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Metaheuristic Method for a Wind-Integrated Distribution Network to Support Voltage Stabilisation Employing Electric Vehicle Loads

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Abstract: Distributed generation (DG) has been incorporated into the distribution networks and, despite the rising prevalence of electric vehicle (EV) loads that are uncertain and cause substantial challenges in their operation, it is necessary to enhance the voltage profile, reduce power losses, and consequently improve the stability of whole networks. The recently proposed beluga whale optimisation algorithm is explored in the optimisation framework to determine the most suitable size of wind turbine generating systems (WTGS), while the optimum placements are determined by minimising the placement index (P-Index) using the distribution load flow (DLF) method. The voltage stability factor (VSF) is employed to formulate the P-Index to enhance voltage sensitivity in distribution systems. The main purpose of this article is to assess the influence of voltage-dependent, uncertain ZIP-form EV loads in order to analyse their potential in the active and reactive power operations of the distribution network while retaining the system voltage within a specified limit by significantly reducing system losses and taking distribution network-level constraints into account. The efficacy of the methodology is validated on the standard IEEE-33 test system by formulating two performance indices to determine a significant enhancement in convergence characteristics and a reduction in system losses.

Keywords: distributed generations; electric vehicle; beluga whale optimisation; optimal location; wind turbine generating system

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Citation: Rehman, N.; Mufti, M.-U.D.; Gupta, N. Metaheuristic Method for a Wind-Integrated Distribution Network to Support Voltage Stabilisation Employing Electric Vehicle Loads. *Appl. Sci.* **2023**, *13*, 2254. https://doi.org/10.3390/app13042254

Academic Editor: Young-Kyu Han

Received: 25 December 2022
Revised: 4 February 2023
Accepted: 8 February 2023
Published: 9 February 2023

1. Introduction

1.1. Background

Distributed generation (DG) is becoming more prevalent as a result of decentralisation and the introduction of new renewable technologies. However, as renewable energy sources (RESs) become more common and are integrated into existing networks, the number of DGs connected to distribution networks has increased significantly. As a result, power systems have increasingly undergone a transformation between traditional networks with unidirectional power flows and active networks with bidirectional power flows, resulting in significant technical hurdles for distribution system operators (DSOs) [1]. The potential benefits of incorporating DGs have been explored in earlier studies [2,3]. A number of challenges must be taken into account in order to integrate DG power sources into distribution networks efficiently. These include reverse power flow, system frequency, protection design, voltage variations, and DG power generation uncertainty.

In addition, the growing numbers of electric vehicles (EVs) have also introduced a new integrative load to the power grid. EVs may dispatch reactive and real power via a bidirectional charger, enhancing the performance of the distribution grid [4]. Reactive power, which may offer auxiliary services, can reduce power losses and enhance voltage management. Even without batteries, EVs can respond to network demands quickly and locally and provide reactive power back into the grid [5]. Since the development of EV technology has coincided with an increased interest in analysing and investigating the effects of EVs on the electrical power system and the integration of RESs in the networks, this problem has drawn great attention from researchers. In brief, EV load analysis is essential to determine any impacts on the power system and evaluate the effect of EVs on active distribution networks. This data collection would allow for the upgrading of the power grid to be planned for in the near future.

Thus, the appropriate placement of DGs and the distribution of EV loads in the system are of utmost importance in distribution systems, and it is essential for a distribution system to utilise optimisation techniques to address the issue of distributed generation planning (DGP). To enhance the voltage profile and system stability of active distribution networks, a wide range of optimisation approaches and their combinations with analytical techniques have been devised.

1.2. Literature Review

Over the past few years, the significance of optimisation strategies has become considerably more apparent due to the rising challenges and complexities of DGP. To analyse the ambiguities in active distribution networks, previous research has employed a number of solution methodologies, including stochastic optimisation [6], Monte Carlo simulation [7], and probability statistical methods [8]. In addition, several methods of effective management, including reconfiguration of distribution networks, demand-side management, voltage profile improvement through reactive power compensation, and distributed energy storage technologies, have been implemented [9,10]. Analytical algorithms are simple and quick to implement and execute. However, their inferences are usually indicative, as they are based on implicit assumptions and the model of the system. Nonlinear programming and sequential optimisation approaches are among the most effective deterministic methods available for DGP [11]. The important feature of the deterministic investigation approaches is that they ensure the identification of the global optimum; however, they are inadequate for large, distributed systems, which is also a drawback of the nonlinear programming method. On the other hand, heuristic approaches are resilient and offer relatively close form solutions for large, complicated DGP challenges without requiring any model of the system [12].

Meta-heuristic algorithms are artificial intelligence frameworks specifically for the purpose of solving complex combinatorial optimisation problems in the real world [13,14]. To ensure optimum positioning and sizing for challenging objectives, which are usually problem-dependent and demand substantial versatility, researchers have adopted a wide variety of optimisation methodologies. Among them are the particle swarm optimisation (PSO), genetic algorithm (GA), artificial bee colony (ABC), and differential evolution (DE) algorithms, to mention a few. These strategies range from simple and basic approaches to comprehensive teaching and learning procedures. The objective of using GA in [15,16] is to determine the optimum position and appropriate size of DG units so as to minimise power losses. In [17], the objective function is to reduce the economic and technical constraints of the distribution network for DG employment. To achieve better voltage stability in the distribution system, a stability index [18] for sizing DGs has been developed to include DGs at appropriate locations. The authors in [19] have considered that DGs be planned through GA in order to decrease the cost of energy loss and improve system advancement. The effectiveness of optimum positioning of multi-DGs considering power losses and reliability on distribution networks adopting the DE methodology is explored in [20]. To minimise system loss, PSO in [21] is used to calculate a cumulative performance index that includes power loss reduction, loss voltage profile enhancement, and voltage stability index. Due to the unpredictable nature of RESs, the artificial hummingbird algorithm in [22] has been carried out to plan the distribution grid. The reactive power management strategy and DG arrangement in [23] have been optimised to reduce cost-related characteristics. Flower-pollination-based optimisation is used to characterise the DG placement aspect [24], with the purposes being to minimise net operating costs, maximise voltage profile performance, improve voltage stability, and minimise real power loss. Furthermore, in [25], a systematic strategy for long-term management is proposed to enhance the voltage stability and reliability of the system. Despite these limitations, meta-heuristic approaches are being explored by a growing number of researchers who are attempting to find the optimal combination of meta-heuristics and other methodologies [26,27].

Meta-heuristic techniques have also been employed to determine the optimum placement of EV charging stations by incorporating uncertainties in charging as well as in demand. The objective functions to be minimised comprise energy loss, voltage deviation of the power system network, and minimisation of resources to incorporate large-scale EV integration. In [28], the optimal placement of EV charging stations is determined in a radial distribution network by using DE and Harris Hawks optimisation methods, while, in [29], the reptile search method is employed to investigate the impacts of adding significant EV loads to active distribution networks. Techno-environmental variables are also included in a distribution system to identify appropriate DG and EV sites using a future search algorithm [30]. The effect of EV charging stations on the 33-bus and 85-bus test systems by minimising power loss and maintaining voltage level in the presence of EVs is discussed in [31]. There have also been a lot of studies regarding managing active and reactive power [32,33] in a smart distribution network with EVs, which has shown that EVs may be utilised to minimise congestion on the power grid [34] or provide auxiliary services, such as frequency management [35].

1.3. Motivation and Approach

The literature is limited in the diversity of strategies and challenges presented by researchers in ascertaining how all of the above-mentioned perturbations adversely affect the voltage stability of systems and their infrastructure. All approaches have advantages and disadvantages that are in accordance with the data and systems under consideration. In order to determine how all of these disturbances adversely affect the voltage stability of systems and their infrastructure, the literature has extensively explored the appropriate positioning and sizing of DGs within the framework of meta-heuristic optimisation algorithms.

In this study, we use a recently developed metaheuristic technique called beluga whale optimisation (BWO) [36] to overcome the challenging concerns involved in the strategic planning of active distribution networks. The BWO algorithm is inspired by the swimming, hunting, and falling (whale fall) behaviours of beluga whales. In the mathematical model of BWO, the characteristics of exploitation, exploration, and whale fall are developed, and the Levy flight function is employed in the exploitation phase to improve the adaptation capability of BWO. The primary objective of BWO is to create sophisticated search techniques that may provide comparatively higher solutions to complicated issues and to achieve the greatest possible results to simplify the resolution of challenging real-world scenarios. In addition to wind turbine generating system (WTGS) integration, optimal placement of EV loads is critical for maintaining a consistent voltage profile in the system. Thus, a placement index (P-Index) is formed considering the voltage stability factor (VSF) to plan and position EV loads in a radial distribution network that satisfy multiple operating characteristics, such as bus voltage limits and feeder current capacity, by restricting DG generation while significantly reducing overall losses.

1.4. Contribution

The exploring approach of BWO is carried out in distribution networks for appropriate sizing of DGs so that various forms of EV loads can be optimally incorporated into the active distribution systems to manage active and reactive power from the EV loads. To determine the superiority of BWO, first the locations of DGs are determined by analytical indices specified using the distribution load flow (DLF) method, then the appropriate sizing of DGs is optimised using BWO in consideration of the incorporation of EV loads. In addition to imposing additional EV load on the active distribution network, EVs also provide the reactive power required to maintain the stability of the network. The integration of various DGs and the proper sizing of EV loads at the appropriate distribution network buses improve the voltage profile and reduce overall losses in the system, which entails the reconfiguration of networks and raises capital expenditures. The main contribution of this work is summarised as follows:

- The incorporation of WTGS in an active distribution network in compliance with the uncertainty of EV loads is addressed.
- A new advanced strategic algorithm based on the behaviour of beluga whales has to be demonstrated to determine the scalability of DGs along with the ideal configuration of EV load units.
- An appropriate EV load distribution has to be determined based on the characteristics of EVs in active and reactive power operations in the distribution network.
- An illustration of the viability of EVs as a distributed source for the support of reactive power.
- The network is integrated with WTGS units and EV loads in such a way that the voltage profile is maintained and overall system losses are minimised, enhancing the stability and performance of the network.

1.5. Paper Organisation

This work is divided into several sections: Section 2 discusses wind power characteristics using mathematical modelling and Section 3 describes EV load characteristics. In Section 4, the problem formulation with an objective function is covered in detail and, in Section 5, the adopted optimisation algorithm is illustrated with mathematical modelling. The proposed methodology in the study is illustrated in Section 6. Results and discussions are presented in Section 7, and the conclusion is made in Section 8.

2. Wind Power Characterisation

Wind power is becoming more important in energy generation. In deregulated electrical networks, the distribution market will vary the most, rendering wind-generated power more expensive for commercial and residential users than industrial customers. Electric power generally flows from the substation to the ends of feeders in distribution networks throughout operation and planning. However, the incorporation of WTGS may result in reverse power flow in the distribution lines. There are various approaches for load flow using WTGS for distribution systems described in the literature. In this study, a matrix-based approach is used to integrate power output from WTGS into distribution systems [37]. Induction generators are explored as WTGS power conversion devices; they primarily function as variable-reactive power generators. For the reliable inclusion of wind energy into the grid, the impacts of wind power, which vary with wind speed, have to be analysed using appropriate models. The wind statistics of wind power are thoroughly illustrated in [38] and are derived as follows:

$$f(V_w) = \frac{k}{c}\left(\frac{V_w}{c}\right)^{k-1} \exp\left[-\left(\frac{V_w}{c}\right)^{k}\right] \tag{1}$$

where V_w represents wind speed, c is the scaling factor, and k is the shape parameter, which modifies the characteristics of the probability density function (PDF). The Weibull continuous PDF is defined as the Rayleigh PDF computed by Equation (2) for k = 2 and is the most commonly used distribution function for estimating wind speeds because it has intervals of low and strong wind speeds. The characteristic feature of such a PDF is the region between any two wind speeds, which represents the possibility that the wind is somewhere between those speeds. The Weibull PDF is the basic foundation for analysing wind speed statistics.

$$f(V_w) = \frac{2V_w}{c^2} \exp\left[-\left(\frac{V_w}{c}\right)^{2}\right] \tag{2}$$

Power output at any specified instant is estimated using the power curve for a specific model of wind turbine. As can be seen in Figure 1, the mechanical power produced by a wind turbine is directly proportional to the wind speed [38].

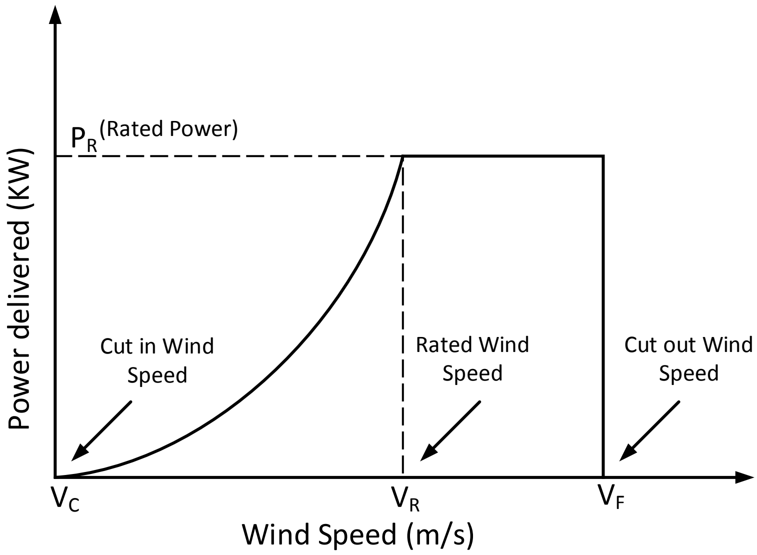

Figure 1. Wind speed power characteristics.

The wind turbine power curve given by the manufacturer is used to determine the active power output and the reactive power required is expressed based on the inverter ratings in this study as follows:

$$Q_w = \begin{cases} 0.3 * Q_{max}, & V_i \leq V_{min} \\ \theta_1 * (V_i - 1), & V_{min} < V_i \leq 1 \\ -\theta_2 * (1 - V_i), & 1 < V_i \leq V_{max} \\ -0.3 * Q_{max}, & V_i > V_{max} \end{cases} \quad (3)$$

where,

$$\theta_1 = \frac{Q_{max}}{V_{min}}, \quad \& \theta_2 = \frac{Q_{max}}{V_{max}}$$

Q_{max} is the maximum limit the inverter can support for reactive power. To account for voltage changes at the buses, the inverter's dynamic characteristics entail adjusting the slope gradients. The inverter is operable in four major zones. If the voltage exceeds the upper or lower limits, the inverter injects or absorbs 30% of Q_{max} in reactive power at the bus terminals. Consequently, the remaining two regions use the droop slope gradients (θ_1, θ_2) to evaluate the output corresponding to the Q_{max} set.

3. EV Load Characterisation

The diverse range of EVs involves a number of various approaches to modelling. In this study, voltage-dependent load (VDL) modelling is utilised to determine the active and reactive powers of the ZIP load model, a prominent form of EV load.

A thorough understanding of the battery profile is required for modelling the EV load for steady-state analysis. Batteries are linked to the distribution system through chargers fitted with two types of bidirectional converters known as AC–DC and DC–DC converters. The detailed analysis of the charger parameters is discussed in [39]. As seen in Figure 2, the grid voltage V_o and grid current I_o are given to the battery charger from the grid side, while the terminal voltage of the battery is V_B and I_B is the current absorbed by the battery. A standard layout of an on-board EV battery charger, which features two converters: an AC–DC converter and a DC–DC converter, is also illustrated in Figure 2 where the dynamic parameters of the battery describe the terminal voltage of the battery (V_B), while charging, the grid-side active (P_o) and reactive (Q_o) powers can be calculated using the following equations:

$$
\begin{aligned}
P_o &= V_o I_o cos\phi \\
Q_o &= V_o I_o sin\phi
\end{aligned}
\tag{4}
$$

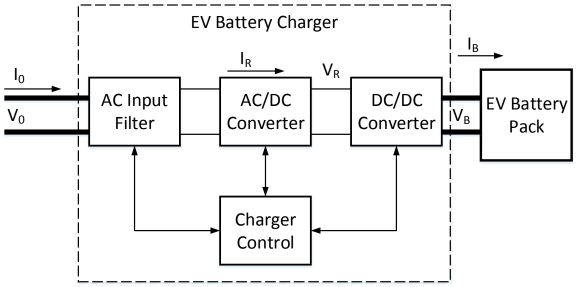

Figure 2. On-board EV battery charger.

The active and reactive powers utilised on the AC side are monitored at each state of charge (SOC) and voltage level, while a set of I_B and V_B values are acquired at various nominal voltage levels for a range of V_o (180 V to 230 V) and SOC (10% to 100%). These acquired values are analysed to evaluate the VDL characteristics of the EV at various levels of SOC. To ascertain the EV-ZIP values, a constrained least-squares approach is employed to generate a best-fit approximation to the monitored values. Finally, the best-fit ZIP values can be used in the ZIP equations shown below:

$$
\begin{aligned}
P_{ZIP} &= P_o\left[p_3\left(\frac{V_i}{V_o}\right)^2 + p_2\left(\frac{V_i}{V_o}\right) + p_1\right] \\
Q_{ZIP} &= Q_o\left[q_3\left(\frac{V_i}{V_o}\right)^2 + q_2\left(\frac{V_i}{V_o}\right) + q_1\right]
\end{aligned}
\tag{5}
$$

where P_o and Q_o are active load power and reactive load power acquired from Equation (4). V_i is the bus voltage at which load is connected and V_o is the nominal rated voltage. p_3, p_2, and p_1 are the constant impedance, constant current, and constant power parameters of the active fraction of the EV load. q_3, q_2, and q_1 are the constant impedance, constant current, and constant power parameters of the reactive fraction of the EV load. The values of these various active and reactive parameters of Equation (5) are detailed in [29].

EVs are substantial loads comparable to all other residential loads; thus, if they do not encourage and sustain the stability of the grid, the DSO will have to acquire additional units to assure power quality, which will raise the cost to customers. Consequently, the converters employed in battery chargers enable the active and reactive power regulation of the EV, allowing it to be used in the operation of the distribution network. The parking lots and parking spots of apartment buildings have access to a distribution network that can supply the necessary energy consumption of EV batteries. As illustrated in Figure 3, the charger must be operated in both charging and capacitive modes if the distribution network demands reactive power while the EV is in charging mode. Consequently, the distribution network provides active power to accommodate EV loads, while EVs introduce reactive power to support the network's reactive requirements [40,41].

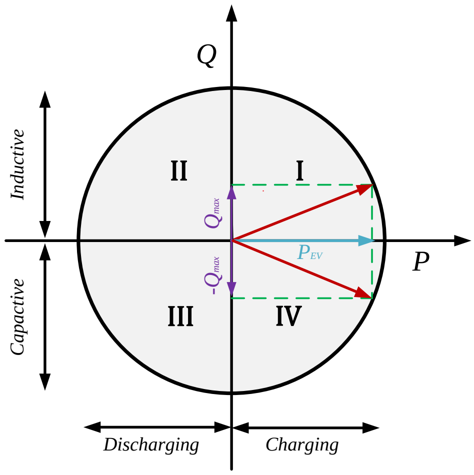

Figure 3. EV charging/discharging quadrants.

4. Problem Formulation

The literature findings demonstrate that proper placement, strategic planning, and the appropriate sizing of DGs in accordance with the distribution of appropriate scaling EV loads in the distribution system are some of the useful assertions to improve system performance and effectiveness. EVs are substantial loads comparable to other household loads; therefore, if they do not support maintaining the stability of the grid, the DSO will have to acquire additional units to assure power quality, which will raise the cost to customers. Therefore, we adopt an approach for multi-objective optimisation issues subject to a number of restrictions. In the sizing of DGs, the most voltage-sensitive bus in the network is considered for the proper placement and appropriate sizing of DGs to form a P-Index as an objective function given in Equation (8), and a few other operational variables such as the bus voltage profile and the current capacity of lines are included as constraints while significantly reducing overall losses. For EV load management, the buses with the highest bus voltages are selected as locations while attempting to maintain the corresponding P-Index at a minimum. Thus, the objective function for scaling EV loads is formulated for the voltage profile given in Equation (9). The primary objective of this study is to explore how uncertain EVs affect the control of active and reactive power in distribution networks. For the sake of convenience, many other sources, like capacitor banks and some other power elements, are ignored.

4.1. Placement Index

The P-Index employed in this research for evaluating the optimal position of appropriately sized DG is framed by stabilising the VSF index while significantly reducing power losses in the network. Buses with a higher-than-average P-Index are given options regarding DG installation.

$$P - Index = \frac{1}{\text{VSF}} \tag{6}$$

The VSF index is developed in order to determine which bus in a network segment is most sensitive to voltage fluctuations [42]. Buses with a low VSF are more likely to encounter a collapse in voltage. The VSF index for the n_{th} bus can be determined as follows [43]:

$$\text{VSF}_n = |V_m|^4 - 4\{P_n \times X_{mn} - Q_n \times R_{mn}\}^2 - 4\{P_n \times R_{mn} + Q_n \times X_{mn}\}^2|V_n|^2 \tag{7}$$

where m represents the sending end bus and n represents the receiving end bus. The sending end bus voltage is V_m and the receiving end bus voltage is V_n. The branch resistance and reactance for buses m to n are represented by R_{mn} and X_{mn}, respectively. The active and reactive loads at receiving end buses are represented by P_n and Q_n, respectively. The buses with the lowest voltage stability index are viewed as an alternative for an appropriate location for DG integration in order to retain the voltage stability of the system.

4.2. Objective Function

In this part of the article, we explore the objective function variables and their constraints in order to carry out a comprehensive evaluation of the various issues used in the conceptualisation of the problem. In identifying the best position, arrangement, and performance of EV loads in both active and passive distribution network situations, the significance of the objective function and constraints is raised in full accordance with the complexity of the system.

- For sizing of WTGS

$$Obj.Fun1 = \min \sum_{i=1}^{nbus} P - Index(i) \tag{8}$$

- For sizing of EV loads

$$Obj.Fun2 = \max \left[\sum_{i=1}^{nbus} (V_i - V_r)^2 \right] \tag{9}$$

where, V_i is voltage at bus i and V_r is rated voltage.

4.3. Constraints

The primary purpose of this study is to ensure that the voltage profile of the network is upheld by the optimisation algorithm while adhering to the constraints imposed by loadflow to keep bus voltages within $+/-5\%$ PU. Furthermore, as general constraints within min and max limitations are established as the optimisation algorithm's lower and upper bounds, the total active and reactive powers offered into the network from both WTGS and EV loads are taken into account.

- Voltage constraint: The voltage at each bus should be limited within minimum and maximum limits.

$$0.95p.u \leq V_i \leq 1.05p.u$$

- DG power generation constraints: The minimum capacity of DG is set as 10 KW and maximum at 2.5 MW.

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

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

- EV power constraints: The EV load capacity is constrained by the resources at certain locations. Thus, limiting EV load capacities is required.

$$0 \leq P_{gev} \leq P_{gev}^{max}$$

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

5. Optimisation Algorithm

The BWO algorithm has been recently developed in [36] and draws its inspiration from the behaviour of beluga whales. The mathematical model of BWO reflects three phases: the swim phase corresponding to exploration, the prey phase corresponding to the exploitive phase, and the whale falls. In addition, the Levy flight function is used during the exploitation stage to enhance BWO's convergence. The following are mathematical representations of these stages that show how the stated BWO algorithm works and how to optimise both complex and basic problems with stated constraints.

5.1. Mathematical Modelling of Algorithm

During the process of optimisation, each beluga whale is considered a possible candidate and carries an update. The belugas are moved from the exploration stage to the exploitation stage by a balance factor in the BWO algorithm. This beluga transformation operation is modelled as follows:

$$B_f = B_0(1 - N/2N_{\max}) = \begin{cases} > 0.5, & \text{exploration stage} \\ \leq 0.5, & \text{exploitation stage} \end{cases} \quad (10)$$

where N_{max} is the highest iterative value of the current iteration (N). At each iteration, B_0 varies at random between the two values, 0 and 1. As the number of iterations (N) increases, the variation in B_f is significantly reduced in the range of values from (0, 1) to (0, 0.5), while the probability of the exploitation phase impacts directly on the variations in N.

5.1.1. Exploration Phase

The swimming behaviour of beluga whales is analysed during the formulation of the exploration stage of BWO. The positions of the beluga whales are defined by their pair swim and these positions are upgraded in the following way:

$$\begin{cases} Y_{i,j}^{N+1} = Y_{i,p_j}^{N} + \left(Y_{r,p_1}^{N} - Y_{i,p_j}^{N}\right)(1 + r_1)\sin(2\pi r_2), & j = \text{ even} \\ Y_{i,j}^{N+1} = Y_{i,p_j}^{N} + \left(Y_{r,p_1}^{N} - Y_{i,p_j}^{N}\right)(1 + r_1)\cos(2\pi r_2), & j = \text{ odd} \end{cases} \quad (11)$$

where $Y_{i,j}^{N}$ is the updated location of i_{th} beluga in the J_{th} dimension and Y_{i,p_j}^{N} is the new current location of i_{th} beluga at P_j position. Y_{r,p_1}^{N} is the updated current location of the r_{th} beluga. P_j is a random number from the j_{th} set. Random numbers r_1 and r_2 are between 0 and 1.

5.1.2. Exploitation Phase

During the exploitative phase of BWO, the Levy flight (L_F) technique is used to improve convergence in the hopes of catching prey with Levy flight planning. The corresponding mathematical modelling of the exploitation process employing Levy flight is as follows:

$$Y_i^{N+1} = r_3 Y_{\text{best}}^{N} - r_4 Y_i^{N} + C_1 \cdot L_F \cdot \left(Y_r^{N} - Y_i^{N}\right) \quad (12)$$

where Y_i^N and Y_r^N represent the current locations of the i_{th} and random beluga whales, respectively, and Y_{best}^N is the best location among them. $C_1 = 2r_4(1 - N/N_{\max})$ measures the intensity of Levy's flight by evaluating the randomisation of its jumps.

5.1.3. Whale Fall

The mathematical expression for the whale fall stage of the algorithm is illustrated as follows:

$$Y_i^{N+1} = r_5 Y_i^N - r_6 Y_r^N + r_7 Y_{step} \quad (13)$$

where r_5, r_6, and r_7 are three random numbers between 0 and 1. The overview of the processes executing in the proposed optimisation algorithm is illustrated in pseudo-code format in the algorithm represented in Figure 4.

Input *Algorithm parameters (population size, maximum iteration*
Output *The best solution*
Initialize the population and evaluate the fitness values, obtain the best solution (P^*)
while N $\leq N_{max}$ **Do**
Obtain probability of whale fall W_f and balance factor B_f by Eq. (10)
For each beluga whale (Y_i) **Do**
If $B_f(i) > 0.5$
% % In the exploration phase
Generate P_j(j=1,2,...,l) randomly from dimension
Choose a beluga whale Y_r randomly
Update new position of i_{th} beluga whale using Eq. (11)
Else if $B_f(i) \leq 0.5$
% % In the exploitation phase
Update the random jump strength C_1 and calculate the levy flight function
Update new position of i_{th} beluga whale using Eq. (12)
End If
Check the boundaries of new positions and evaluate the fitness values
End for
For each beluga whale (Y_i) **Do**
% % In the whale fall phase
If $B_f(i) \leq W_f$
Update the step factor C_2
Calculate the step size Y_{step}
Update new position of i_{th} beluga whale using Eq. (13)
Check the boundaries of new positions and evaluate the fitness values
End If
End for
Find the current best solution (P^*)
N= N+1
End while
output the best solution

Figure 4. Pseudo-code of BWO algorithm.

6. Methodology for the Proposed Approach

In this study, the BWO methodology has been used to determine the appropriate size of DGs, and strategic planning as well as scaling of EV loads are performed in the distribution networks. The step-by-step procedure of approach in the statement of the problem is outlined as follows:

- The bus data and line data of the test systems are initialised.
- Bus injections to branch currents and branch current to bus voltage matrices are formed to obtain the DLF method.
- The P-Index is formulated using Equation (6), by estimating VSF at all buses given in Equation (7).
- To determine the most suitable place for DGs and their appropriate size, the BWO is used, which utilises the P-Index as an objective function.
- The size of WTGS as DGs to be connected are decided as candidates for the initialisation of BWO.
  - The collection of candidates produces the search agents that explore the search space by updating their position vectors using Equation (11). The model for the matrix is framed by minimum and maximum DG size for the first phase of optimisation.
  - The sizing (candidate solutions) are employed at specified buses to determine appropriate sizing.
  - The best solutions are identified, depending upon the intricacy of the approach.
- The WTGS as DGs are installed at the determined buses to enhance the voltage stability of the system.
- The bus data and line data of the system are updated for the incorporation of EV loads.

- The EV loads are modelled as ZIP loads and are placed on high-voltage buses to ensure the voltage stability of the system. The BWO algorithm is used to restrict the charging and discharging modes of EVs, utilising the voltage deviation at buses as an objective function.
- The EV loads are integrated at best candidate solutions.
- After the participation of EV loads, the bus and line data of the integrated system are updated to assess the voltage profile and losses of the system.

7. Results and Discussion

An IEEE-33 test bus system is used to validate the performance and scalability of the presented BWO algorithm and the outcomes are then compared to the standard PSO approach. The DLF method is primarily applied to a test bus system to determine unstable buses by evaluating voltage limit breaches in line with the voltage stability indices derived analytically using Equation (7). The P-Index is formulated using Equation (6), considering the VSF index, demonstrating weak buses as given in Table 1. The scalability of DGs is optimised using the objective function by minimising Equation (8) to integrate appropriate-sized DGs at buses determined using Equation (6). When WTGS-DGs are added to the system, the voltage profile improves, as seen graphically in Figure 5. Incorporating appropriately sized WTGS-DGs enhances the P-Index for all buses and stabilises the VSF, as illustrated in Figures 6 and 7, respectively.

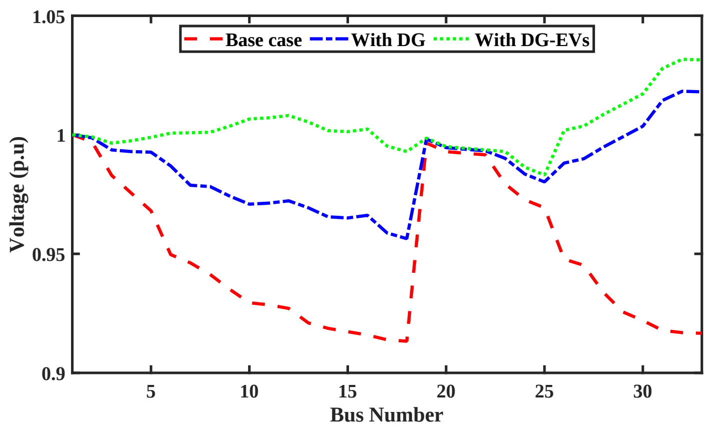

Figure 5. Voltage profile of modified test system.

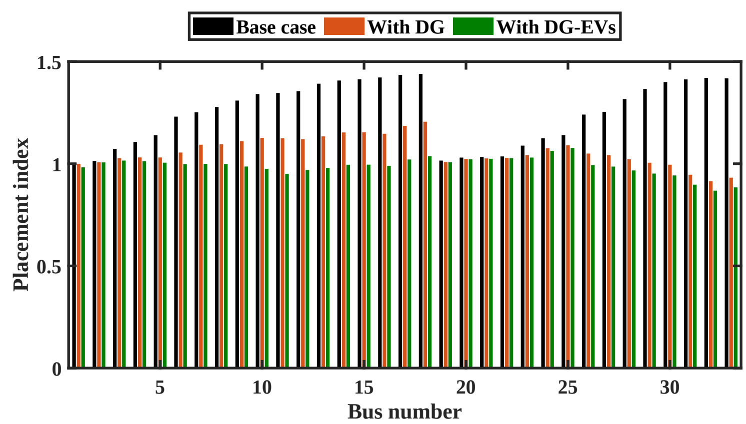

Figure 6. P-indexes at 33 buses of modified test system.

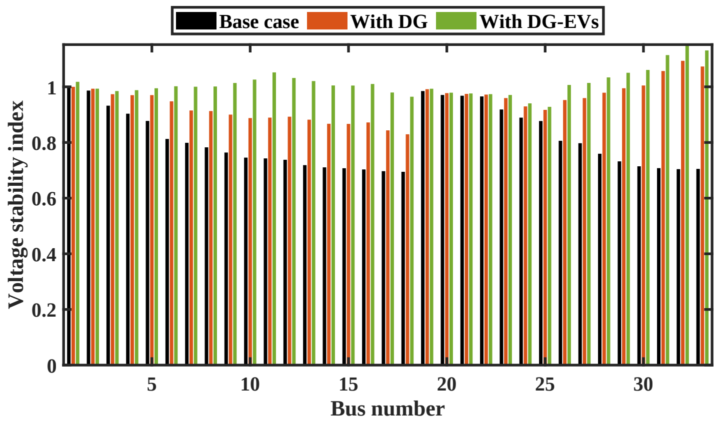

Figure 7. Voltage stability factors at 33 buses of modified test system.

The BWO approach is then used to optimise the number of EV load capacities such that the enhanced voltage at buses stays within the permissible range by incorporating additional EV loads with minimal impact on active power losses. The preferred position and appropriate size of EV loads are optimised using quadrant operation of EV charging, and the implications are graphically displayed in Figures 5–7 for voltage profile, P-Index, and VSF, respectively. The voltage profile is further improved despite the addition of EV loads, as shown in Figure 5, because EV loads not only add demand to the network but also provide reactive power to maintain network voltage stability. In summary, the network voltage profile is the highest possible in this scenario and the system loss rate is the lowest possible. Table 1 outlines all the voltage level profiles in p.u. and VSF values for all of the buses for three distinct scenarios following WTGS-DG as well as the EV load.

Table 1. Data estimated on IEEE-33 test buses with and without DGs and EV loads.

	Voltage (p.u.)			VSF (Index Value)		
Bus Number	**Base Case**	**With DG**	**With DG and EV Loads**	**Base Case**	**With DG**	**With DG and EV Loads**
1	1	1	1	1	1	1.018
2	0.997	0.9987	0.9991	0.9866	0.9932	0.9933
3	0.9829	0.9936	0.9965	0.9322	0.9735	0.9847
4	0.9755	0.9929	0.9975	0.9034	0.97	0.9879
5	0.9681	0.9927	0.9989	0.8774	0.9702	0.9948
6	0.9497	0.9869	1.0007	0.8127	0.9479	1.002
7	0.9462	0.9788	1.0008	0.7988	0.915	1.0004
8	0.9414	0.9783	1.0011	0.7826	0.913	1.0012
9	0.9351	0.9742	1.0036	0.7639	0.9002	1.0138
10	0.9294	0.9709	1.0066	0.7456	0.8877	1.026
11	0.9286	0.9713	1.0071	0.7428	0.8893	1.0518
12	0.9271	0.9723	1.0081	0.7379	0.8927	1.0318
13	0.921	0.9693	1.0054	0.7186	0.8819	1.0207
14	0.9187	0.9655	1.0017	0.7106	0.8672	1.0049
15	0.9173	0.9651	1.0013	0.7074	0.8668	1.0046
16	0.9159	0.9662	1.0024	0.7031	0.872	1.0102
17	0.9139	0.9588	0.9953	0.6969	0.8435	0.9796
18	0.9133	0.9564	0.993	0.6946	0.8295	0.9644
19	0.9965	0.9982	0.9986	0.9848	0.9914	0.9931
20	0.9929	0.9946	0.995	0.9707	0.9773	0.9789
21	0.9922	0.9939	0.9943	0.968	0.9745	0.9762
22	0.9916	0.9933	0.9937	0.9655	0.9721	0.9737
23	0.9794	0.9901	0.993	0.9186	0.9596	0.9707

Table 1. *Cont.*

Bus Number	Voltage (p.u.) Base Case	With DG	With DG and EV Loads	VSF (Index Value) Base Case	With DG	With DG and EV Loads
24	0.9727	0.9835	0.9864	0.8893	0.9296	0.9405
25	0.9694	0.9802	0.9831	0.8771	0.9172	0.9281
26	0.9478	0.9881	1.0019	0.8061	0.9525	1.0067
27	0.9452	0.9899	1.0037	0.7974	0.9595	1.014
28	0.9338	0.9949	1.0086	0.7595	0.9788	1.0339
29	0.9255	0.9992	1.0129	0.7321	0.9949	1.0505
30	0.922	1.0036	1.0172	0.7144	1.0048	1.0607
31	0.9178	1.0144	1.0279	0.7078	1.0568	1.114
32	0.9169	1.0183	1.0317	0.7042	1.0934	1.1516
33	0.9166	1.018	1.0315	0.7051	1.0731	1.1308

7.1. Relative Comparison of BWO with Conventional PSO

The implemented BWO method has been compared with conventional PSO to assess its performance. The voltage profile of the IEEE-33 test bus after the integration of WTGS-DGs as well as EV loads is graphically shown in Figure 8. Moreover, Table 2 illustrates the comparison between the determined DG and EV load locations and their appropriate sizes using BWO and PSO. It is apparent that the presented methodology works comparatively more effectively than conventional techniques by stabilising bus voltages at weak locations in a distribution system, as shown in Figure 9, which eventually leads to a higher rate of efficiency. In conclusion, this method achieves the best network voltage profile with the fewest system losses.

Table 2. Comparison of BWO with PSO.

		BWO				PSO			
DG locations (Bus Nos)		16	17	18	32	16	17	18	32
DG size	P (Mw)	0.9425	0.6812	0.01	2.5	0.3108	1.1555	0.01	2.5
	Q (Mvar)	−0.4975	−0.4975	−0.4975	−0.0289	0.0455	0.0559	0.055	0.0549
EV locations (Bus Nos)		1	1	2	11	1	1	21	33
EV load size	P (Mw)	0	0.5082	0.0651	0.6629	1.9445	3.0799	2.0022	0.113
	Q (Mvar)	0	−1.694	0.0701	−2.2097	−2.0711	0.5229	−1.5308	−0.3767

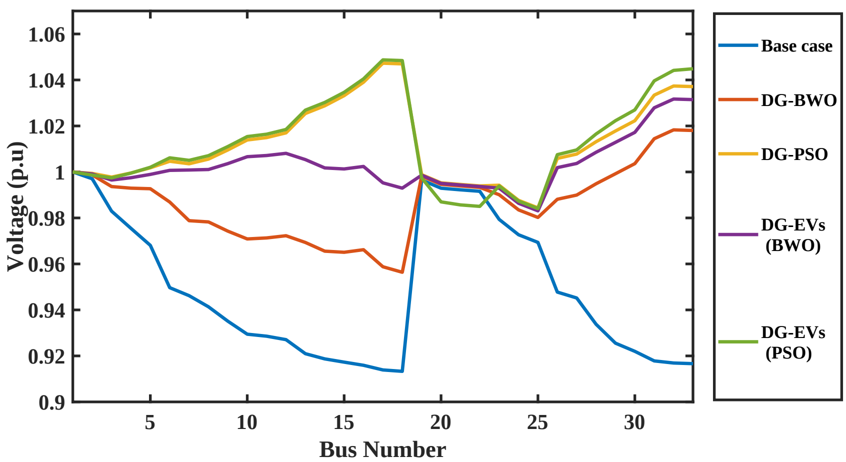

Figure 8. Voltage profile of modified test system using BWO and PSO.

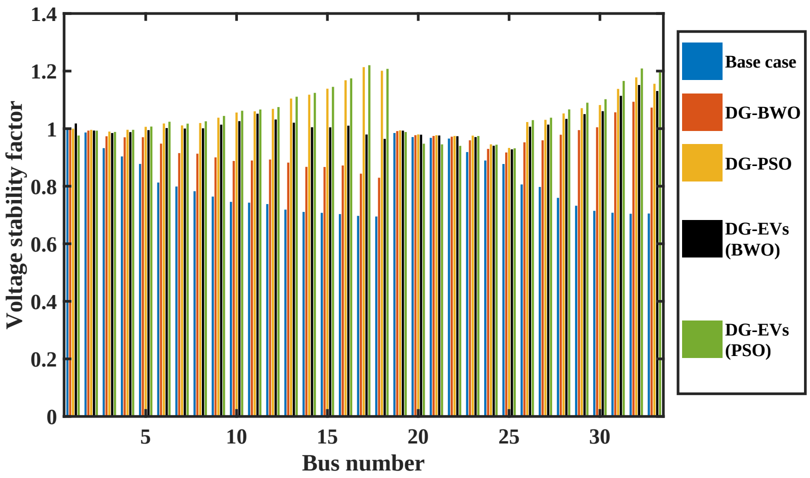

Figure 9. Voltage stability factors at 33 buses of modified test system using BWO and PSO.

7.2. Performance Indices

To evaluate the performance of the presented methodology scheme, two customised performance indices (η & ξ) based on the integral square error of the voltages (ISE) and the integral absolute error (IAE) of the voltages at different buses were calculated, both of which are used to quantify the performance of the proposed scheme. The higher the values of the ISE and IAE, the poorer the performance, and vice versa [44]. Mathematically, the performance indices ISE and IAE are given by Equations (20) and (21), respectively:

$$\eta = \sum_{n=1}^{4} (V_{nom} - V_n)^2 \tag{14}$$

$$\xi = \sum_{n=1}^{4} |V_{nom} - V_n| \tag{15}$$

where V_{nom} represents the nominal bus voltage, $n = n^{th}$ DG unit, and V_n represents the voltage of the n^{th} DG connected bus.

To demonstrate the superiority of the proposed method, the following scenarios are used: base case (without DG and EV loads), WTGS-DG incorporated, and with both WTGS-DG and EV loads. In Table 3, the determined values for all three scenarios applying ISE and IAE are presented in tabular format.

Table 3. Performance comparison of indices.

	ISE					IAE				
	η_1	η_2	η_3	η_4	η	ξ_1	ξ_2	ξ_3	ξ_4	ξ
Base Case	0.0071	0.0074	0.0075	0.0069	**0.0289**	0.0841	0.0861	0.0867	0.0831	**0.3400**
With DG	0.0011	0.0017	0.0019	0.0003	**0.0051**	0.0338	0.0412	0.0436	0.0183	**0.137**
With DG and EV loads	0	0	0.0078 (* 10^{-4})	0.5099 (* 10^{-4})	**0.5177** (* 10^{-4})	0	0	0.0009	0.0071	**0.008**

The effectiveness of the proposed methodology is further validated and highlighted by graphical representations of these two performance indices for each of the three scenarios obtained by employing both BWO and PSO. The IAE and ISE for all three scenarios obtained by using BWO are less than the values obtained using PSO, as shown in Figures 10 and 11.

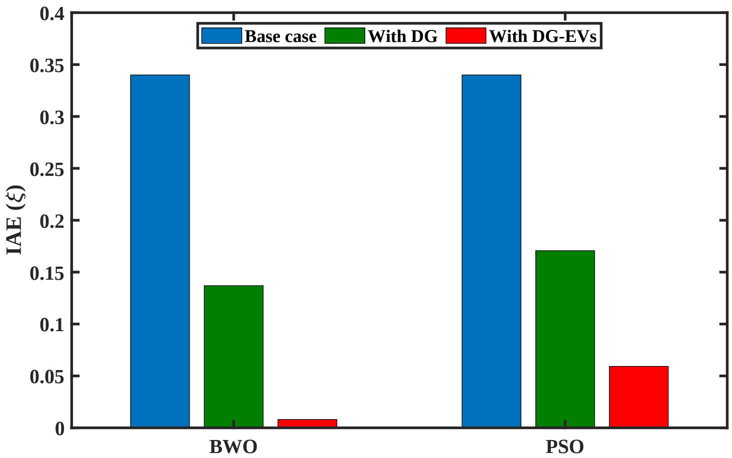

Figure 10. Integral absolute error using BWO and PSO.

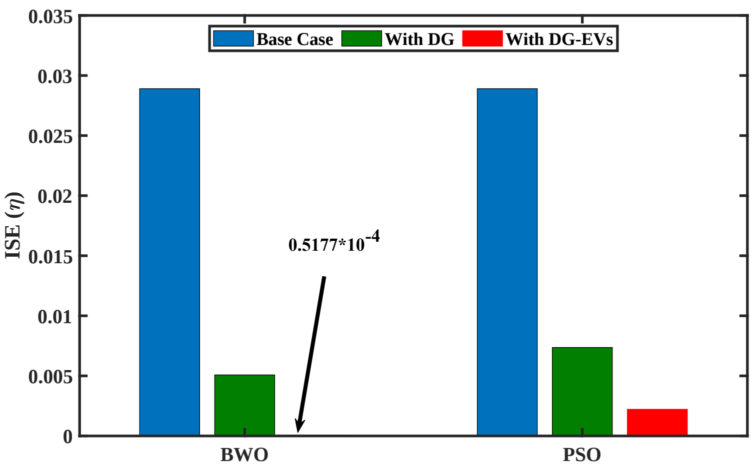

Figure 11. Integral square error using BWO and PSO.

8. Conclusions

This paper presents the application of the beluga whale optimisation (BWO) algorithm to determine the appropriate size of wind turbine generating systems (WTGS), while the optimal positions have been identified using the distribution load flow (DLF) method by minimising the P-Index, which was specified by taking voltage stability into account. In addition, optimal electric vehicle (EV) load distribution has been assessed in order to analyse the characteristics of EV load units in active and reactive power operations of the active distribution network. The BWO-optimised EV load units, along with the WTGS, effectively minimise the overall active power loss, leading to a stable bus voltage profile at weak nodes of the system. To summarise, the work presents:

- The optimal location of WTGS is established using analytical methods based on the matrix approach of DLF.
- The application of the BWO technique determines the suitable size of WTGS in accordance with the ideal configuration of EV load units, consequently enhancing the stability and performance of the network.
- The influence of integrating uncertain voltage-dependent ZIP forms of EV loads is analysed by minimising overall power losses and keeping bus voltages within acceptable parameters.

The future expansion of this study may incorporate different power distribution challenges, such as active power curtailment of distributed generator units to prioritise reactive power, determining the charging and discharging characteristics of EVs, and energy storage devices employing meta-heuristic methodologies.

Author Contributions: Conceptualization, N.R., M.-U.D.M. and N.G.; methodology, N.R., M.-U.D.M. and N.G.; software, N.R.; validation, N.R., M.-U.D.M. and N.G.; formal analysis, N.R., M.-U.D.M. and N.G. investigation, N.R., M.-U.D.M. and N.G.; resources, N.G.; data curation, N.R. and N.G.; writing—original draft preparation, N.R.; writing—review and editing, N.R. and N.G.; visualization, N.R.; supervision, N.R., M.-U.D.M. and N.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All the data generated in present work is already available in the reported manuscript or cited accordingly.

Acknowledgments: The authors express their thanks to the Ministry of Education, Government of India, for funding a scholarship during N.R.'s Ph.D.

Conflicts of Interest: The authors state that there are no conflicting interests.

Nomenclature

DG	Distributed generation
EV	Electric vehicle
WTGS	Wind turbine generating system
P-Index	Placement index
DLF	Distribution load flow
VSF	Voltage stability factor
RES	Renewable energy source
DSO	Distribution system operator
DGP	Distributed generation planning
PSO	Particle swarm optimisation
GA	Genetic algorithm
DE	Differential evolution
BWO	Beluga whale optimisation
PDF	Probability distribution function
VDL	Voltage dependent load
SOC	State of charge
ISE	Integral square error
IAE	Integral absolute error

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