branches.

Voltage Limit:

Each bus's voltage (Vi) is to be set within an approved range. Typically, a nominal voltage value difference of up to 10% is permissible. As a result, the limits of voltage can be defined in the following manner:

$$V_{i-min} \leq V_i \leq V_{i-max} \tag{20}$$

Power flow limit:

The apparent power through each branch (l) of our distribution system should not exceed the maximum thermal limit:

$$S_l \leq S_{l-max}$$

(21)

DG penetration limit:

These limits of active and reactive ensure the DG operates within specified bounds:

$$P_{DGi}^{min} \leq P_{DGi} \leq P_{DGi}^{max}$$

(22)

$$Q_{DGi}^{min} \leq Q_{DGi} \leq Q_{DGi}^{max}$$

(23)

Limit of ratings of each DG for this research are considered to be 0.1 MVA to 1.48 MVA, with a constant power factor of 0.9 per unit (p.u).

RDG Capacity Constraints:

The active power capacity of each Renewable Distributed Generation (RDG) farm is set to a fixed value. The capacity constraint is given by:

$$N_{RDGi} * P_{RDGi} \leq NRDGi_{max} * P_{RDGi}$$

(24)

Here the number of primary RDG units consisting the RDG farm at location i is represented by by N_{RDGi}. The rated power of that primary unit is represented by by P_{RDGi} at the location i and $NRDGi_{max}$ is the highest number of allowable RDG units allowed at location i.

3.5 Optimization Algorithm

3.5.1 Pelican Optimization Algorithm

In this study, a new meta-heuristic method called the Pelican Optimization Algorithm (POA) is used. Pelicans frequently cooperate when hunting. When the pelicans locate their prey, they dive to it from a height of 10 to 20 meters. To entice fish into shallow waters, they then spread their wings on the water's surface where they can easily catch them. When catching fish, the pelican's beak fills up with a lot of water, which causes it to tilt its head forward before swallowing the fish to spit out the extra. Pelicans have become skilled hunters as a result of their intelligent hunting behavior and tactics. [46]

Mathematical Model of the POA

The proposed POA, which is an algorithm based on populations (pelicans) in its population. where each pelican symbolizes a prospective solution. Conditional on their position in the search space, each member of the pelican proposes values for the variables in the optimization problem. On the basis of the problem's bottom bound and upper bound, fellows of the populace are primarily adjusted at random using equation (1).

$$x_{i,j} = l_j + rand \cdot (u_j - l_j), i = 1,2, \dots, N, j = 1,2, \dots, m \tag{25}$$

In this equation, N is the number of pelicans, m is the number of issue variables, rand is a random number in the series [0, 1], and $x_{i,j}$ is the value of the J_{th} variable signposted by the *ith* candidate solution. l_j is the J_{th} minor bound and u_j is the J_{th} major bound of problem variables.

To categorize the pelicans, the population matrix is built. Each row of this matrix epitomizes a prospective solution and the columns represent the suggested values for the problem variables. Each member of the population in the suggested POA is a pelican, which is a potential fix for the stated issue. The updated candidate of this matrix solutions based on the possible solution of the assessment of the objective function, simulates pelicans' behavior and tactics when attacking and hunting prey. Two stages of the hunting strategy are simulated: [38]

I. Stirring toward prey (exploration phase)

II. Speeding on water surface (exploitation phase)

Phase 1: Stirring toward prey (exploration phase)

A crucial element of POA is the random generation of the prey's location within the search space. As a result, POA is better able to analyze the world of problem-solving with greater precision. Equation (26) below illustrates the mathematical representation of the aforementioned ideas as well as the pelican's approach to its prey.

$$x_{i,j}^{P_1} = \begin{cases} x_{i,j} + rand \cdot (p_j - I \cdot x_{i,j}), & F_p < F_i; \\ x_{i,j} + rand \cdot (x_{i,j} - p_j), & else \end{cases} \tag{16}$$

Where, p_j is the location of prey in the j_{th} dimension, and F_p is its objective function value. $x_{i,j}^{P_1}$ is the new status of the i_{th} pelican in the j_{th} dimension based on phase 1, I is a random number which is equal to 1 or 2,

During this type of updating, also known as effective updating, the algorithm is prevented from moving to less-than-ideal locations. This process is simulated using Equation (27):

$$X_i = \begin{cases} X_i^{P_1}, F_i^{P_1} < F_i; \\ X_i, else, \end{cases} \tag{27}$$

Where, $X_i^{P_1}$ is the new status of the i_{th} pelican and $F_i^{P_1}$ is its objective function value based on phase 1.[46]

Phase 2: Speeding on the Water Surface (exploitation Phase)

The pelicans reach the water's surface in the second stage of feeding, spread their wings to high the fish uphill, and then exclusive it up in their neck pocket.

Modeling this behavior of pelicans leads to better locations in the hunting area for the proposed POA. This process increases POA's capacity for local search and exploitation.

Equation (28) uses mathematics to simulate the pelican's hunting behavior.

$$x_{i,j}^{P_2} = x_{i,j} + R \cdot \left(1 - \frac{t}{T}\right) \cdot (2 \cdot rand - 1) \cdot x_{i,j}, \tag{28}$$

Where, $x_{i,j}^{P_2}$ is the new status of the i_{th} pelican in the j_{th} dimension based on phase 2, R is a constant, which is equal to 0.2, $R \cdot \left(1 - \frac{t}{T}\right)$ is the neighborhood radius of $x_{i,j}$ while, t is the iteration counter, and T is the maximum number of iterations. [46]

The coefficient $R \cdot \left(1 - \frac{t}{T}\right)$ represents the area of the locality of the population members to search locally near each member to converge to a improved solution. This agrees us to test the area around each member of the population with smaller and more perfect steps, so that the POA can converge to solutions nearer to the global (and smooth exactly global) optimal based on the usage notion.

At this phase, operative updating has also been used to receive or discard the new pelican position, which is modeled in Equation (29).

$$X_i = \begin{cases} X_i^{P_2}, F_i^{P_2} < F_i; \\ X_i, \quad else, \end{cases} \tag{29}$$

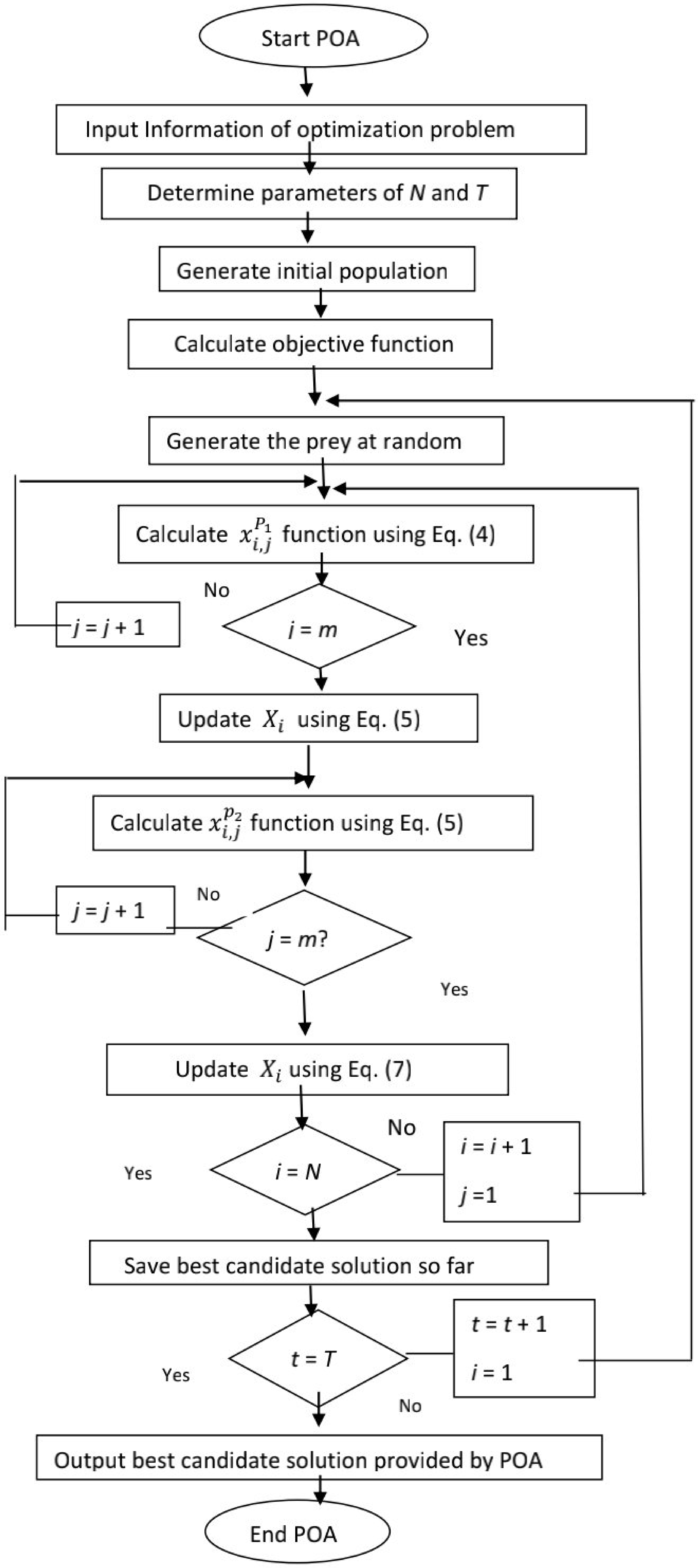

Fig. 3.7 Flowchart of Pelican Optimization algorithm

Table 3.2 Pseudo Code of POA

Algorithm: Pseudo-code of POA
Start POA *Input the optimization problem information* *Determine the POA population size (N) and the number of iterations* *Initialization of the position of pelicans and calculate the objective* *For t = 1:T*   *Generate the position of the prey at random*   *For I = 1:N*   *Phase 1: Moving towards prey (exploration phase)*   *For j = 1:m*   *Calculate new status of the jth dimension using*   *End*   *Update the ith population member using Equation (2)*   *Phase 2: Winging on the water surface (exploitation phase)*   *For j = 1:m*   *Calculate new status of the jth dimension using*   *End*   *Update the ith population member using Equation (4)*   *End*   *Update best candidate solution* *End* *Output best candidate solution obtained by POA* *End POA*

3.5.2 Improved Pelican Optimization Algorithm

The proposed algorithm described in this work initially follows the Pelican Optimization Algorithm's equations (1) through (3) but, in equation (4), a chaotic local search approach based on search strategy is presented to improve the performance of POA in obtaining the best solution. The factor $(2 \cdot rand - 1)$ in equation 4 instead of utilizing the $rand$ function which denotes random number, deploys a localized search. Natural nonlinear systems frequently experience chaos, and its ergodic property—specifically, its ability to traverse all states within a certain range without recurrence—is frequently used as an additional means of escaping from local optimums. The chebyshev map was employed to produce the chaotic sets.[47]

$$x(t+1) = \cos(t \cdot a\cos(x(t)) \tag{30}$$

$$G(t) = \frac{((x(t) + 1) \cdot chvalue)}{2}$$

(31)

The chaotic chebyshev map gives the following output:

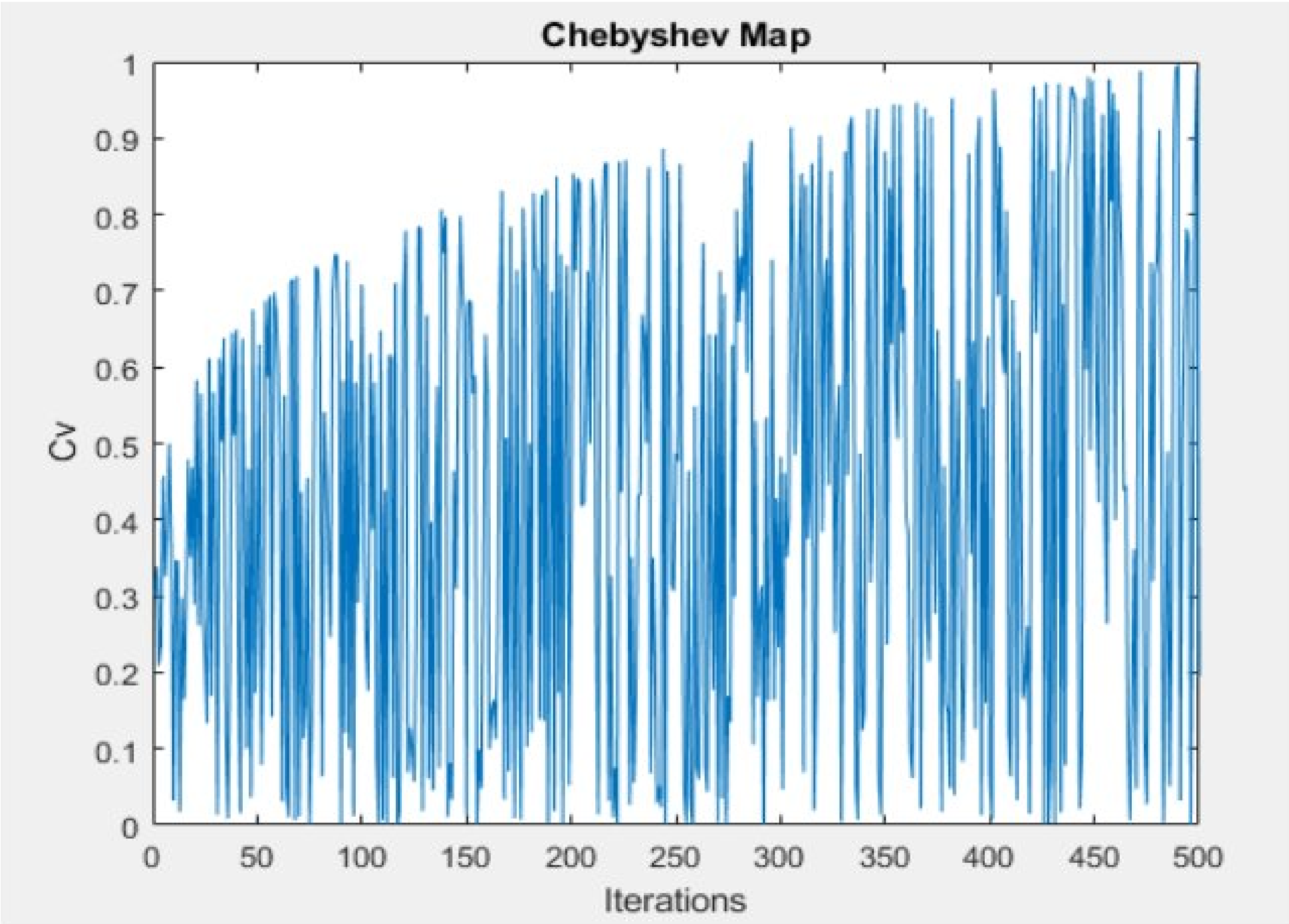

Fig. 3.8 Iterative Chebyshev chaos map

3.5.3 Dandelion Optimizer

The newest novel swarm intelligence bioinspired optimization algorithm is called the Dandelion Optimizer (DO), and it is used to solve continuous optimization issues. Three stages make up DO's simulation of the long-distance, wind-dependent flight of dandelion seeds.

When seeds are in the growing stage, waves from above cause them to rise spirally, or they can travel regionally in communities depending on weather conditions. Flying seeds regularly alter their direction in outer space as they drop during the descending stage. Seeds are placed in randomly assigned spots during the landing stage in order for them to grow. Here for the dandelion optimization algorithm, it is to referred to the flight of a seed during its descending and landing stages, correspondingly by mathematical functions.

Mathematical models of dandelion seeds are created from the rising stage, descending stage, and landing stage under various weather conditions in accordance with the characteristics of the long-distance flight of dandelion seeds. Two stages for this algorithm are:

I. Seed dispersal (exploration phase)
II. Selection (exploitation phase)

The proposed DO first presents the biological mechanism and motivation. Then, in accordance with the formulation of the mathematical model of DO, its expressions are produced. [48]

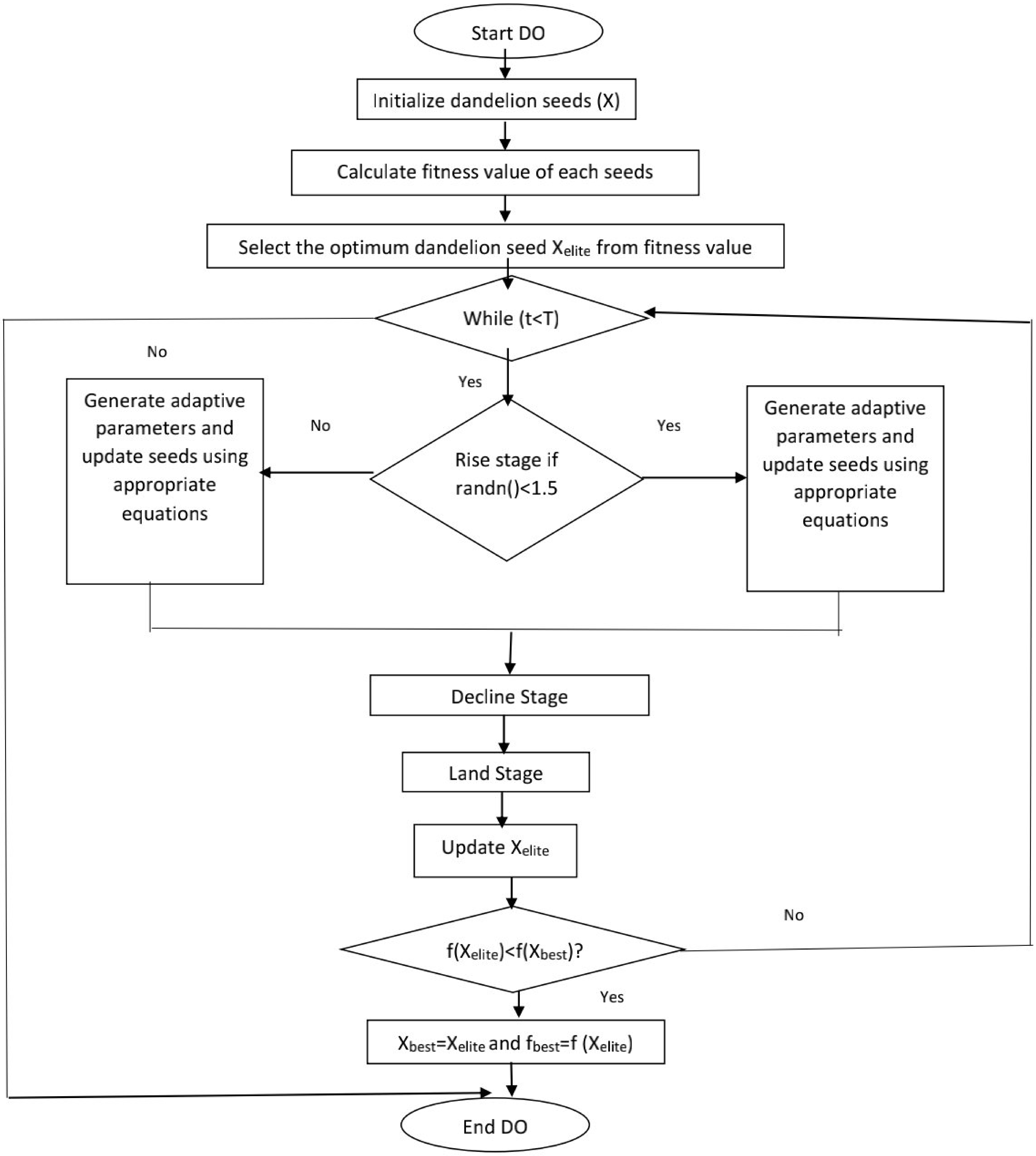

Fig. 3.9 Flowchart of Dandelion Optimization algorithm

Table 3.3 Pseudo Code of DO

Algorithm: Pseudo-code of DO

```
Start DO
Input the dandelion seeds X
Calculate fitness value f of each dandelion seeds
Select the Xelite according to fitness value
while (t<T) do
        if randn()<1.5
             Generate adaptive parameters using appropriate eq^n
              Update dandelion seeds using appropriate eq^n
        else if do
             Generate adaptive parameters using appropriate eq^n
              Update dandelion seeds using appropriate eq^n
        end
 Update dandelion seeds for decline stage
 Update dandelion seeds for land stage
Arrange dandelion seeds from good to bad
Update  Xelite
          if  f(Elite)<f(Xbest)
              Xbest=Xelite and fbest=f (Xelite)
          end
end
Return Xbest and fbest
End DO
```

Other optimization algorithms

The POA and DO are compared with some state of the art metaheuristic algorithms. These are as follows:

- Particle Swarm Optimization (PSO)[49]
- Equilibrium Optimizer (EO)[50]

CHAPTER 4
RESULT DISCUSSION AND ANALYSIS

4.1 Method of load flow analysis

There are various approaches to measuring parameters like power loss or voltage deviation in test bus systems, with or without the inclusion of DGs. Newton-Raphson and Backward-Forward methods are two of them that are taken into consideration. According to a number of previous studies in the area of load flow analysis of power systems, the Newton-Raphson method typically converges more quickly than the Backward-Forward method. Furthermore, the earlier method enables more accurate modeling and analysis of voltage control devices than the later method. Although, compared to the Backward-Forward Method, the Newton-Raphson method may exhibit a few minor issues with computational complexity and memory requirements

As a result, load flow analysis was performed on the two trial subject's bus systems using both the Backward-Forward Method and the Newton Raphson Method. In both cases, the former method provided us with improved outcomes than the latter one in terms of power loss and voltage deviation in the p.u. unit which can be observed in figure 4.1, 4.2 and 4.3. This led us to use the Newton Raphson's Tangent Based Method for the remaining portion of this research for load flow analysis.

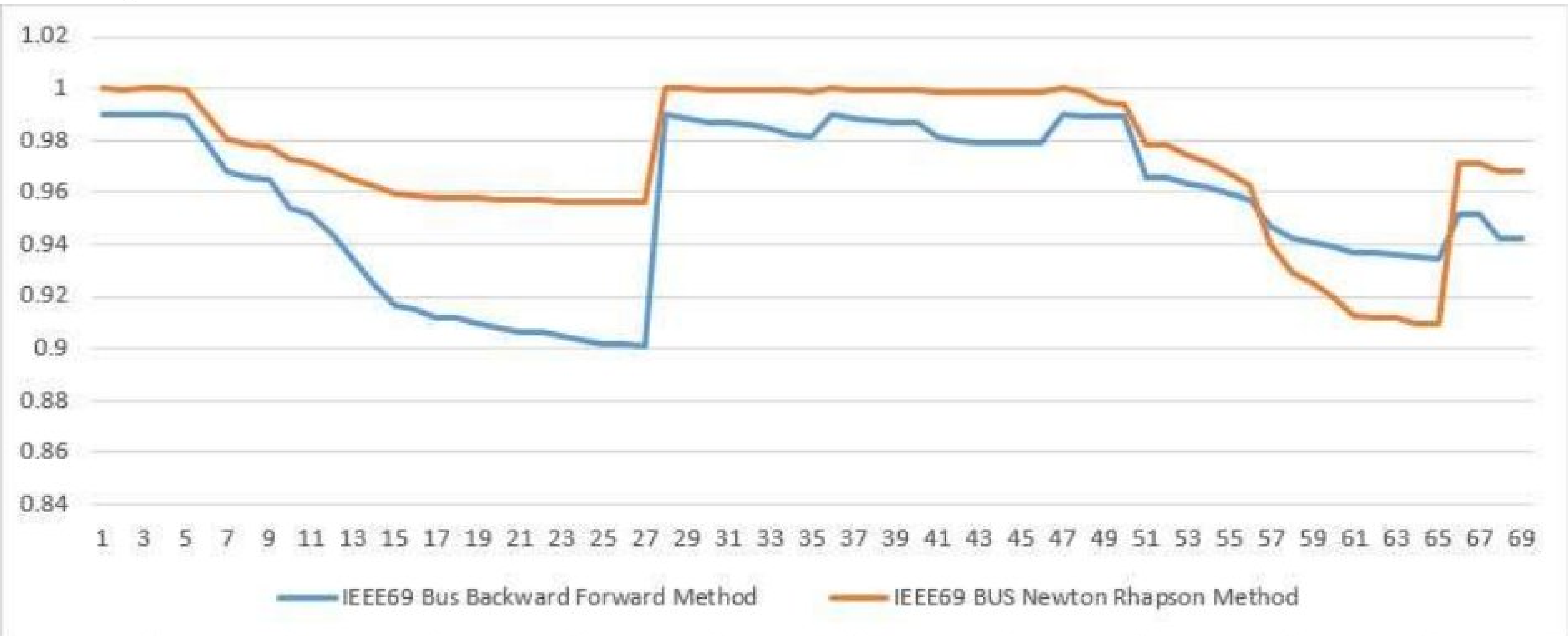

Figure 4.1 Voltage profile in p.u of IEEE 69 bus system without DG

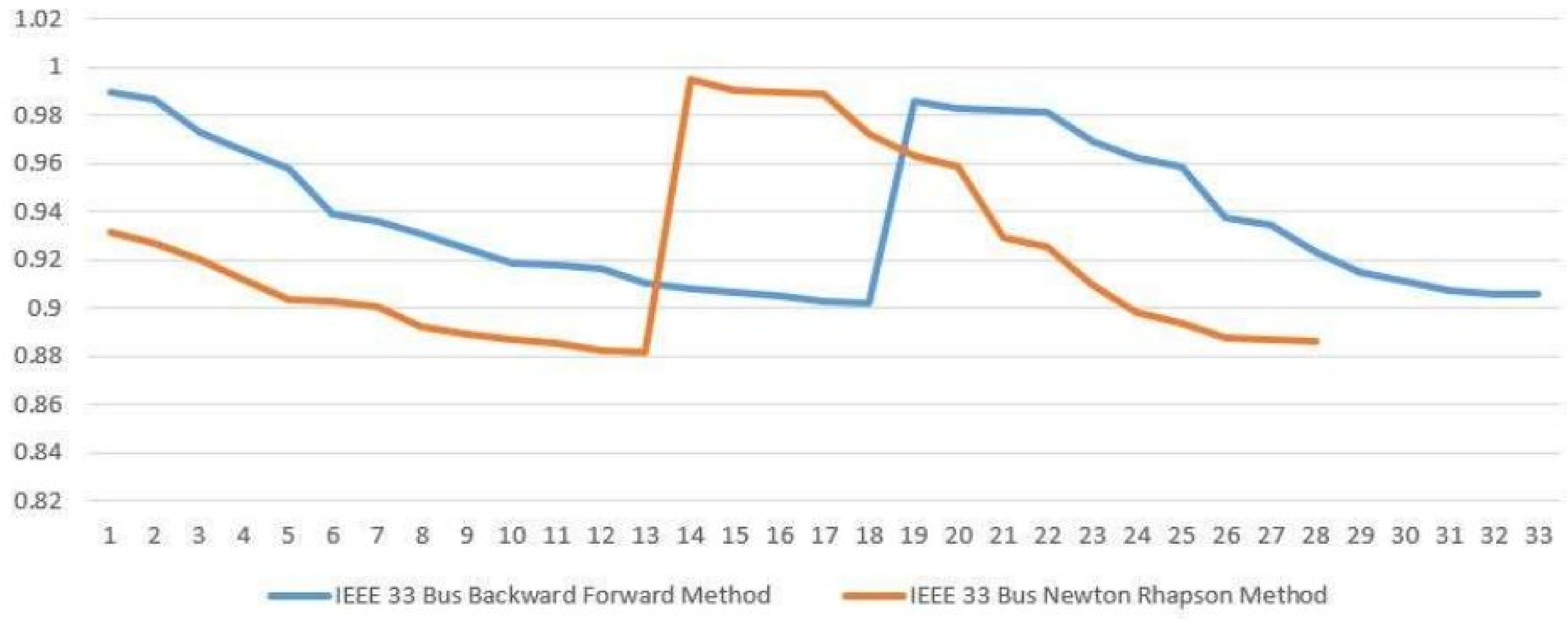

Figure 4.2 Voltage profile in p.u of IEEE 33 bus system without DG

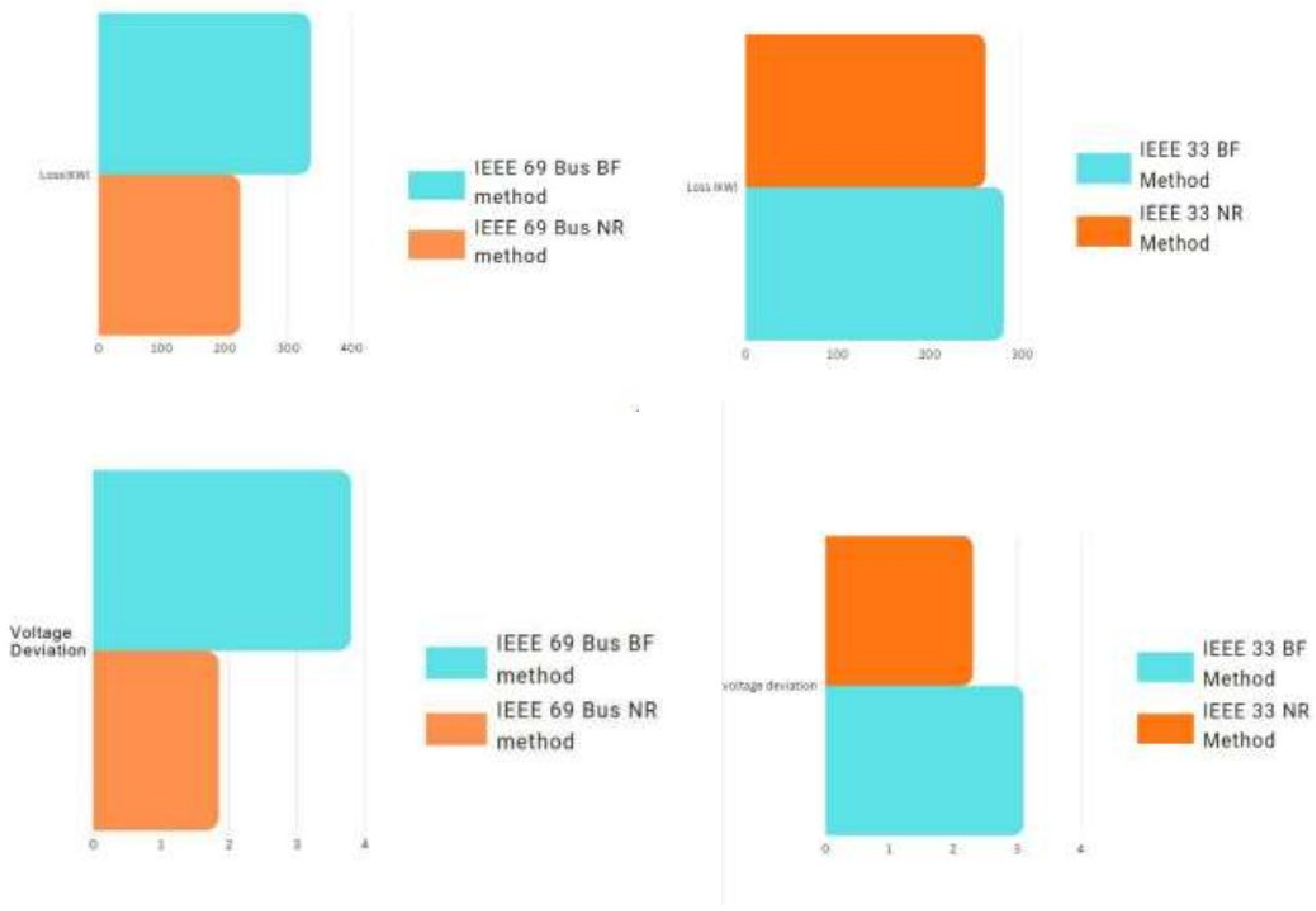

Figure 4.3 Power loss and voltage deviation of IEEE 69 and 33 bus system without DG

4.2 Comparison of algorithms after incorporating RDGs

In the IEEE 69 bus distribution system, Table 4.1 lists the RDG location, size, power loss, bus voltage deviation, and total simulation time for each of the four optimization algorithms: PSO, EO, POA, and DO. The Dandelion Optimizer (DO), when compared to all the other optimization algorithms, performed the best, as shown by the results analysis. When compared to the others, the DO performed significantly better. Voltage deviation and elapsed time both show a noticeable improvement. When compared to EO, PSO, and DO, the Pelican Optimization Algorithm is seen to perform better.

In the IEEE 33 bus distribution system, Table 4.2 lists the RDG location, size, power loss, bus voltage deviation, and total simulation time for each of the four optimization algorithms: PSO, EO, POA, and DO. The Pelican Optimization Algorithm performs better than all the other algorithms in this situation, with the exception of elapsed time, according to the results. Due to the larger search space in this instance, the elapsed time is higher. All other parameters work well for POA aside from that. In this thesis, Dandelion Optimizer comes in second place, significantly outperforming both PSO and EO.

We get two standout performers from the two tables: DO for the IEEE 69 bus distribution system and POA for the IEEE 33 bus distribution system. This gives us sufficient data to state with certainty that both DO and POA are advised for issues relating to RDG placement, and that performance may differ depending on the distribution system.

Table 4.1: IEEE 69 bus systems optimized results

IEEE 69 Bus System						
Cases of RDGs used	Optimization Algorithm	RDG Location	RDG Size (MVA)	Power Loss (KW)	Voltage Deviation	Elapsed time for 50 iterations
Wind Solar Bio	Particle Swarm Optimization	7 7 4	0.98 0.89 0.6	200	1.65	934 seconds
Wind Solar Bio	Dandelion Optimizer	69 68 5	0.6 1.4 0.1	180	1.10	791 seconds
Wind Solar Bio	Pelican Optimizer	4 21 5	0.4 0.3 0.1	190	1.5	1600 seconds
Wind Solar Bio	Equilibrium Optimizer	57 58 3	1.18 0.97 0.67	195	1.35	1400 seconds

Table 4.2: IEEE 33 bus systems optimized results

IEEE 33 Bus System						
Cases of RDGs used	Optimization Algorithm	RDG Location	RDG Size (MVA)	Power Loss (KW)	Voltage Deviation	Elapsed time for 50 iterations
Wind Solar Bio	Particle Swarm Optimization	11 11 4	0.36 0.43 0.67	175	1.7	494 seconds
Wind Solar Bio	Dandelion Optimizer	9 10 4	0.15 0.95 0.1	149	1.4	503 seconds
Wind Solar Bio	Pelican Optimizer	4 8 4	0.23 1.5 0.1	124	1.11	1000 seconds
Wind Solar Bio	Equilibrium Optimizer	5 22 4	0.16 1.3 0.10	200	2	440 seconds

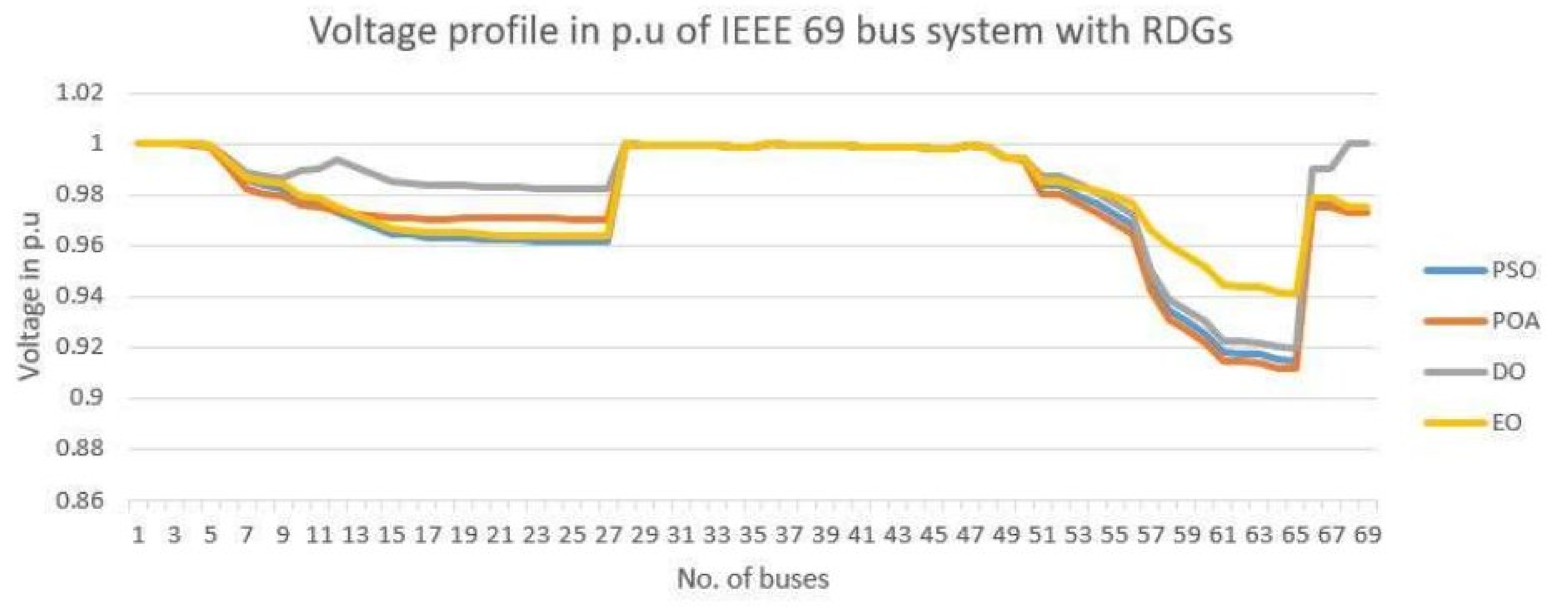

Fig 4.4 Voltage profile in p.u of IEEE 69 Bus Systems with RDGs for different algorithms

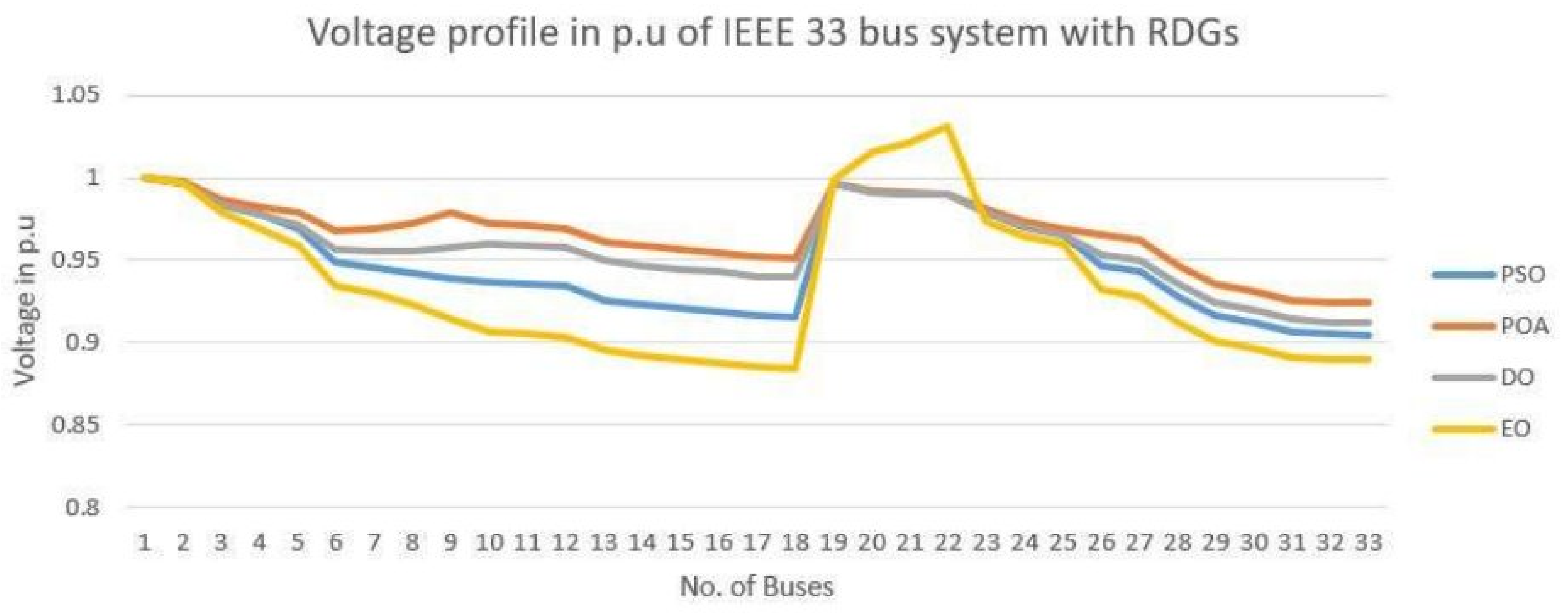

Fig 4.5 Voltage profile in p.u of IEEE 33 Bus Systems with RDGs for different algorithms

The voltage profile obtained in figure 4.4 shows the p.u. voltages of 69 buses in the distribution system after implementing PSO, EO, DO and POA. The profile shows that DO provide the highest voltage in the buses during the integration of DG units and thus, it is the best performer for this case.

Figure 4.5 shows the profile for IEEE 33 bus distribution system and the result that can be concluded here is that POA is the best performer overall for this case.

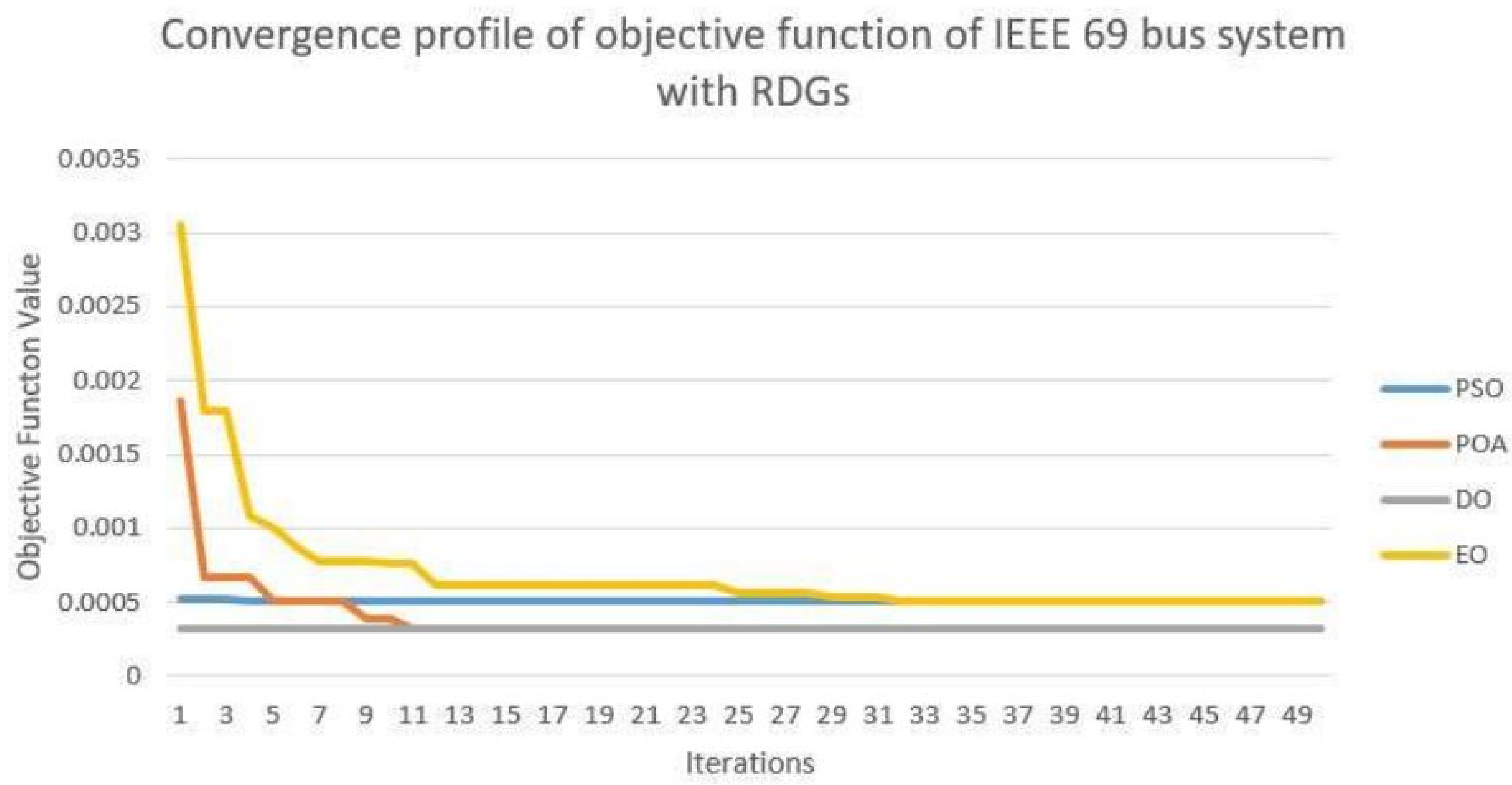

Fig 4.6 Convergence profile of objective function of IEEE 69 bus system with RDGs for different optimization algorithms

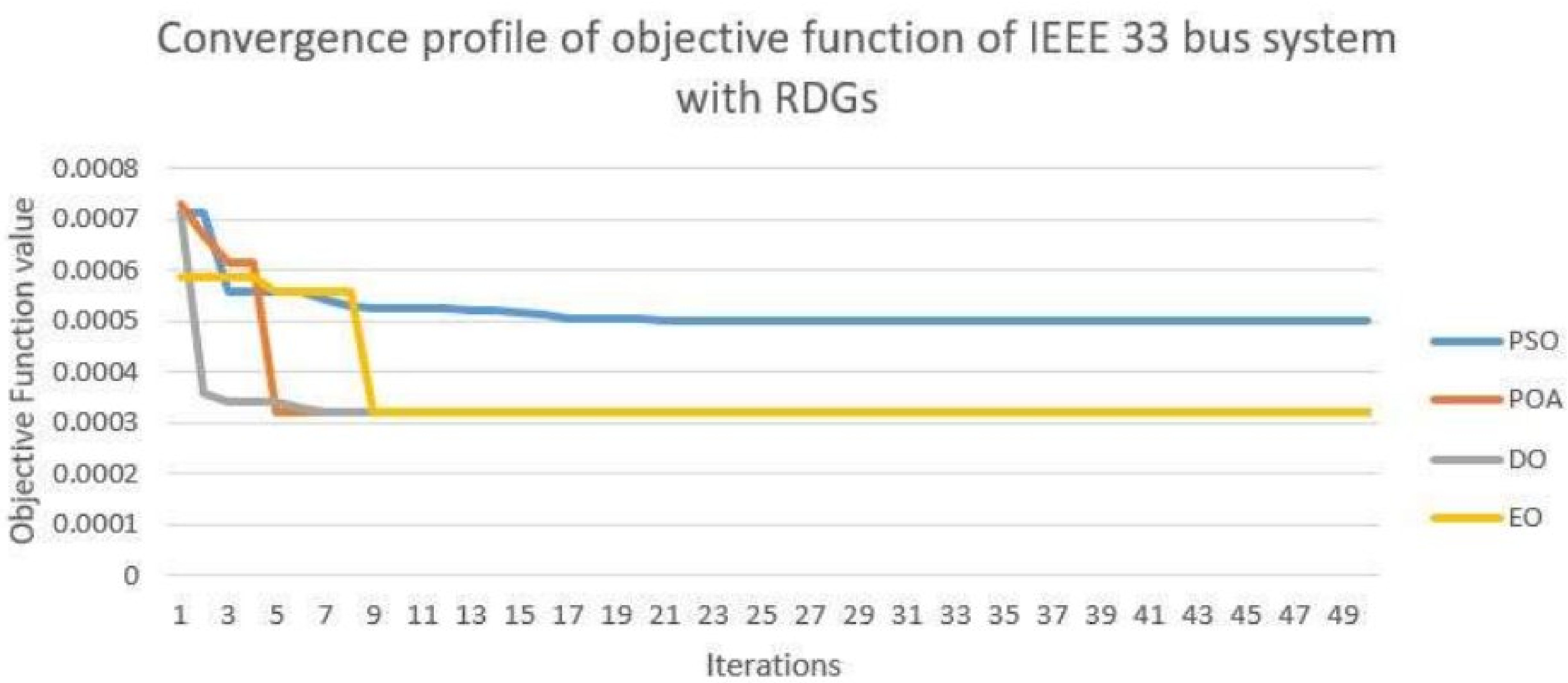

Fig 4.7 Convergence profile of objective function of IEEE 33 bus system with RDGs for different optimization algorithms

From figure 4.6 and 4.7 shows the convergence profile for the applied algorithms with respect to the fitness value. In IEEE 69 bus system, the DO converges the fastest with the least value of fitness function. Whereas, in IEEE 33 bus system, POA gives the lowest value of fitness function although, DO had the fastest convergence.

CHAPTER 5
CONCLUSION

5.1 Remarks:

This study suggests a novel method for determining the ideal size and location of RDGs in distribution networks. The idyllic dimension and site of DG were determined using two parameters. These include abating the inclusive active power loss and the complete bus voltage deviation. Pelican Optimization Algorithm (POA) and Dandelion Optimizer (DO), two recent metaheuristic optimization algorithms, were used to improve the results before being contrasted with Equilibrium Optimizer (EO) and Particle Swarm Optimization (PSO), two additional algorithms. All algorithms are outperformed by the POA and DO. It has been observed that DA occasionally performs slightly better than POA. Consequently, the suggested DO and POA may be used to choose the ideal RDG unit size and location in the distribution system.

5.2 Future Work Scope:

1) Instead of using IEEE test distribution systems, RDG units could be applied to existing distribution networks.

2) In addition, to the proposed function, a multi-objective function can be created by researching the economic implications of including RDG units.

3) Additionally, another project might involve installing an energy storage system for a continuous supply in the distribution system.

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