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Improving Allocation Models in Smart Grid Planning Frameworks using Novel Optimization Schemes and Planning Mechanisms

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Declaration

I declare that this thesis report is my own original work, submitted to the University of the Witwatersrand for the degree of Doctor of Philosophy. This work **has not** been submitted to any institute of learning for a degree.

Kayode Emmanuel Adetunji

Braamfontein, Johannesburg

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Dedication

To my parents.

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To God be all the glory!

Abstract

The inception of smart grids has increased the popularity of integrating multiple Distributed Energy Resources (DERs) and Flexible Alternating Current Transmission System (FACTS) units. This interest is due to promoting sustainability through boycotting fossil fuels to using Renewable Energy Sources (RES). These units also offer an economic advantage since DERs are installed close to service load areas, having no need to transfer large pools of energy over long transmission lines. The interest in Electric Vehicles (EVs) has also peaked, given their capability to mitigate carbon emissions and improve grid performance. However, these units require careful integration since they can cause adverse effects such as voltage instability and extreme power loss. Therefore, smart grid planning frameworks are developed to find optimal allocation schemes for DER and FACTS units, including EV charging stations while considering their technical, economic, and environmental benefits. These frameworks are equipped with uncertainty models, constraints, and power flow algorithms, which increases their time complexity burden. Hence, an efficient optimization algorithm is necessary.

This research makes unique contributions, toward hybridizing metaheuristic algorithms for the optimal allocation of multiple DER and FACTS units, including EV charging stations in planning frameworks. In contrast to the current application of hybrid metaheuristic algorithms, which uses high computational time, this thesis presents the decomposition method for the allocation problem and assigns each algorithm to a problem. As a result, the optimization scheme becomes more computationally efficient.

EV charging can also potentially cause grid instability. To reduce the effect of this drawback, previous studies have worked on the optimal placement of EV charging stations in distribution networks. However, these studies have not considered the random behaviour of EV charging. An oversight of random EV charging can cause unprecedented peak times, negatively affecting grid stability. Hence, there is a need to model the distribution of EV charging. To handle this task, this research developed an EV charging coordination model. This model considers a normal distribution of EV charging and uses a reinforcement learning technique to find optimal locations of EV charging stations.

Necessary for dealing with bias and representational issues in multiobjective optimization (MOO), which are ongoing issues in planning frameworks, a game-based MOO is developed to minimize bias between smart grid players (or decision-makers) — EV aggregators and distribution network operators in a centralized EV charging scheme. Furthermore, a novel category-based MOO scheme is developed to tackle the difficulty of representing many objectives. The results show a minimal bias among similar to dissimilar objective functions, particularly technical objectives.

The final part of the research proposes an adaptive-dynamic planning mechanism and is validated on varying distribution networks, including 15-, 33-, 69-, and 118-bus distribution test networks. It is shown that the proposed mechanism yields a more extensive solution space, making it possible to find better solutions than in conventional planning mechanisms.

Academic Papers

Journals

1. *K.E. Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng*, "A Review of Metaheuristic Techniques for Optimal Integration of Electrical Units in Distribution Networks". *IEEE Access, vol. 9, pp. 5046-5068, 2021*, doi: 10.1109/ACCESS.2020.3048438.

2. *K.E. Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng*, "Category-based Multiobjective Approach for Optimal Integration of Distributed Generation and Energy Storage Systems in Distribution Networks". *IEEE Access, vol. 9, pp. 28237-28250, 2021*, doi: 10.1109/ACCESS.2021.3058746.

3. *K.E. Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng*, "An optimization planning framework for allocating multiple distributed energy resources and electric vehicle charging stations in distribution networks". *Applied Energy, vol. 322, p. 119513*, doi: 10.1016/j.apenergy.2022.119513.

4. *K.E. Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng*, "A novel dynamic planning mechanism for allocating electric vehicle charging stations considering distributed generation and electronic units". *Energy Reports.* - ***Accepted***.

Conferences

1. *K.E. Adetunji, I. Hofsajer, and L. Cheng*, "A Coordinated Charging Model for Electric Vehicles in a Smart Grid using Whale Optimization Algorithm", *In IEEE 23rd International Conference on Information Fusion (FUSION), July 2020.*

2. *K.E. Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng*, "Miscellaneous Energy Profile Management Scheme for Optimal Integration of Electric Vehicles in a Distribution Network Considering Renewable Energy Sources", *IEEE SAUPEC/RobMECH/PRASA, January 2021.*

3. *K.E.Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng*, "A Game-based Stochastic Optimization Technique for Optimal Coordination of EV charging and Navigation", *To be presented.*

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Notations

P_p	real power at bus p.
Q_p	reactive power at bus p.
P_{p+1}	real power at the next bus to bus p.
Q_{p+1}	reactive power at the next bus to bus p.
P^{RES}	real power from renewable energy.
P^{BATT}	real power from battery energy storage systems.
$P_{n,t}^{\mathbf{EV}}$	real power consumed by charging EVs at bus n at time t.
$P_t^{\mathbf{PV}}$	real power supplied from PV at time t.
Q_p^{CAP}	reactive power compensation from capacitor to bus p.
Q_p^{STATCOM}	reactive power compensation from capacitor to bus p.
V_p	voltage at bus p.
δ_i	voltage at bus i.
$R_{p,p+1}$	resistance on line connecting bus p and bus $p+1$.
$X_{p,p+1}$	reactance on line connecting bus p and bus $p+1$.
α	efficiency of battery charging or capacitor.
DG_{IC}	installation cost of allocated DERs.
DG_{OC}	operation cost of allocated DERs.
w_n	weight assigned to the n_{th} objective.
$\mathcal{P}^*$	Pareto optimal solution.
$\mathcal{P}F^*$	Pareto optimal solutions.
T	time horizon.
X_{pop}	planning solution vector in a population, pop.
$f(X)$	objective function of planning solution vector X.
$Q(\mathcal{S}_t, \mathcal{A}_t)$	Q-value for state and action.
$\mathcal{S}_t$	state of distribution network environment at time t.
$\mathcal{A}_t$	action taken for a charging station in an environment at time t.
$\mathcal{R}_t$	reward received after action.
T	state transition function.
γ	discount factor for updating $Q(\mathcal{S}_t, \mathcal{A}_t)$ pairs.

Abbreviations

ABC	**A**rtificial **B**ee **C**olony
ACO	**A**nt **C**olony **O**ptimization
ALO	**A**nt **L**ion **O**ptimizer
CoSGADE	**C**ooperative **S**piral based **G**enetic **A**lgorithm **D**ifferential **E**volution
CS	**C**uckoo **S**earch
DE	**D**ifferential **E**volution
DLSA	**D**iscrete **L**ightning **S**earch Algorithm
FA	**F**irefly **A**lgorithm
FPA	**F**lower **P**ollination **A**lgorithm
GA	**G**enetic **A**lgorithm
GWO	**G**rey **W**olf **O**ptimizer
HHO	**H**arris **H**awks **O**ptimization
HSA	**H**armony **S**earch **A**lgorithm
ICA	**I**mperialistic **C**ompetitive **A**lgorithm
BESS	**B**attery **E**nergy **S**ource **S**ystem
CS	**C**harging **S**tation
D-STATCOM	**D**istributed **S**ynchronous **S**tatic **C**ompensator
DER	**D**istributed **E**nergy **R**esources
DG	**D**istributed **G**eneration
EV	**E**lectric **V**ehicles
PE	**P**ower **E**lectronic
PV	**P**hoto**V**oltaic
RES	**R**enewable **E**nergy **S**ources
V2G	**V**ehicle to **G**rid
WT	**W**ind **T**urbine
MCS	**M**onte **C**arlo **S**imulation
GRP	**G**rey **R**elational **P**rojection
WSA	**W**eighted **S**um **A**pproach
AHP	**A**nalytical **H**ierarchical **P**rocess
TOPSIS	**T**echnique for **O**rder **P**reference by **S**imilarity

	to **I**deal **S**olution
MOALO	**M**ulti-**O**bjective **A**nt **L**ion **O**ptimizer
MCMOO	**M**ulti-**O**bjective **M**ulti **O**bjective **O**ptimization
MOO	**M**ulti **O**bjective **O**ptimization
MOPSO	**M**ulti-**O**bjective **P**article **S**warm **O**ptimization
NSGA-II	**N**on-dominating **S**orting **G**enetic **A**lgorithm
PSO	**P**article **S**warm **O**ptimization
TLBO	**T**eaching **L**earning **B**ased **O**ptimization
WCA	**W**ater **C**ycle **A**lgorithm
WOA	**W**hale **O**ptimization **A**lgorithm
LSF	**L**oss **S**ensitivity **F**actor
PDF	**P**robability **D**ensity **F**unction
PLI	**P**ower **L**oss **I**ndex
MILP	**M**ixed **I**nteger **L**inear **P**rogramming
MINLP	**M**ixed **I**nteger **N**on-**L**inear **P**rogramming
NLP	**N**on-**L**inear **P**rogramming
SOCP	**S**econd **O**rder **C**one **P**rogramming
VSI	**V**oltage **S**tability **I**ndex

Chapter 1

Introduction

With the potential depletion of fossil fuels, such as coal, diesel, and natural gas, the world may face an energy crisis. What is worse is the increase in energy demand, intensifying the potential of an energy crisis. Furthermore, these fossil fuels, in addition to their unsustainable use, emit greenhouse gases, which cause global warming. Traditional power system networks depend on these fossil fuels, making them unreliable. Hence, the idea of a smart grid is conceived to address the pertinent issues. The inception of smart grids promises an efficient energy delivery using state-of-the-art technologies. The European Union Commission, from Article 2(7), has defined a smart grid as "an electricity network that can cost-efficiently integrate the behaviour and actions of all users connected to it – generators, consumers, and those that do both – to ensure economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety." [1]. In other words, we could say that the fundamental planning of a smart grid network will require Distributed Energy Resources (DERs) and Flexible Alternating Current Transmission System (FACTS) devices to provide and maintain a high required level of energy security.

Smart grid planning frameworks have been the tool for designing different smart grid networks, primarily based on the optimal allocation of DER units in distribution networks by optimizing the objective functions, such as power loss minimization, voltage deviation reduction, and voltage stability improvement. However, Renewable Energy (RE)-based DERs, such as Photo-Voltaic (PV) plants and wind turbines, causes high variability, negatively affecting the grid, especially for distribution networks, due to their vulnerable radial topology [2, 3]. Battery Energy Storage Systems (BESS) and Flexible Alternating Current Transmission System (FACTS) devices, such as capacitors, voltage regulators, and Static Compensators (STATCOM), can be integrated to cushion these adverse effects of Renewable Energy Source (RES) integration [4, 5]. However, these units are expensive to install or implement and they add more complexity to such planning frameworks. Additionally, while Electric Vehicles (EVs) can play a significant role in improving the stability and performance of the grid, these EVs can potentially cause disruptions in the grid. The random and uncoordinated charging of EVs can cause these disruptions, through severe voltage deviations, peak loading, and high power loss [6].

Constraint handling is an essential feature in the framework that ensures a practical modelling but this feature increases complexities, given its non-linear nature. It is also crucial to consider the uncertainties from load consumption according to weather conditions and electricity tariffs. Other uncertainties are PV power output, majorly caused by the intermittent nature of solar irradiance and temperature. The processing of these uncertainties also complicates the modelling of the planning framework. These features emphasize the need for an efficient optimization scheme in a smart grid planning framework.

Optimization schemes and optimal control strategies are the core of these planning frameworks, designed and developed to find appropriate bus locations to allocate DER units and EV charging. The primary objective is to improve grid operation performance.

Among the types of optimization algorithms, metaheuristic optimization algorithms have proven to solve complex engineering problems in an efficient manner. These algorithms solve highly computational tasks using stochastic operators to search for optimal solutions based on a balance between diversification and intensification [7]. Compared to other algorithms, metaheuristic algorithms are independent of any problem, and their high-level nature permits them to roam in and out of several local optima. Numerous works have used these algorithms, e.g., Genetic algorithm, Particle Swarm Optimization, and Whale Optimization Algorithm, to develop a smart grid planning scheme through optimally allocating DER and FACTS units in distribution networks. The crucial part of these algorithms that determines their optimality rate is that the mechanism intelligently finds global and optimal solutions within a considerably minimal computational time.

Another essential consideration in smart grid planning is optimizing multiple objective functions. Like other real-world projects, planning a smart grid requires numerous objectives, mainly to attain technical, economic, and environmental benefits. Studies have adopted Multi-Objective Optimization (MOO) approaches to optimize these multiple objectives simultaneously, but these objectives stand the risk of not being optimized correctly and may affect the quality of planning solutions from the planning framework. For example, the Weighted Sum Aggregate (WSA) approach has been adopted to simultaneously optimize multiple objectives in a planning optimization framework. The WSA approach involves the prior assignment of weights to objective functions to determine a preference by a decision-maker. The computation of all objective functions yields a *utility value*, which determines the quality of planning solutions. Although simple, this approach is prone to bias due to the rigid and subjective preference of objectives. Generation of Pareto optimal solutions is the recent alternative to WSA since a preference is chosen after evaluating all objectives. Even with the significant advantage of this approach, there are some drawbacks such as high complexity, uncontrollable bias in similar objectives [8], and wrong and difficult representation of many objectives [9].

Previous studies have simultaneously applied optimization algorithms and MOO approaches in smart grid planning. Many works have been on modifying or hybridizing metaheuristic algorithms for planning frameworks. However, very few works have been carried out on developing efficient hybrid algorithms that require a lower computational time. There are also a few studies on developing MOO techniques to find appropriate utility values for planning frameworks. This research focuses on developing novel hybrid optimization algorithms and MOO techniques for improving distribution networks through smart grid planning frameworks.

1.1 Research Question, Motivation, and Contributions

The research question is:

How can unit allocation models be developed to improve the technical, economic, and environmental benefits of a smart grid network?

This question is further expanded as follows:

Can a hybrid metaheuristic algorithm be efficiently developed and applied to handle complexities from a comprehensive, robust smart grid planning framework?

Hybrid metaheuristic algorithms have been proposed to improve planning solutions from a smart grid planning framework. However, their efficiency still needs exhaustive study. The basic approach directly hybridizes two or more algorithms to find optimal solutions, with or without conditions of in-iteration optimality, hence consuming intense computational resources. For example, some works [10, 11] have reported better-minimized power loss and voltage deviation but with high computational time. Another drawback in hybridizing algorithms is the uncertainty of its convergence, reported by [12,13]. This research proposes novel hybrid metaheuristic algorithms that decompose the planning problem to be solved by each algorithm's unique mathematical techniques, such that it requires a substantial amount of computational resources. Chapters 4 and 7 describe this work in detail.

Given the optimal allocation of multiple DER & FACTS units and EVCS facilities, can planning mechanisms be developed to improve planning solutions from smart grid planning frameworks?

Previous works have developed planning frameworks based on two major mechanisms — sequential (or multi-stage) and simultaneous. These mechanisms are the underlying blueprint for the framework in which the optimal planning solutions are determined. However, most studies have chosen these mechanisms arbitrarily and have not investigated their impacts on planning frameworks. Given the dependence of optimization algorithms on planning mechanisms, it is hypothesized that there should be a significant impact of these mechanisms on optimal planning solutions. This research investigates these impacts and proposes an adaptive-dynamic planning mechanism that uses a recombination technique for a feedback action given a current unit location or size in a smart grid planning framework, comprehensively reported in Chapters 6 and 7.

In a smart grid planning framework, can a MOO framework be modeled to handle many objectives, addressing the technical, economic, and environmental benefits?

Knowing that smart grid planning projects must have numerous benefits, it is required for planning frameworks to optimize many objectives. Therefore, it is important to find a suitable MOO framework that simultaneously optimizes all objectives with fairness. However, current literature [8] reports that the optimization of dissimilar and closely-related objective functions can cause uncontrollable bias in final results. Therefore, most works [14, 15] optimize only technical or economic objectives to prevent this issue. Another setback in optimizing many objectives is the difficulty in characterizing and representing more than three objectives [9]. Many studies have avoided this setback by adopting a maximum of three objectives for planning a smart grid. However, these makeshift solutions hinder the optimization of many objectives, thus reducing the robustness of the planning framework. This research proposes a category-based MOO framework that intelligently accommodates and optimizes all objectives through a multi-stage process to avoid the previously mentioned setbacks. More of this work is discussed in Chapter 4. The results show that the proposed MOO reduces the bias among the technical, economic, and environmental benefits. Results also show the even and compact distribution of Pareto optimal solutions, hence validating the MOO approach.

Can reinforcement learning technique be used to optimally allocate EV charging stations facilities in distribution networks?

EV charging station (EVCS) allocation is still relatively new, mainly done through Capacitated Flow Refueling Location Model (CFRLM) and EV load allocation. Either of these approaches does not consider the random behaviour of EV drivers. In light of this observation, this research develops an EVCS allocation model that firstly, models EV charging distribution and then applies a reinforcement learning-based EV charging control strategy to the current distribution. Finally, the control strategy is ran for potential EVCS bus locations while monitoring the grid performance, primarily based on the technical benefits — power loss, voltage stability, or voltage deviation. Chapter 6 gives a well-detailed explanation, with the results validating the novel EVCS allocation model in terms of statistical metrics.

1.2 Thesis Outline

This thesis is structured into chapters that address the research questions in Section 1.1. Chapter 2 provides a background on smart grid planning, focusing on the preliminaries required for developing distribution network models and designing of optimization schemes. Chapter 3 is a comprehensive review of recent related works and the gaps. Chapter 4 discusses the development of a novel hybrid metaheuristic algorithm. The chapter also addresses the multiobjective problem in a unit allocation model. Chapter 5 addresses the multiobjective problem in an EV charging coordination model, using a game-based MOO to find decisions between an EV aggregator and a distribution network operator. In chapter 6, a reinforcement learning-based EV control strategy is introduced. The strategy provides a new method to allocate EV charging stations in distribution networks. The chapter also introduces a novel dynamic mechanism for allocating units. Chapter 7 discusses the improvement of the dynamic planning mechanism, providing extensive results. Finally, Chapter 8 provides a conclusion of all findings in this thesis. Future recommendations are also discussed.

Chapter 2

Background

2.1 Introduction

With the increasing penetration of RES-based Distributed Generation (DG) units and electric vehicles in transmission and distribution networks, planning and operation of these networks have taken a turn with new challenges. The motivation for carrying out research in this field is the ability to find appropriate locations and sizes of DG units, to produce practical results. Phases, such as the distribution network type, power flow models, objective functions, constraints handling, optimization techniques, and uncertainty handling techniques, are necessary to solve the optimal integration problem to produce practicable results. Therefore, previous studies have worked on the problem while focusing on peculiar phases of interest.

2.2 Unit Integration in Smart Grids

The National Institute for Standards and Technology (NIST) coined out concepts from a standard smart grid as "architecture, architecture process, energy services interface, functional requirement, harmonization, interchangeability, and inter-operability" [16]. All of these concepts are related to the optimal integration problem in microgrids, distribution, and transmission networks. They come into play depending on the
(i) number of integrated units
(ii) type of units
(iii) mode of operations.

For example, RES-based DG units can be integrated to serve the smart grid at their peak hours, or they can be merged with BESS to store energy for high-demand hours, promoting the demand side management in a smart grid. In addition, the BESS unit can be used for smoothening power output through frequency variation [17, 18]. A representation of the integration of BESS, solar PV plant, wind turbine plant, and

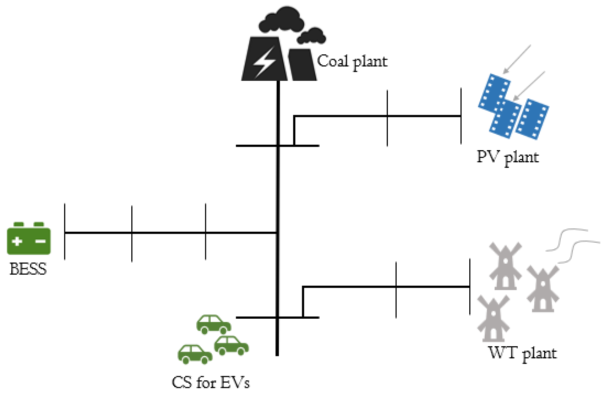

FIGURE 2.1: Configuration of a distribution network with the integration of different electrical units (adapted from [19, 20])

EVs in a distribution network is shown in Figure 2.1 [19,20]. Some common integrated units are discussed below.

2.2.1 Energy Sources

Research such as in [21–24] proposed algorithms to find optimal size and location of BESS in distribution networks. The authors of [25–29] have also developed meta-heuristic algorithms to optimally size and place BESS-based DG units in distribution networks. Independent energy sources such as PVs and wind turbines have also been optimally placed and sized for optimum energy transfer [30]. Most of the energy sources have also been integrated into microgrids to reduce cost of energy, net present cost, etc. [31,32].

2.2.2 Flexible Alternating Current Transmission System Units

The inception of the smart grid comes with the power delivery problem, mostly power stability. FACTS units have been used to compensate for distorted power, thereby enhancing power quality. Over time, these units have been sized and placed at strategic locations. Examples are capacitors (or capacitor banks), Distributed STATCOM (D-STATCOM), and Dynamic Voltage Restorer (DVR). Capacitors are generally the most economical; hence they attract more studies. Chunks of research such as in [33–38] worked on the optimal sizing and allocation of capacitors in a distributed network through the use of meta-heuristic algorithms. Other FACTS devices such as STATCOM, which consists of coupling transformers, energy storage devices, and inverters [39], have also been optimally placed and sized.

2.2.3 Electric Vehicles

Energy sources are central to the development of smart grids. These energy sources can be RES-DG units and may be configured as single or multiple DG units. Either type of energy source configuration should have an appropriate size and location of the energy source itself [40]. Some energy sources used in the literature are BESS, wind turbines, PV modules, and diesel generators. BESS units are mainly used to compensate for the intermittent nature of the RES. While BESS units have been enhanced with improved chemical composition and structure [41], there is also a need to optimally place them at strategic locations to achieve optimum power delivery.

Electric vehicles are emerging technology that can be an energy source or a FACTS device. They are eco-friendly vehicles that are fully or partially powered by electric propulsion. These vehicles are categorized into three which are Plug-in Hybrid Electric Vehicles (PHEV), Fuel Cell Electric Vehicles (FCEV), and Battery Electric Vehicles (BEV). The PHEV combines the Internal Combustion Engine (ICE) with an onboard battery system to enhance fuel economy. FCEVs are powered by hydrogen fuel cells, the newest and developing technology. BEVs are only run on battery technology and are considered the most efficient way to reduce carbon emissions. This distinction has made the BEV draw more attention than other EV categories [42], both in the global market and research. Naturally, the use of EVs in any form (as a load or support) will always cause a deterrent to the grid; hence, there is a need to control its implementation.

Firstly, charging an EV is an extra load to the grid network, causing voltage fluctuations and sudden peak loads if charging is uncoordinated. An uncoordinated charging refers to an arbitrary charging of EVs [43]. Ahmadi et al. [42] highlighted the impacts of EVs on distribution networks. One method to control EVs is optimal EV scheduling, assigning time slots for EV charging. To encourage the participation of EV owners, charging costs are minimized along with other objectives. Adetunji et al. [44] proposed an EV charging model that reduces the charging cost and minimizes power loss and load variance.

Secondly, EVs can discharge power to support the grid. Optimal EV scheduling can control this phenomenon. Another method to control EV implementation in a grid network is the Energy Management System (EMS), which incorporates DG units. EMS is the maximum strategic utilization of energy sources in a smart grid while considering its technical, economic, and environmental impacts. EVs are implemented to charge from or discharge to the grid network using the Vehicle-to-Grid (V2G) technology.

V2G is the management and control of EVs to the distribution network, which involves an aggregator and a distribution system operator (DSO). Some common objectives of the V2G technology are to minimize charging costs, maximize profit, improve power quality, and reduce carbon emissions. V2G technology is categorized based on power flow direction, unidirectional and bidirectional. Unidirectional V2G uses a one-way power flow to control the charging rates of EVs. It primarily provides ancillary services to the grid. These ancillary services must involve energy trading policies that should encourage the participation of EV owners [45]. Bidirectional V2G uses a two-way power flow between the grid and EV. In addition, there are other benefits, such as frequency regulation, voltage regulation, reactive power support, and peak load shaving.

Furthermore, EV charging stations are also an important factor in the mix because their allocation to the bus locations may deter the technical characteristics of the network. Some studies have formulated and solved the charging station allocation problem as in [46–49].

2.3 Phases in the Optimal integration of Electrical Units

This section discusses the phases and factors involving optimal integration in a distribution network. The following are discussed: power flow models, objective functions and constraints.

2.3.1 Power Flow Models

Power flow is an essential factor in distribution systems. Power flow methods range from optimal power flow (OPF), continuous power flow (CPF), probabilistic power flow (PPF), and so on. These methods have been used to analyze the components on a power bus line, determining the calculation of power losses and voltage stability on such lines. However, power loss equations will be based on the type of generator source. For example, the output power of diesel generators will defer from the power from PVs or WT. Also, a single- or three-phase type will change the model of its power flow. A schematic diagram for the single-phase power supply is shown in Figure 2.2 [50].

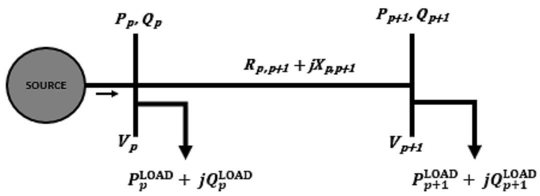

FIGURE 2.2: Schematic of a single line illustration of a distribution network

Figure 2.2 is represented with the equations below.

$$P_{p+1} = P_p - P_{p+1}^{\mathrm{LOAD}} - R_{p,p+1}\frac{(P_{p,p+1}^2 - Q_{p,p+1}^2)}{|V_P|^2}, \tag{2.1}$$

$$Q_{p+1} = Q_p - Q_{p+1}^{\mathrm{LOAD}} - X_{p,p+1}\frac{(P_{p,p+1}^2 - Q_{p,p+1}^2)}{|V_P|^2}, \tag{2.2}$$

$$\begin{aligned} |V_{p+1}|^2 = |V_p|^2 - 2(R_{p,p+1}^2 P_{p,p+1}^2 + X_{p,p+1}^2 Q_{p,p+1}^2) + \\ (R_{p,p+1}^2 + X_{p,p+1}^2)\frac{(P_{p,p+1}^2 + Q_{p,p+1}^2)}{|V_P|^2}, \end{aligned} \tag{2.3}$$

where p is the sending bus and $p+1$ is the receiving bus. P, Q, and V are respectively the real power, reactive power, and voltage at bus p or $p+1$, while R and X are the resistance and reactance at branch $p, p+1$.

The total power loss of the system is represented as

$$P_{total}^{\mathrm{loss}} = \sum_{p=1}^{n-1} P_{p,p+1}^{\mathrm{loss}}. \tag{2.4}$$

The derived equations from Eq. (2.1) can be supplemented by the addition of energy devices such as capacitors and STATCOM. Capacitors are used for supporting power flow through reactive power enhancement. On the other hand, STATCOM devices consist of Voltage Source Converters (VSCs) coupled with transformers and energy devices. It dynamically injects and/or absorbs reactive power for improving voltage stability and profile [51].

With the addition of other energy sources, Eqs. (2.5) - (2.7) may be updated as follows:

$$
\begin{aligned}
P_{p+1} = P_p - P_{p+1}^{\mathrm{LOAD}} - R_{p,p+1}\frac{(P_{p,p+1}^2 - Q_{p,p+1}^2)}{|V_P|^2} \\
+P^{\mathrm{RES}} + P^{\mathrm{BATT}},
\end{aligned}
\tag{2.5}
$$

$$
Q_{p+1} = Q_p - Q_{p+1}^{\mathrm{LOAD}} - X_{p,p+1}\frac{(P_{p,p+1}^2 - Q_{p,p+1}^2)}{|V_P|^2} + \alpha_q Q_{p+1}^{C}. \tag{2.6}
$$

The reactive power can be updated as

$$
Q_{p+2} = Q_{p+1} + Q_{p+2}^{\mathrm{STATCOM}}, \tag{2.7}
$$

where P^{RES} can be integrated as solar modules or wind turbines, αQ^C is the reactive power compensation by the capacitor with an α factor and $Q_{p+2}^{\mathrm{STATCOM}}$ is the reactive power compensation by the STATCOM at bus $p + 2$.

2.3.2 Common Objectives Functions

Objective functions are mainly mathematical equations that are formulated to simulate the characteristics of a system. The most common objective function in the smart grid planning problem is real power loss minimization, followed by others, such as voltage stability improvement, voltage profile improvement, cost minimization, and profit maximization. Figure 2.3 illustrates the different types of objectives.

2.3.2.1 Power Loss Minimization

Power loss is almost inevitable in power systems, yet its mitigation cannot be overemphasized. The objective is the most common objective of optimal integration. It can be formulated using Kirchhoff's laws, where the total distribution network loss is the summation of injected power on each bus, given the impedance, voltage magnitude, and angle. A miscalculation of power loss can cause a shortage of power supply or oversupply, which can quickly become economically undesirable. The power loss minimization is defined as

$$
\min \sum_{i=1}^{N} I_{i,t}^2 R_i. \tag{2.8}
$$

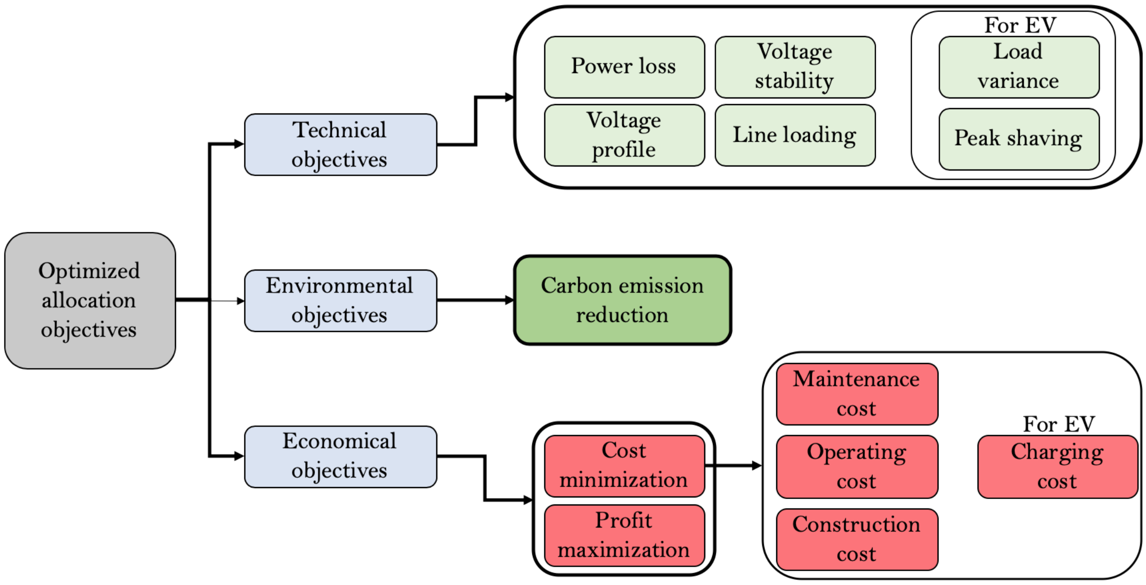

FIGURE 2.3: Common objectives of optimal integration in distribution networks

Here, $I_{i,t}$ is the current on the i^{th} at time t and R_i is the resistance of the i^{th} line. Power loss is also calculated as the function of real/reactive power and voltage magnitude/angle, expressed as

$$P_t^{\text{LOSS}} = \sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_{ij}\left(P_i^t P_j^t + Q_i^t Q_j^t\right) + \beta_{ij}\left(Q_i^t P_j^t - P_i^t Q_j^t\right) \tag{2.9}$$

where

$$\alpha_{ij} = \frac{r_{ij}}{V_i V_j} cos(\delta_i - \delta_j) \tag{2.10}$$

and

$$\beta_{ij} = \frac{r_{ij}}{V_i V_j} sin(\delta_i - \delta_j). \tag{2.11}$$

Here, i and j are the sending and the receiving bus indices respectively, while $Z_{ij} = r_{ij} + jx_{ij}$ represents the branch impedance from bus i to bus j, with r_{ij} and x_{ij} respectively representing the resistance and reactance of the branch (or line) connecting bus i and j. P and Q are the real and reactive power at each bus while the voltage magnitude is represented as V_i or V_j and the voltage angles are represented as δ_i or δ_j.

2.3.2.2 Voltage Stability Improvement

Voltage stability is a crucial factor in loading distribution networks. A sudden increase or fluctuations in the network can cause a voltage collapse. The inability to compensate for reactive power loss will also cause voltage instability [39], especially with small-scale network microgrids. Voltage Stability Index (VSI) is used as an indicator for network stability and loadability and can be used alone to solve the planning of distribution systems. In place of this, several methods have been developed with deviating strategies [39]. Some of the proposed methods are Line Stability Index, Line Stability Index, Novel Line Stability Index, Line Voltage Stability Index, Fast Voltage Stability Index, Voltage Collapse Proximity Index, etc. Over time, VSI has been combined with meta-heuristic algorithms for distribution network planning. A standard equation for solving VSI is described in Eq. (2.12);

$$\begin{aligned} \mathrm{VSI}_{(i+1)} = V_i^4 - 4[P_{(i+1)}X_i - Q_{(i+1)}R_i]^2 - \\ 4[P_{(i+1)}R_i + Q_{(i+1)}X_i]^2 V_i^2, \end{aligned} \tag{2.12}$$

$$VSI_{i,t} \;=\; \frac{1}{\mathrm{VSI}_{(i+1)}}, \tag{2.13}$$

$$VSI = \frac{1}{24}\sum_{i=2}^{N}\sum_{t=1}^{24} VSI_{i,t}. \tag{2.14}$$

2.3.2.3 Load Variance Minimization

This objective is related to the integration of EVs. Given the fact that EVs act as a load, there is a need to minimize the fluctuations on the grid through a proper scheduling. An optimal cancellation of this objective can reduce power loss. A typical load variance objective is formulated as

$$\min \frac{1}{T}\sum_{t=1}^{T}\left[(P_t^{\mathrm{conv}} + \sum_{n=1}^{N} P_{t,n}^{\mathrm{EV}} - \beta)\right]^2, \tag{2.15}$$

where

$$\beta = \frac{1}{T}\sum_{t=1}^{T}\left(P_t^{\mathrm{conv}} + \sum_{n=1}^{N} P_{t,n}^{\mathrm{EV}}\right). \tag{2.16}$$

Here, P_t^{conv} is the conventional load without the EV load at time t; $P_{t,n}^{EV}$ is the charging power of the n^{th} EV at time t. It is crucial to note that N is the maximum number of charging stations which is assumed to be occupied by EVs at a predetermined time slot, t.

Theoretically, this objective should also cater for peak shaving and load leveling to improve the grid efficiency. A well-controlled load variance will improve network stability (synonymous with VSI).

2.3.2.4 Peak Load Shaving

Peak shaving is a key objective in the EV charging coordination model, where electricity demand is met by utilizing available resources, rather than increasing the grid capacity. In a PV- and EV-present distribution network, the peak load can be reduced through

$$\min \left\{P_t^{\mathrm{conv}} + \sum_{n=1}^{N} P_{n,t}^{\mathrm{EV}} - P_t^{\mathrm{PV}}\right\}, \tag{2.17}$$

where P_t^{conv} is the conventional load at time t, which is the base load without the EV load; P_t^{PV} is the PV output power at time interval, t and $P_{n,t}^{\text{EV}}$ is the rated power of charging the n^{th} EV.

2.3.2.5 Cost Minimization

The economic aspect of optimal integration has to be considered for sustainability and acceptability. Without this consideration, most projects might not be signed off for commencement. Therefore, there is a need to minimize the cost of carrying out the optimal integration of the DG units project. Most studies sum the total cost as the summation of installed DG units construction cost and operation and maintenance cost [52, 53]. A typical example of optimal integration of DG units is shown as

$$DG_{IC} = \sum_{i=1}^{N_{\text{DG}}} P_i^{\text{DG}} \times INV_{\text{cost}}, \tag{2.18}$$

where DG_{IC} is the installation cost of DG units, P_i^{DG} represents the capacity of the i^{th} DG unit, and INV_{cost} investment costs of the DG units. The operation and maintenance cost is defined as

$$DG_{OM} = \sum_{i=1}^{N_{\text{DG}}} \sum_{j=1}^{N_N} P_i^{\text{DG}} \times OM^{\text{cost}} \times R \times CF_i \times T, \tag{2.19}$$

where OM^{cost} is the operation and maintenance cost, R is the approximate value of interest and inflation rate, CF_i is its capacity factor, and T is the duration of the planning period (counted in days). The cost of purchasing excess power from substation can be expressed as

$$COST_{\text{sub}} = \sum_{t=1}^{24} P_t^{\text{sub}} \times P_{\text{cost}} \times R \times T, \tag{2.20}$$

where P_t^{sub} is the summation of the active load connected to the distribution network, the power generated from DG units, and the accumulated power loss. P_{cost} is the cost of active power from the substation. Since investment costs are dependent on the installed DER and FACTS units, the above equations may be repeated but based on the units to be allocated.

For EVs, there is a need to reduce the cost of charging. This act is beneficial to the grid and EV drivers. A load-shifting scheme is applied where cheaper tariffs will be available as an incentive at off-peak hours. The standard form of charging cost minimization is defined as

$$min \sum_{n=1}^{N} \sum_{t=1}^{T} P_{n,t}^{\text{EV}} \cdot C_t \cdot \triangle t, \tag{2.21}$$

where N is the total number of plugged-in EVs; $\triangle t$ is the time horizon; C_t is the current Time-of-Use (TOU) price at time t; $P_{n,t}$ is the n^{th} EV charging power at time t.

2.3.2.6 Operating Profit Maximization

Investing in the improvement of power systems should also be profitable for investors. Taking an EV scheduling as an example, an aggregator should serve an appealing charging cost while considering profits. In the same vein, an investor in the construction of a DG integration project should have a projected profit [52].

2.3.2.7 Emission Cost Reduction

The emission cost objective is formulated as the carbon emission value of real power from a substation [11], and can be defined as

$$\sum_{y=1}^{Y}\sum_{t=1}^{24} P_{t,s}^{\mathrm{ss}} \times E_f, \tag{2.22}$$

where E_f is the emission in kg/kWh and $P_{t,s}^{\mathrm{ss}}$ is the real power from the substation. The index s for the substation, which is assumed to be coal-powered.

2.3.3 Constraints

For a more practical scenario, constraints are modeled into an optimization problem in order to limit specific parameters. Constraints are mostly applied to technical objectives, where power, voltage, and current flow within and into the grid are confined. Some essential constraints are highlighted

- *Bus voltage limits* are applied to maintain the stability of the grid. While injecting power from DG units or EVs, a permissible voltage is allowed on each bus, which has a maximum variation of 5%, as in [54].
- *Bus capacity limits* are applied to regulate the maximum allowable load to a bus. This constraint is well applicable to EV charging, where some number of EVs are only allowed to be charged from a bus. This inequality constraint must be equal or lesser than the sum of conventional (residential or commercial) load and the total number of EVs connected to the same bus.
- *DG penetration limit* refers to the maximum allowable power from installed DG units like PV and WT. EV penetration is also controlled except when gradual steps are allowed [43], or maximum penetration is used, as in [44].
- *Power flow balance* ensures that the total real and reactive power of the grid network is equal to the sum of real and reactive power flowing from DG units, substation, and real and reactive power loss in the network.

2.4 Optimization Aspect

2.4.1 Unit Allocation Process

Given the explained model, a number of units are allocated to buses in a distribution network. These units are formulated as a vector, $X = \{x_1, x_2, ..., x_n\}$, where elements in the vector can be discrete or continuous variables representing unit location or sizes, respectively. Given the mixed integer linear structure of the allocation problem, the optimization problem takes the form,

$$\begin{aligned} \min \quad & C^T X = f(X) \\ \text{s.t.} \quad & g(X) \leq 0 \\ & h(X) = 0 \\ & x_n^{\text{LB}} \leq x_n \leq x_n^{\text{UB}} \\ & x \in X \end{aligned} \quad . \tag{2.23}$$

In the unit allocation problem, C will be the *value* of each potentially allocated unit in a set of variable X. The objective function will be represented as $f(\cdot)$ subject to inequality constraints, $g(\cdot)$ and equality constraints, $h(\cdot)$, mostly used for balancing power flow in a power system network. The x_n^{LB} and x_n^{UB} are the lower and upper bounds of the n^{th} decision variable, respectively.

In order to find the optimal solutions, the decision vector, X is initialized into a population of solutions feasible to the region bounded to the constraints, expressed as

$$\overrightarrow{X}_{\text{pop}} = \begin{pmatrix} x_1^1 & x_2^1 & \cdots & x_n^1 \\ x_1^2 & x_2^2 & \cdots & x_n^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^m & x_2^m & \cdots & x_n^m \end{pmatrix} . \tag{2.24}$$

Each of these vector is manipulated and evaluated to find the best solution at every iteration. The evaluation is done using the objective function $f(X)$ values of each vector.

2.4.2 Reinforcement Learning Approach

The RL approach can be applied by first formalizing the problem as a Markovian decision process (MDP). The MDP possesses a vector $\mathcal{M} = \langle \mathcal{S}_t, \mathcal{A}_t, \mathcal{R}_t, T, \gamma \rangle$, where $\mathcal{S}_t$ is the sate of the environment, usually the distribution network model, $\mathcal{A}_t$ is the action taken by an agent to change the state of the environment, $\mathcal{R}_t$ is the reward received after an action $\mathcal{A}_t$ is taken, T is the transition from a current state $\mathcal{S}_t$ to another state $\mathcal{S}_{t+1}$, and γ is the discount factor for evaluating the expectation of rewards for all action taken. Figure 2.4 [55] shows the illustration of the RL environment.

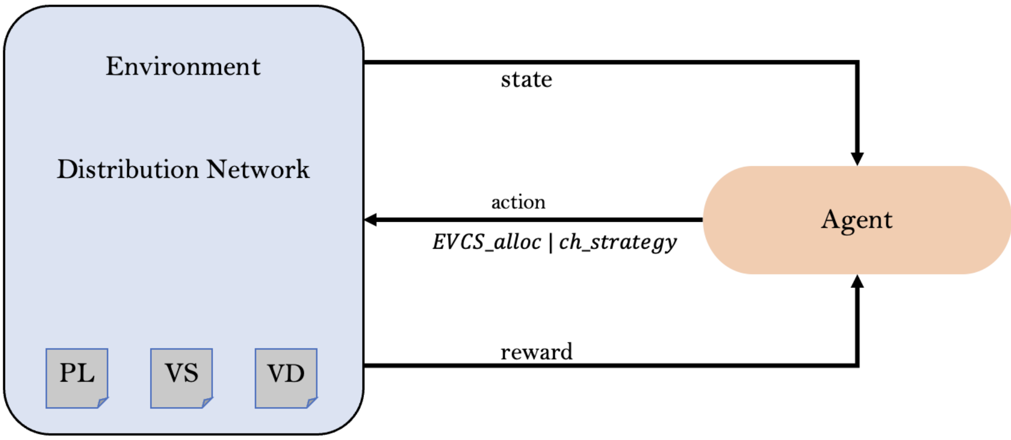

FIGURE 2.4: Reinforcement learning framework (adapted from [54])

The environment is the distribution network, which is a factor of the power loss (PL), voltage stability (VS), and voltage deviation (VD). The agent carries an action, which is the EVCS allocation, given the charging strategy, represented as $EVCS\_alloc|ch\_strategy$ that yields a reward in a state. The state transitions to another state following the same action-reward process. Therefore, the outcome of carrying out all actions in different states yielding rewards will follow policies π, represented as

$$Q^{\pi}(\mathcal{S}_t, \mathcal{A}_t) = \mathcal{E}^{\pi}\left[\sum_{t=1}^{T} \mathcal{R}_t(\mathcal{S}_t, \mathcal{A}_t) + \gamma Q^{\pi} p(\mathcal{S}_{t+1}, \mathcal{A}_{t+1})\right], \tag{2.25}$$

where γ is the discount factor, always a value between 0 and 1, determines rewards for actions over an expectation $\mathcal{E}$ given a time horizon, T. Given Equation (2.25), an optimal policy which maximizes the grid performance is expressed as

$$Q^{*}(\mathcal{S}, \mathcal{A}) = \max_{\pi} Q^{\pi}(\mathcal{S}_t, \mathcal{A}_t). \tag{2.26}$$

This optimal policy is learned using a recursive algorithm to update the state-action pairs, mapped as

$$Q^{*}(\mathcal{S}_t, \mathcal{A}_t) = (1 - \alpha)Q(\mathcal{S}_t, \mathcal{A}_t) + \alpha[Q^{\pi}(\mathcal{S}_t, \mathcal{A}_t)], \tag{2.27}$$

where α is the learning rate of the algorithm, chosen between 0 and 1.

2.4.3 Multiobjective Optimization

Using the structure

$$\min F(X) = [f_1(X), f_2(X), ..., f_n(X)]. \tag{2.28}$$

These objectives can be optimized using weights to rate the level of preference, expressed as

$$F(X) = \sum_{n \in N} w_n f_n(X) \mid \sum_{n \in N} w_n = 1. \tag{2.29}$$

A fairness-centric approach will produce Pareto optimal solutions from the evaluation of objectives. This approach produces all solutions that are not better than each other or that do not dominate each other. In other words, for example, solutions x_1 and x_2 will be Pareto optimal, if at least one of the objective value (say, $f_2(x)$) of solution x_1 is better than the solution x_2's objective value ($f_2(x)$) and solution x_2 also produces at least one objective value ($f_1(x)$) better than solution x_1's objective value. All computed non-dominated or Pareto optimal solutions are stored in a Pareto optimal set, $\mathcal{P}^*$, and are formed into a Pareto optimal set, using

$$\mathcal{P}F^* = F(x)|x \in \mathcal{P}^*. \tag{2.30}$$

Using the allocation example to explain the concept of the Pareto optimal solutions, we illustrate the variable solution for a two-objective optimization framework in Figure 2.5.

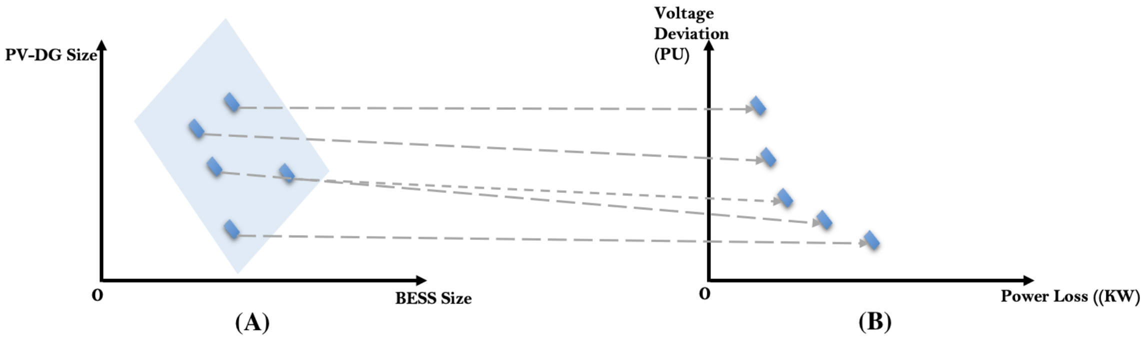

FIGURE 2.5: Illustration of decision (variable) space and objective space in a multiobjective optimization framework

Each variable in the search (or decision) space corresponds to values in the objective space. The decision space contains the Pareto optimal solutions, while the objective space is the Pareto optimal set.

2.5 Summary

This chapter discussed the preliminaries of this thesis. The discussion entails modelling the distribution network, problem definition - objective functions and constraints, optimization modelling, and multiobjective optimization structure.

The next chapter discusses the review of current works in the field of smart grid planning, specifically towards the optimal allocation of DER and FACTS units. The chapter also uncovers the gaps and potential solutions using metaheuristic optimization algorithms, reinforcement learning techniques, multiobjective optimization approaches and planning mechanisms.

Chapter 3

Metaheuristic Techniques for Optimal Integration of Distributed Energy Sources in Distribution Networks

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This chapter is adapted from the following publication:

K.E. Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng, "A Review of Metaheuristic Techniques for Optimal Integration of Electrical Units in Distribution Networks". *IEEE Access, vol. 9, pp. 5046-5068, 2021*, doi: 10.1109/ACCESS.2020.3048438.

The author of this thesis conceptualized the study, partook in the formal analysis, developed the models and algorithms, and wrote the original draft of the paper.

3.1 Introduction

This chapter reviews related works on optimal smart grid planning, particularly in relation to optimization algorithms, multiobjective optimization algorithms, reinforcement learning, and planning mechansims. The chapter identifies the gaps and proffers potential solutions.

Metaheuristic algorithms have been used extensively because of their ability to produce near-optimal results in a computationally efficient manner. They have also been used for solving multiobjective optimization problems in the optimal integration of electrical units in distribution networks. However, the application of these algorithms have not been compared in literature. This chapter discusses the different categories of metaheuristic techniques, and their applications to the single and multiobjective problems in smart grid planning frameworks. We review the effect of planning mechanisms in planning frameworks and investigate

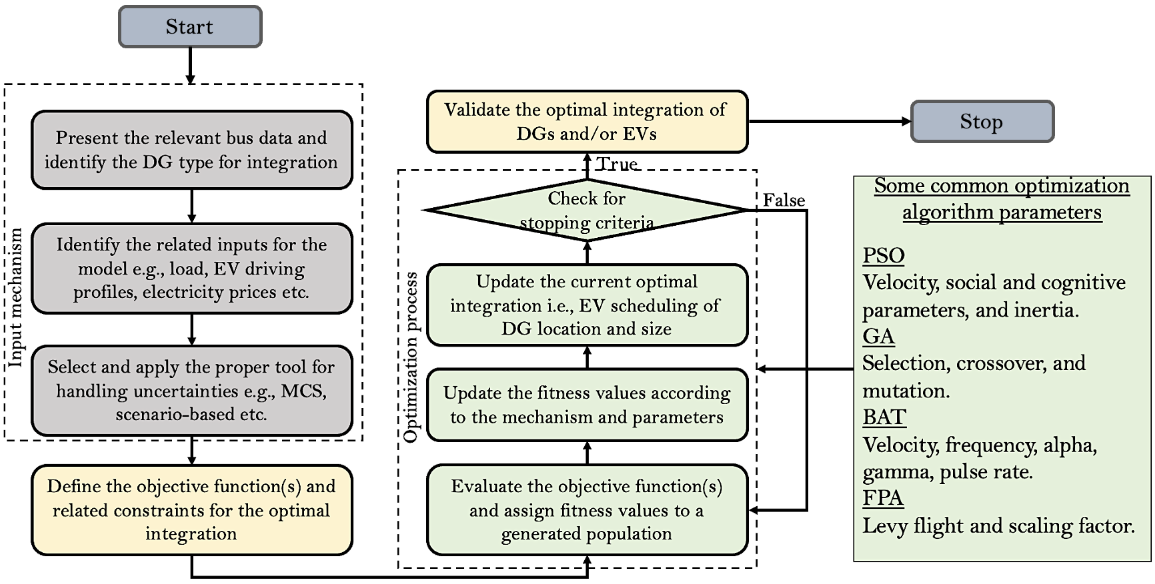

Figure 3.1: Generic flowchart of a meta-heuristic algorithm application to the optimal integration problem

the impact of EV charging on distribution networks. Finally, we identify gaps in each study and suggest potential solutions.

3.2 Metaheuristic Algorithms for Planning Frameworks

The concept of most metaheuristic algorithms is based on a characterized agent or set of agents that operate without human interaction, to achieve an objective or a set of objectives [56]. Figure 3.1 shows a general framework of these algorithms to solve the optimal integration problem. We discuss the different applications of these algorithms in a smart grid planning framework. Metaheuristic algorithms are mainly categorized into three types; evolutionary-based, swarm-based, and physics-inspired algorithms.

Evolutionary-based algorithms are popular for their use of the Darwinian evolution theory to select the optimal solution from a population of solutions after a number of generation. Like the evolution process, a generation will consist of parents and children who inherit their parents' features. An example is the GA, which has been applied to allocate different DER and FACTS units in distribution networks, considering the technical benefits, such as power loss minimization and voltage stability improvement [57, 58]. The Differential Evolution (DE) is another evolutionary algorithm, known for its fast convergence. Through the addition of difference and trial vectors, the DE can handle continuous variables. Hence, they are applied to find optimal DER or FACTS unit sizes [59,60]. Other evolutionary-based algorithms are Modified Shuffled Frog Leaping Algorithm (MSFLA) and Evolution Strategy (ES) [61, 62].

Swarm-based algorithms are based on simulating the interaction among a swarm (or flock) of animals (called search agents or particles) to achieve a common goal. Unlike evolutionary algorithms where planning solutions are chromosomes, swarm-based algorithms take the planning solutions as agents' positions relative to the goal, which is the “best” position. Depending on the algorithm, different mechanisms and parameters are used to change the positions of agents. The Particle Swarm Optimization (PSO) is a good example, used for allocating units in a planning framework [63–65]. Others are Artificial Bee Colony (ABC) [66], Ant Colony Optimization (ACO) [67].

The other type of metaheuristic algorithm is the physics or nature-based algorithms. A significant distinction between them is that, instead of a swarm of search agents, the physics-based algorithms can use one search agent to interact within a solution search space or vice-versa. Ali et al. [36] proposed the Improved Harmony Algorithm (IHA) for optimally sizing capacitors in a distribution network, where the Power Loss Index (PLI) determines possible buses for the optimal installation of capacitors. The algorithm was tested on a 69-bus distribution system and was compared to other algorithms such as the PSO, ABC, DE, and HSA. The HSA is another efficient metaheuristic based on the aesthetic combination of sounds. A well-detailed approach can be found in [68] and Askarzadeh [69] extensively discussed its implementation in power systems improvement. Liu et al. [70] implemented an improved HSA for the optimal integration of units in a distribution network to minimize the total operating cost. Other algorithms have also been applied to the optimal integration problem, such as in [71], which used the Discrete Lightning Search Algorithm (DLSA) has also been used for optimal placement of capacitors in wind farms. The DLSA minimizes energy loss and reduces management cost than the GA and HSA.

The efficiency of metaheuristic algorithms is primarily based on the search mechanism, moving between exploring or exploiting a solutions space. One major drawback of swarm- or physics-based algorithms is the subjective tuning of parameters. The inappropriate setting of parameters can lead to a premature convergence [72], which can produce local optima results. A simple hack is to find efficient ways to minimize or, if possible, eliminate parameter tuning. For example, Kumar and Chakraborty [73] applied a chaotic operator to a DE to avoid premature convergence while solving the optimal DG unit integration problem in distribution networks. This chaotic concept has been studied in [74], where a Chaos Symbiotic Organisms Search (CSOS) algorithm with fewer parameters, was developed to place and size DG units in distribution networks. In order to find a good compromise between the exploration and exploitation areas of the genes. Celli et al. [75] varied both crossover and mutation operators for properly installing BESS units in a distribution network. A blend crossover operator was used to uniformly select a value within two parents’ genes. The mutation operator uses a non-uniform approach based on a polynomial probability distribution function and a mutation clock scheme. The mutation clock’s addition enhances the computational time because unlike in [76], where the number of extraction is based on the number of genes, it allows for only one extraction of genes per chromosome. In [77], a Normal Distribution Crossover (NDC) was used to produce new chromosomes to optimize power loss and voltage deviation. It was reported that the NDC-based GA converges faster than the PSO and PSO-GA algorithms.

In light of implementing a minimal number of parameters, new algorithms like Whale Optimization Algorithm (WOA), Ant Lion Optimization (ALO), and JAYA were developed and applied to smart grid planning frameworks. George et al. [78] used the ALO-based optimization technique to optimally place fixed shunt capacitors in a distribution system, considering the minimization of total power loss and total annual cost. The JAYA algorithm was used by [79] for optimal flow in a renewable energy-present distribution network. The JAYA algorithm is parameterless and quite simple to implement in the optimal integration problem [80]. Wong et al. [81] applied the WOA to investigate the impacts of optimal integration of BESS and PV-DG units in different scenarios. In the results, the WOA and PSO performed distinctively better than FA, with the WOA surpassing the PSO by a small margin. The Flower Pollination Algorithm (FPA) uses a Levy flight based on a heavy-tailed probability distribution to attain global optimal solution, implemented by [34] to reduce the total cost of installed capacitors while solving the optimal capacitor sizes in a distribution network.

Hybridization of algorithms have also been applied in smart grid planning frameworks to improve planning solutions, Hybrid algorithms are a combination of two or more metaheuristic algorithms. The algorithms can either be combined as a single algorithm to solve the whole optimization problem, or used separately to solve different subproblems. Some applied examples are seen in works of literature. From [26], a hybrid algorithm, PSO-GA, was proposed to optimally allocate energy storage systems in a wind farm grid to improve voltage deviation and to reduce operating costs and carbon emissions. The proposed algorithm was tested on the IEEE 30-bus system, and was reported that the PSO-GA performs better than the GA on all the objectives except for voltage deviation. Deb et al. [82] developed a hybrid algorithm (comprising chicken swarm optimization and TBLO) in a multi-objective space to improve grid stability while allocating charging stations in the IEEE 33-bus network. The CSO and TLBO are directly merged to speed up convergence and to reduce the likelihood of a premature convergence. The INV parameter in the CSO-TLBO, just like in the CSO, is user-defined and must be tuned properly to avoid local optima solutions. It was reported that the CSO-TLBO converges faster than the Multi-Objective Evolutionary Algorithm with Decomposition (MOEA/D) and the NSGA-II but with a higher computational time.

Jeddi et. al [10] hybridized the HSA and FA (CHSFA) to maximize profits of distribution network companies by reducing operational costs and increasing income in a distribution network. The CHSFA uses the HSA mechanism to search towards the best objective values in the harmony memory and uses the FA mechanism for a random search. This process is repeated twice to achieve an optimal solution. Although the computational time comparison was not reported, it is assumed that the CHSFA, due to its complex mechanism, will have a higher computational time than the HSA.

Zeynali et al. [11] hybridized a family of the evolutionary algorithm: GA, DE, and Strength Pareto Evolutionary Algorithm (SPEA-II) to simultaneously integrate RES-based DG units (solar and wind), capacitor banks, and EV in a distribution network. The algorithm uses a varietized crossover function to select from three mutation strategies randomly. The objectives are voltage stability improvement, gas emission reduction, and installation cost reduction.

The summary of reviewed hybrid metaheuristic algorithms with their applications, objective functions, strengths and drawbacks, is shown in Table 3.1.

Table 3.1: Hybridized metahueristic optimization algorithms for smart grid networks

Ref.	Algorithm	Application	Objective	Strength	Drawbacks
[26]	GA & PSO	ESS allocation	Carbon emission reduction Voltage deviation improvement Operating cost reduction	High accuracy of results	High computational time
[12]	PSO & MS-FLA	Capacitor allocation	Voltage stability improvement	High accuracy of results	Uncertain convergence
[28]	GA & IWD	DG units location and sizing	Power loss minimization	Very good computational time,	Uncertain convergence
[82]	CSO & TBLO	CS allocation	Power loss minimization Voltage stability improvement	Fast convergence	High computational time Good results subject to prameter tuning
[83]	DE & HSA	STATCOM allocation	Cost reduction Voltage stability improvement Power loss minimization	Fast convergence	High computational time
[11]	GA & DE & SPEA-II	DG units location and sizing Capacitor allocation EV scheduling	Voltage stability improvement, Emission reduction, Cost reduction	High accuracy of results	High computational time Uncertain convergence Multiple parameters
[10]	HSA & FA	DG units location and sizing	Profit maximization Cost reduction	High accuracy of results	High computational time

3.3 Multiobjective Optimization Methods in the Optimal Integration of Electrical Units

Smart grid planning has many benefits and could have negative effects. For example, the allocation of units can reduce power loss but can also potentially cause voltage deviation or destabilize the grid. Therefore, we have to minimize power loss and also monitor the voltage deviation and stability of the grid. There might also be a need to reduce the carbon footprints or minimize the cost of planning. Hence, it is necessary to consider the simultaneous optimization of objectives. Since smart grid planning frameworks are already *complex enough*, previous studies tends to use a simplistic MOO approach. A simple method is the sequential programming, where different objectives are dependent on each other. The first objective must be solved to calculate the second objective, or two objectives can form an equation to determine the main objective. This approach was used in [84], where real power loss minimization and voltage stability index are optimized simultaneously under different load variations. The main disadvantage of this approach is that it does not guarantee overall optimality.

The weighted sum aggregate (WSA) is another typical method, where objective functions are assigned different weights according to their importance, where the sum of the weights is always approximate to one. This method is quite simple since all objectives are weighted according to a preference and summed for a final objective value (or a utility value). El-Ela et al. [85] applied the WSA to handle multiple objectives while integrating DG units and capacitor banks in a distribution network. The weights were applied in different scenarios such that it alternatively reflects grid performance, economic benefits, and environmental benefits. Mukhopadhyay and Das [86] focused on optimizing the technical objectives of planning a reconfigurable distribution network while using the PSO to optimally allocate PV-DG and BESS units. The objectives, which are, power loss minimization, voltage deviation minimization, and line loading maximization, were normalized before applying an equal weighting to them. However, the values of weights are subjective and bias to the researchers. In lieu of this, some studies have tried to subdue the subjectivity of weight values by applying an additional technique to generate weights with respect to the objective functions.

In [87], a fuzzy-based MOO approach was applied to allocate DG units, capacitors, and EVCS while reducing real power loss and improving power factor and voltage profile. To reduce the subjectivity of weights, the study applied weights with a fuzzified voltage limit to all objectives. Adetunji et al. [44] also proposed a concept of fuzziness to assign different weights to objective functions, using a game approach to determine the utility value. The weights were assigned to represent different decision-maker preferences and find a solution through a competition model. It is to note that varying of the weights does not produce a Pareto optimal solution set. Shaheen et al. [88], instead of directly assigning weights to the objective functions, used the Analytical Hierarchical Process (AHP) for calculating the weights to reduce bias while applying the Enhanced Grey Wolf Algorithm (EGWA) to optimally integrate DG units, capacitors banks, and voltage regulators. The relationship between objective functions is graded according to a certain level of importance, which forms a pairwise matrix. Gangwar et al. [89] also used the AHP to assign weights to objective functions while solving the optimal DG units location problem in a reconfigurable distribution network. However, these approaches only, to an extent, reduce the bias and are still susceptible to the subjectivity from one decision-maker.

To at least remove the rigidity of accepting the solution from one decision-maker, studies have implemented the *aposteriori* approach. The *aposteriori* approaches involve the processing of multiple objective functions before sorting the values. All objective functions are optimized collectively, and the non-dominating solutions are selected as the best outputs [90]. A non-dominating solution means that two or more sets of objective function values are not better than one another. The set of non-dominating solutions, also called the Pareto optimal set, is solved by a decision-making technique to find the best solution.

Metaheuristic-based MOO approaches are quite popular for their capability to generate many potential solutions from a set of objective functions. There are two important stages in this approach; the generation of non-dominated solutions (or Pareto optimal solutions) and the selection of a compromise solution from the list of non-dominated solutions. The NSGA-II technique is the commonly used approach, uses a domination-based approach to assign fitness through non-domination ranking and crowding distance to choose a compromise solution [91]. Khalid et al. [21] proposed the NSGA-II for solving the optimal integration in a distribution network, reducing the energy losses and the total investment cost of DG and BESS units. A Utopian method was used to select the compromise solution from a NSGA-II-based MOO in a DG and BESS units allocation planning framework. The method involves the running of the optimization algorithm for each normalized objective to derive the Utopian point, the calculation of the Euclidean distance between the Utopian point and each solution in the Pareto set, and the selection of the solution with the shortest distance as the compromise solution. This method, although not frequently used, eliminates the subjectivity in assigning importance to objectives. The study used voltage regulation and temperature to increase the lifespan of the BESS units. The algorithm was tested on an IEEE 906 bus European test feeder.

The NSGA-II technque has been modified to improve the quality of Pareto optimal solutions, especially in a complex problem such as smart grid planning. Huiling et al. [77] formed a stochastic fuzzy chance-constrained model for coordinated charging and discharging of EVs and the integration of RES-based DG units in a multi-objective space. A modified NSGA-II algorithm was developed for minimizing power loss and voltage deviation. Instead of using the crowding distance, the study proposed a congestion comparison operator for calculating the distance among three close solutions of each objective function, to avoid overconcentration and improve the uniform distribution of the Pareto front. In [92], a decomposition approach was used to produce final utility value from a Pareto set in the optimal integration problem in distribution networks. The approach decomposes the main problem into numerous subproblems in order to assign a set of evenly-spread weights to each subproblem. This approach enables the emulation of a uniformly distributed set of solutions in a multiobjective space. However, the adopted objectives, real power loss and reactive power loss, are not clearly conflicting, which may not reveal the full strength of the proposed approach. Conflicting objectives should be adopted to solve the nonconvex Pareto front problem from weight assignments [93, 94].

The selection of compromise solutions from sets of Pareto optimal solutions can also be a complicating task. As a result, studies have focused on applying less complex decision-making techniques. For example, Battapothula et al. [95] simultaneously allocated DG units and EV charging stations in a distribution network while minimizing power losses, energy consumption, charging station development cost, voltage deviation of the system. The min-max technique was used to determine the compromise solution in an NSGA-II MOO framework. The min-max method is adopted from goal programming where distances between large deviations are minimized to obtain a final solution. Jannat et al. [96] also developed a method based on the min-max technique to determine a compromise solution from Pareto fronts. Unfortunately, the min-max falls among the categories of varied weights and ϵ-constraints where a weakly set of Pareto solutions are produced. Only recently have studies [97, 98] improved the min-max to produce better Pareto optimal solutions. Selim et al. [99] optimized total real power loss minimization, voltage deviation reduction, and voltage stability index, based on different operating power factors in DG allocation model. The Grey Relational Projection (GRP) technique was used to identify the best compromise solution from non-dominating solutions. Although computationally efficient, the GRP method can only be used to select compromise solutions among closely related objectives; hence, only the technical objectives were considered.

One main motivating factor for MOO application is practicality. Planning frameworks should be able to emulate the patterns of real-world projects. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach is the most recent decision-making technique for smart grid planning frameworks. TOPSIS selects a compromise solution based on the relative closeness index. The approach uses the Euclidean geometry such that it minimizes the Euclidean distance between each alternative and its best solution set (positive ideal solution), and simultaneously maximizes each alternative from its worst solution set (negative ideal solution). Sharma et al. [100] applied the TOPSIS approach with the NSGA-II to optimally allocate BESS for demand response in the presence of WT-based DG units and capacitors. Meena et al. [14] also used TOPSIS to select a compromise solution from a multiobjective Elephant Herding Optimization (ELO) algorithm. The approach used for selecting Pareto optimal solutions is unclear; however, a spacing metric was used to quantify the quality of Pareto solutions for comparison with other variants of the ELO. The spacing metric was used to measure statistical values to compare with other variations of the ELO. The framework was applied to optimize power loss minimization, voltage deviation, and voltage stability.

Game techniques have also been applied in smart grid planning frameworks to choose compromise optimal solutions. Recently, Nagaballi and Kale [101] used a minimax-based game theory approach to choose the compromise solution among non-dominating solutions from the Improved Raven Roosting Optimization (IRRO) algorithm application in the optimal allocation of DG units in distribution networks. The minimax algorithm uses a competitive two-player mode, where each player tries to reach the optimal minimum or optimal maximum for the final utility value. This approach proves to be computationally efficient than other methods such as the TOPSIS and fuzzy decision-making technique. Adetunji et al. [44] also applied a game-based approach to find a compromise solution between two decision- makers; a distribution network operator and an EV aggregator in an EV charging model.

In fact, due to the ambiguity of using a simple and yet robust MOO approach, some studies have ignored the decision technique. Zhang et al. [102] used Chance Constrained Programming (CCP) to solve the probabilistic power flow in the optimal planning of distribution systems. The objective was to reduce economic cost through the correlation of uncertainties using NSGA-II for the Pareto optimal fronts. However, no comparison was made with other algorithms to test for performance. Also, a decision technique was not implemented to select compromise solutions. The same decision was made in [103], where the compromise solution is left for the decision-maker to choose. In the study, Fault Current Limiters (FCL) were installed in series with DG units to reduce the adverse effects on the grid while finding an optimal location.

While the primary application of a multiobjective framework is to simultaneously optimize multiple objectives, there should be a consideration of the types of objectives to optimize in smart grid planning problem. In modern distribution networks, it is more practical to consider the simultaneous optimization of grid performance (technical), economic, and environmental benefits for network planning. Fewer research works [11, 26, 104] have implemented such studies.

Zeynali et al. [11] developed a multi-objective optimization framework to simultaneously integrate RES-based DG units, capacitor banks, and EV in a distribution network. A family of the evolutionary algorithm was hybridized as a GA-DE-SPEA-II algorithm, which has its strength from a varietized crossover function and synthesized mating strategy to produce good Pareto optimal solutions. The study considered one objective from all collective objectives, which are voltage stability, carbon emissions, and installation cost. The Fuzzy decision-making technique handled the selection of compromise solutions from the Pareto front, and a non-parametric test was performed to compare the proposed algorithm's performance to other multi-objective algorithms such as MOGA, MOPSO, and NSGA-II. In [26], a hybrid MOPSO and NSGA-II and a multiobjective GSA was proposed to optimally allocate energy storage systems in a wind farm-infused IEEE 30-bus meshed network. Their objective was to improve voltage deviation and to reduce operating costs and carbon emissions while using TOPSIS to select compromise solutions from the generated Pareto set. The authors formulated a single-, two-, and three-objective study to compare the best objective values for each formulation. The single objective produced the best voltage deviation and emission cost value while the three-objective produced the best installation cost value. Further work can be done to compare the quality of Pareto solutions distribution.

3.4 Planning Mechanisms for Allocating Multiple Units in Smart Grid Planning Frameworks

Given the longevity of power system networks, it is crucial to have an extensive smart grid planning framework; a framework that involves multiple DER units and/or FACTS devices. Such planning framework requires a planning mechanism for allocating different unit types in a particular manner. Planning mechanisms are the underlay for optimzation algorithms. In other words, they can affect the planning solutions from planning frameworks. To understand the concept of planning mechanisms, we need to first define the low-level problem, starting with unit type.

Definition 1: In this thesis, unit type is defined as the category of DER or PE units according to their functionality to the grid. For example, a DG unit is a unit type that supplies power to the grid irrespective of the generation source, e.g., Wind, Solar, Diesel, etc.; hence, any form of DG unit is categorized as a unit type. A BESS unit is another unit type since its operation is coordinated to optimally charge and discharge to and from the grid, primarily dependent on renewable-based DG units. Other unit types that can be optimally allocated are capacitors, voltage regulators, fault limiters, and EVCS facilities.

Definition 2: In this thesis, planning mechanism is defined as the underlying design in a planning framework to allocate more than one unit type in a power system network. The optimisation scheme uses the design to find the optimal planning scheme. Planning mechanisms are more significant when two or more unit type allocation is considered for a smart grid planning framework.

Previous studies on the smart grid planning have considered two or more of these units. Rodríguez-Gallegos et al. [23] proposed a novel method to allocate multiple, different DER units - PV-DG, BESS, and diesel generators. The procedure is based on a sequential planning mechanism that first considers finding the total BESS power and not considering power losses while defining a fixed PV power through a time horizon into the distribution network. Mouwafi et al. [105] developed a two-stage approach to solve a multiple DG units and capacitors problem. The adopted approach is similar to the sequential mechanism, using optimal capacitor locations for optimally allocating DG units in a 34- and 118-bus distribution network. However, the mechanism is chosen arbitrarily, with no motivation. Although Biswal et al. [106] identified the lack of simultaneous planning mechanism in literature, there was no comparative study on the developed mechanism with the sequential mechanism. They however varied the power factor while finding the optimal location and sizes of DG units and capacitors.

Gampa et al. [87] used the simultaneous and sequential mechanisms to allocate DG units, capacitors, and EVCS facilities in the distribution network, implementing a weighted sum assignment (WSA)-based MOO framework to optimize objective functions. The DG and capacitors are simultaneously allocated in the first stage, followed by the allocation of EVCS facilities, making it sequential to the first stage. In [107], a simultaneous approach was proposed to allocate multiple unit types optimally - PV-DG, shunt capacitors, and on-load tap changers. This approach combines all decision variables into a single one-dimensional vector, making the computation less expensive. However, no investigation was carried out on the strength of the mechanism.

Some studies investigated the effect of different variables on installed DER and PE units. For example, Janamala and Reddy [108] implemented a robust optimal DG and BESS model that considers the varying nature of EV loads while finding optimal DG/BESS locations and sizes. El-Ela et al. [109] varied the number of PV-DG units and BESS units, and BESS state of charge limits to the optimal allocation suitable for a 33-bus distribution network. In [110], a simultaneous planning mechanism was used to allocate DG and capacitor units, considering the effects of applying the sequential Monte Carlo technique to correlate stochastic historical data. Wong et al. [81] investigated the comparison of a two-step and a simultaneous approach to allocate PV-DG and BESS units in the IEEE 33-bus distribution network. However, both approaches are not based on planning mechanism, but rather a method that allocates only BESS units regarding their locations and sizes.

Dynamic planning mechanism is another one that has been scarcely implemented in literature. Although very computationally expensive, it is effective for finding improved planning solutions since it generates a larger solution space. Pirouzi et al. [111] considered proposing a dynamic planning model that will allocate DG units and capacitors in future work. Thokar et al. [112] developed a nested dynamic mechanism that dynamically allocates BESS units given the group installation of solar PV panels in a planning framework. Using the CMSO, the optimal coordination of the BESS units is achieved, considering the WSA-based optimization of objective functions. In [113], a dynamic planning mechanism was implemented to allocate PV-DG and BESS units in an MOO framework. However, the improved technical, economic, and environmental benefits was traded off for a high computational time.

Table 3.2 shows the taxonomy of previous related studies on smart grid planning regarding the allocation of multiple DER, FACTS, or EVCS facilities.

TABLE 3.2: A chronological taxonomy of smart grid planning frameworks involving multiple unit type allocation

Ref.	**Year**	**Algorithm**	**Planning mode**	**Planning mechanism**	**DG**	**BESS**	**CB**	**EVCS**	**VR**
[23]	2018	GA	Loc. & size	Simultaneous	✓	✓			
[81]	2019	WOA	Loc. & size	Simultaneous	✓	✓			
[15]	2020	CMSO	Loc. & size	Simultaneous	✓	✓			
[114]	2019	LP solver	Allocation & EMS	Sequential	✓	✓		✓	
[86]	2020	PSO	Loc. & size	Sequential	✓	✓			
[115]	2020	SOCP solver	Loc. & size	Simultaneous	✓	✓		✓	
[87]	2020	GOA	Loc. & size	Simultaneous & Sequential	✓		✓	✓	
[109]	2021	equilibrum	Loc. & size	Simultaneous	✓	✓			
[113]	2021	WOAGA	Loc. & size	Dynamic	✓	✓			
[116]	2021	MIDACO	Allocation & EMS	Sequential	✓	✓			
[106]	2021	QRSMA	Loc. & size	Simultaneous	✓		✓		
[105]	2021	CBA	Loc. & size	Sequential	✓		✓		
[108]	2021	Coyote	Loc. & size	Sequential	✓	✓			
[117]	2021	HGSO	Loc. & size	Simultaneous	✓	✓			
[88]	2021	EGWA	Loc. & size	Simultaneous	✓		✓		✓
[112]	2021	CMSO	Loc. & size	Dynamic	✓	✓			
[111]	2022	MILP solver	Loc. & size	Simultaneous	✓	✓			
[110]	2022	GA	Allocation & Automation	Simultaneous	✓		✓		

3.5 Comparisons and Discussions

This study identified many significant issues by reviewing metaheuristic techniques for the optimal integration of distributed generation and FACTS units in distribution networks. This section discusses the observations and suggestions regarding the development of smart grid planning frameworks.

3.5.1 Discussions on Metaheuristic Techniques for Smart Grid Planning Frameworks

As explained previously in Section 3.2, metaheuristic algorithms are the common choice for solving optimal integration problems in smart grids due to their flexibility. However, in this context, flexibility might not necessarily mean simplicity. The successful implementation of metaheuristic algorithms requires a good knowledge of both the algorithm's inner workings and the optimal allocation problem. Although studies may directly apply algorithms to the optimal allocation problem, due to their availability as a toolbox or library in optimization software applications and its simplicity, the researcher or engineer may omit some important details. Hence, studies may not attain optimal or practical results. The GA is a typical example.

The GA is the most commonly used evolutionary algorithm, which may be due to its availability as a toolbox or library in optimization software applications, or its efficiency to produce good results from the optimal allocation problem. It is observed that other algorithms in the evolutionary algorithms category, such as the DE, have fewer studies when compared to the GA. The DE has been reported to perform better in other studies than the GA, as shown in [118]. Moreover, the DE primary operators are synonymous to the recently modified GA operators, which means that current GA research can be used to improve the DE. Therefore, future research works can explore the DE algorithm to achieve better results from the optimal integration problem.

As seen in the study, swarm and physics-inspired algorithms have also been widely applied to smart grid planning frameworks. They have been modified by tuning their parameters, which shows the high impact of parameter values on planning solutions. A high number of parameters may increase the subjectivity of the algorithm's performance, which is why studies carry out statistical analysis of proposed algorithms. It is suggested that future studies focus on finding a minimal amount of the algorithm's parameters. For example, dimensionality reduction techniques, such as factor analysis and principal component analysis, can be used to find an optimal amount of parameters for any algorithm. Although this process may be exhaustive, it will aid studies on the optimal allocation of DER and FACTS units to further improve grid performance and boost economic benefits.

It is also observed that hybrid algorithms are trending because they can be easily implemented to produce good results from the optimal integral problem. However, some studies directly merge two or more mechanisms to produce improved planning solutions. This effort poses a risk of increasing the algorithm runtime, and they therefore become computationally inefficient. This is evident in works of [10, 26]. One approach to overcome this setback is to find and eliminate duplicate steps or attributes of the algorithms. Future studies on applying hybrid algorithms to smart grid planning frameworks can focus on implementing each algorithm's unique features rather than directly implementing the whole features of each algorithm.

3.5.2 Discussions on Multiobjective Optimization for Smart Grid Planning Frameworks

As discussed in Section 3.3, metaheuristic algorithms deal with multiobjective problems in two major ways, either by computing preference aggregation before or after problem manipulation. The *apriori* approach is quite easy to implement and is computationally efficient. However, based on intuition for a better practical scenario, most *aposteriori* methods are preferred to the *apriori* ones. Furthermore, *aposteriori* approaches offer the option of choosing from a list of optimal solutions after computation. Studies on the optimal integration of electrical units have implemented both approaches according to different philosophies. A comparison of different multi-objective optimization techniques is shown in Table 3.3.

TABLE 3.3: Comparison of decision-making techniques

Techniques	**Strengths**	**Drawbacks**
WSA	-Easy to compute -Suitable for professional decision makers	-Results may be flawed by bias
Fuzzy decision method	-Rich in Literature -Easy to implement	-Some level of subjectivity with the input of weights
Min-max method	-Easy to implement -Low computational complexity	-May be unrealistic for real-world problems
Utopian method	-Eliminates subjectivity -Easy to implement	-Few studies in literature -Mostly suitable for two objective functions
GRP	-Easy to implement -Low computational complexity	-Only suitable for closely similar objectives
TOPSIS	-Can handle several objectives in form of alternatives -Weights assignment can be skipped -Can involve many decision makers	-High computational complexity -Some level of subjectivity if weights are assigned

Previous studies have handled multiple objectives in a non-categorized manner, where, irrespective of the multiobjective handling method used, every objective function is pushed to a multiobjective framework for a final decision value. This approach may not represent a practical scenario where all collective objectives, such as technical (or grid performance), economic, and environmental objectives are thought differently from each other. For example, studies in [83] adopted two objective functions for grid performance and one for economic benefits but assigned equal weighting for all objectives in the decision making phase. An equal assignment of weights or direct summation already shows a high preference for grid performance than economic benefits. Some studies have avoided this drawback by either focusing on only one of the collective objectives or selecting one objective to represent each collective objective. For instance, Sharma et al. [100] adopted power loss minimization and grid demand cost reduction to represent grid performance and economic benefits, respectively. Another example is from [86], where all adopted objectives represent only the grid performance.

These examples beg the questions:

1. Can one objective, such as power loss minimization, satisfactorily represent grid performance?
2. Can we always optimize only a collective objective, such as grid performance, without including economic or environmental benefits?

The encompassing question would be "how can many objectives be simultaneously optimized in a smart grid planning framework?". This question may be answered by developing a multi-stage multiobjective framework to find a balance among all collective objectives, where all similar objectives can be optimized categorically.

3.5.3 Discussions on Planning Mechanisms for Smart Grid Planning Frameworks

The trend of allocating DER and FACTS units in a distribution network grid is gradually shifting towards a full-blown smart grid, where clean energy will be prevalent while maintaining high power quality and grid stability. Hence, more studies will need to develop a robust smart grid planning framework that can allocate a wide range of DER and FACTS units, such as BESS, wind turbines, solar PVs, capacitors, STATCOM, voltage regulators and EVs. In fact, recent studies have started working on allocation many unit types. In light of this development, planning mechanisms becomes very vital to allocate multiple units in smart grid planning frameworks. Sequential and simultaneous planning mechanisms are the most used in literature, and only few works have tried to investigate their effects on optimal planning solutions. Dynamic planning mechanisms, which are proven to produce better planning solutions than other mechanisms, have been rarely used in literature. Although understandable that studies may not have considered it because of it extreme time complexity; however, it gives an avenue for research. It is recommended that dynamic mechanisms be applied in different approaches, such that optimal solutions can be traded off for lower time complexity.

3.5.4 Discussions on EV charging in Smart Grid Planning Frameworks

Another observation is the trend in the integration of EV units in recent studies, where EVs are used to support the grid in terms of voltage regulation or power compensation. The EV aggregator (EVA) has been added to new optimal integration models to communicate EV data for charging or discharging schedule. They are practically in the business space, while the Distribution Network Operator (DNO) is concerned about the performance of the distribution network. Hence, the EVA can also become a decision-maker along with the DNO. It is only practical since the EVA is an integral part of the model. Future studies can explore the possibilities of including the DNO and EVA as major decision makers in the optimal integration of EVs and other allocation model. Furthermore, it is also observed that studies on the allocation of the EV charging stations do not consider the random EV charging. This omission may produce unrealistic planning solutions.

3.6 Summary

This chapter reviewed the application of metaheuristic algorithms in smart grid planning frameworks were discussed extensively, considering areas of single and multiobjective optimization, planning mechanisms, and electric vehicle charging. The review on metahueristic algorithms shows how algorithm parameters can affect planning solutions. It was highlighted that hybrid metaheuristic algorithms are developed to produce better planning solutions but have high complexity. Current works on multiobjective optimization in smart grid planning frameworks still need researching. Studies have reduced the robustness of planning frameworks to avoid issues such as the uncontrollable bias in optimizing dissimilar objectives and the difficulty in representing many objectives. Planning mechanisms have also been highlighted as a critical research area, since they are crucial to the development of the recent, extensive smart grid planning framework, which requires multiple allocation of different unit types. Finally, the importance and effect of EV charging in distribution networks is discussed. The review of studies on EV charging allocation showed that current studies have not considered the random charging of EVs.

The following chapters address the gaps in the review, including answering the questions and discuss the implementation of the suggested solutions. The hybrid metaheuristic problem from Section 3.2 is addressed in Chapters 4 and 7. The issue of uncontrollable bias and underrepresentation of many objectives in a smart grid planning framework in Section 3.3 is solved in Chapters 4 and 5. Planning mechanisms from Section 3.4 is addressed in Chapters 6 and 7. Finally, Chapter 6 addresses the EV charging station allocation problem in Section 3.5.4. The next chapter discusses the development of a hybrid metaheuristic algorithm in a smart grid planning framework, focusing on improving computational efficiency. The chapter also discusses the development of a category-based MOO for optimizing many objective functions.

Chapter 4

Category-based Multiobjective Approach for Optimal Integration of Distributed Generation and Energy Storage Systems in a Smart Grid Planning Framework

This chapter is based on the following publication:

K.E. Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng, "Category-based Multiobjective Approach for Optimal Integration of Distributed Generation and Energy Storage Systems in Distribution Networks". *IEEE Access, vol. 9, pp. 28237-28250, 2021*, doi: 10.1109/ACCESS.2021.3058746.

The author of this thesis conceptualized this work, partook in the formal analysis, developed the models and algorithms, and wrote the original draft of the paper.

4.1 Introduction

The integration of Distribution Generation (DG) units is an essential feature in the modern-day electric utility grid. Certain parameters can be considered, such as quantity and size of DG units, the best location, bus configuration, and even the most suitable DG unit technology to be used [119]. A common and central problem is the placing and sizing of DG units [119]. Inappropriate installation of DG units can have adverse effects on power flow and voltage stability, which can cause an upsurge in line losses [120, 121], thereby inferring an increase in economic costs [122]. Besides, the installation of DG units is a non-linear problem, which means that the increase in the number of DG units does not directly improve grid performance. Therefore, it is essential to find the optimal location and size of DG units in power networks to solve certain objectives. To reduce carbon emissions, most studies have integrated the renewable energy-based DG units in distribution networks. However, renewable energy (RE) sources, such as Photo-voltaic (PV) panels intermittent power supply is a setback for constant power flow. To obviate this drawback Battery Energy Storage Systems (BESS) are integrated into the grid to store energy from the renewable energy DG units at their peak times. The integration of BESS units also comes with additional time complexity and extra cost; therefore, there is a need to (i) apply an efficient optimization algorithm and (ii) mitigate its cost effect. Several methodologies have been proposed for solving the optimal integration, such as the analytical approaches (mathematical methods) and metaheuristic techniques. The combined combinatorial and nonconvex nature of the placing and sizing problem has influenced the frequent use of metaheuristic algorithms which is mainly because of its better computational time and efficiency rate [123, 124].

While some techniques have been developed to reduce the problem's complexity, they do not guarantee suboptimal solutions. They are mostly used to grade the current technical status of each bus in a distribution network. By that, the technique would suggest the bus location for DG units. Some examples are power loss index (PLI), voltage stability index (VSI), and most recently, loss sensitivity factor (LSF). These techniques have also been researched and improved over time [125].

Numerous optimization techniques have been applied to solve the optimal integration problem in distribution networks and have been in a multiobjective space. Although some recent studies have focused on one objective (mostly power loss minimization), some of those studies emphasize more on new models and then validate it by formulating and optimizing an objective function. Otherwise, a multiobjective framework will be formulated. Related studies are discussed in Section 4.2.

To the best of the authors' knowledge, researchers have not studied the categorization of objectives in a multiobjective optimization framework. This is corroborated by [126] where it is reported that previous studies have only handled multiple objective functions in a non-categorized manner where all adopted objective functions are pushed to a multiobjective framework for a final decision value. For instance, when power loss, voltage stability, and installation cost are optimized simultaneously, the final utility value will automatically have a bias towards the technical objective because they possess similar parameters. As explained in [8], uncontrollable bias will occur when there are closely similar parameters in some objectives. Unless the decision-maker prefers this bias, the optimal integration problem's final objective values will be termed flawed.

Another instance is where a study focuses on only one collective objective, where power loss, voltage stability, and line loading can be the adopted functions in a multiobjective framework. While this type of study focuses on the project's technical aspects, it lacks an equilibrium approach to handle all collective objectives. Hence, the practicality of the study is questionable. The two instances previously mentioned may not represent a practical scenario where all collective objectives are thought differently from each other. In a real-world scenario, modern distribution networks' planning should compulsorily consider the technical, economic, and environmental aspects.

Another vital point is explained in [127,128] where it is discussed that the higher number of objectives in a multiobjective optimization framework increases the number of nondominated solutions, which adversely affects the computational burden of the optimization model. To avoid the aforementioned setbacks, this chapter proposes a multi-stage multiobjective framework, which uses a categorical approach that can intelligently accommodate and optimize all collective objectives. A categorical approach can separately handle a group of objectives, followed by the final objective handling (the conventional method).

The main contributions of this chapter can be stated as follows.

- The investigation for the optimal integration of PV-DG and BESS units is carried out by focusing on power loss minimization, voltage stability improvement, voltage deviation reduction, installation cost reduction, operational cost reduction, and emission cost reduction. Research works [81,100,129] have studied one or more of these objectives in different variations but not all of the objectives.
- A novel approach for optimal distribution network planning is introduced, where PV-DG and BESS units are integrated simultaneously by injecting real power from the PV modules and the BESS units. The proposed approach enables a seamless interactive mechanism between DG allocation and BESS allocation, unlike in [81,129] where PV is either fixed or initially integrated based on physical observation before the integrating the BESS units, the approach assigns bus locations to PV-DG units at every second round of iterations.
- In contrast to developing a hybrid metaheuristic algorithm that requires the whole mechanism of each algorithm to solve the optimal integration problem (as in [10]), we split the problem into subproblems and assign each algorithm according to their strengths. As a result, the proposed algorithm becomes more computationally efficient.
- A new approach based on a multistage multiobjective framework is proposed to optimize all objectives in a categorized manner. Earlier studies have either applied weights to multiple objectives or produce Pareto optimal solutions from the objectives without considering each objective's categories.
- A Technique Order for Preference by Similarity to Ideal Solution (TOPSIS) approach is combined with the crowding distance technique to produce Pareto optimal solutions from the multiple objectives.

The rest of the chapter is organized as follows. Section 4.2 discusses the related works. Section 4.3 discusses the problem formulation of the work which explains the handling of uncertainties and all adopted objectives. The section further explains the power flow constraints and BESS constraints. The optimization strategy is discussed in Section 4.4. Here the new multi-stage multiobjective framework is discussed, and the multiobjective approach is introduced. The proposed algorithm and its implementation to the optimal integration of PV-DG units in distribution networks are also discussed. Section 4.5 presents the results from the analysis. In doing so, the IEEE 33-bus test network is used as the testbed for evaluation. Finally, the conclusion is entailed in Section 3.5.

4.2 Related Works

According to literature, optimization in distribution network planning can be categorized into deterministic and stochastic algorithms. The algorithms can be subdivided into single objective and multiobjective frameworks. Some significant contributions have been made in applying stochastic algorithms, such as metaheuristic algorithms, to distribution network planning. Xiao et al. [130] used the GA to optimally allocate and size BESS units in a renewable energy-present distribution network. The algorithm was implemented such that every violated constraint in the solution is discarded during each generation, making the algorithm computationally efficient. Xiao et al. [131] used a bi-level optimization approach to allocate DG and BESS units to plan distribution networks optimally. The first level minimizes the overall costs using a summation method while the second level ensures optimal coordinated operation of the integrated units. It is to note that handling multiple objectives is as important as the optimization technique applied. Das et al. [129] used the summation method to simultaneously optimize voltage deviation, flickers, power losses, and line loading while using the fitness-scaled chaotic Artificial Bee Colony (ABC) to optimally allocate and size BESS units in a distribution network. Although simple and less complex, the summation approach is arguably not a proper approach to simultaneously handle multiple objectives. Wong et al. [81] applied the WOA to minimize the real power loss. The study experimented with two methods of siting and sizing BESS DG units in a conventional and PV-integrated distribution network: the (i) two-step method and (ii) simultaneous siting and sizing method. The performance of both methods was validated by comparing the WOA to the firefly algorithm and the Particle Swarm Optimization (PSO).

Previous studies have developed hybrid metaheuristic algorithms to solve the optimal integration problem in distribution networks. Moradi and Abedini [28] proposed a hybrid algorithm of Intelligent Water Drops (IWD) and GA for optimally allocating and sizing DG units in a microgrid for solving objectives such as power loss minimization, voltage stability improvement, and total voltage variation improvement. The proposed algorithm was applied in a stepwise manner where the GA finds the optimal location while the IWD finds the optimal sizes. The authors handled the multiple objectives by assigning weights before the optimization process, which is not a very practical solution in a multiobjective space. They, however, varied the weights to observe the effect on simulation results. In [132], the PSO and ABC were hybridized to optimally size capacitor banks while minimizing power loss and energy loss in a 34-node and 69-bus distribution network. A summation method was used to handle the objectives which may not produce accurate results for real-world scenarios. Jeddi et al. [10] hybridized a Harmony Search Algorithm (HSA) and the Firefly Algorithm (FA) in a chaotic model (dubbed CHSFA) to maximize profits of distribution network companies by reducing operational costs and increasing income in a distribution network. The proposed algorithm uses the HSA mechanism to search towards the best objective values in the harmony memory and uses the FA mechanism for a random search, was validated on a 38-bus distribution network and reported to converge faster than the HSA. Since the process is repeated twice to achieve an optimal solution, it is assumed that the CHSFA, due to its complex mechanism, will have a higher computational time than the HSA.

The handling of multiple objectives is a crucial feature in the optimal integration problem in distribution networks, and proper handling is synonymous to the practicality of results. A direct weight assignment approach (WSA) is the simplest form of handling multiple objectives and has been used in the optimal integration problem, as in [85]. The authors created different multiobjective aggregation scenarios for siting and sizing capacitors and DG units. The WSA technique always comes with bias since the preference level is carried out before the optimization process. Shaheen and El-Sehiemy [88] considered four objective functions, and unlike a direct WSA method like in [3], the Analytical Hierarchical Process (AHP) was used to determine the weights for each objective function. They proposed an enhanced grey wolf optimizer to optimally allocate DG units, capacitor banks, and voltage regulators. The AHP was also used in [86] and [89] to select the weights required for each objective in a multiobjective integration of DG and BESS units in distribution networks. The AHP technique only douses the effect of weight input bias in the optimization process. The *aposteriori* method proves to overcome the bias problem since preference evaluation is done after the optimization process.

Selim et al. [99] proposed an improved Harris Hawks Optimization (IHHO) algorithm to allocate and size DG units in a multiobjective framework. The multiobjective framework was based on the Pareto optimal front, where the power loss minimization, voltage deviation reduction, and voltage stability improvement were considered as the objectives. The final solution was determined using the Grey Relational Projection (GRP) method and was tested on the IEEE 33- and 69-bus distribution networks. Although computationally efficient, the GRP method can only select compromise solutions among closely related objectives; hence, only the technical objectives are considered. Zeynalli et al. [11] hybridized the GA, DE, and Strength Pareto Evolutionary Algorithm (SPEA-II) to generate Pareto optimal solutions from the integration of RES-based DG units (solar and wind), capacitor banks, and EV in a distribution network. The study considered voltage stability, carbon emissions, and installation cost as objectives, and the fuzzy decision-making technique was used to handle the selection of compromise solutions from the Pareto optimal solutions. The fuzzy-based technique applies a three-scale fuzziness to each alternative solution and compares each solution to the best individual solution to select the compromise solution.

Recent studies have used the Technique for Order Preference by Similarity to Ideal Solution approach to finding the best solution from a set of alternatives in the field of multiobjective DG unit integration. The TOPSIS approach efficiently chooses a compromise solution based on the relative closeness index. The approach minimizes the Euclidean distance between each alternative solution and its best solution set (positive ideal solution) and simultaneously maximizes each alternative solution from its worst solution set (negative ideal solution). Meena et al. [14] used the TOPSIS approach to (i) produce non-dominating solution from the proposed multiobjective Elephant Herding Optimization (ELO) algorithm and (ii) select a compromise solution. The proposed algorithm was applied to optimize power loss minimization, voltage deviation, and voltage stability and the spacing metric was used to measure statistical values to compare with other variations of the ELO. From [26], a multiobjective hybrid algorithm PSO and GA was proposed to optimally allocate energy storage systems in a wind farm-infused IEEE 30-bus meshed network, considering the uncertainties. Their objective was to improve voltage deviation and reduce operating costs and carbon emissions while using TOPSIS to select compromise solutions from the generated Pareto set.

The authors formulated a single-, two-, and three-objective study to compare the best objective values for each formulation. The single objective formulation produced the best voltage deviation and emission cost value, while the three-objective produced the best installation cost value. However, further work can be done to compare the quality of Pareto solutions distribution. The TOPSIS was also used in [100] to select the compromise solution from a Pareto optimal set. The authors implemented the Non-dominating Sorted Genetic Algorithm (NSGA-II) to allocate and place BESS units in a distribution network while minimizing power loss and grid demand cost.

Despite the multiobjective techniques seen in literature, a categorical approach of handling multiple objectives simultaneously in a distribution network planning problem has not been studied. Furthermore, most studies used a one-way approach to allocate DG and BESS units in a distribution network, although this approach reduces the computational time complexity, it may not produce practical results. This chapter implements a novel iterative approach to allocate DG and BESS units in distribution, and a hybrid metaheuristic algorithm is developed to handle the additional computational complexities.

4.3 Problem Formulation

This section discusses the modelling that aims to find the optimal locations and sizes of multiple PV-DG and BESS units while observing the objective functions. The uncertainty handling approach, adopted objective functions, and constraints are explained in the following subsections.

4.3.1 Modelling Uncertainty

The work involves taking PV power output and electricity pricing as uncertain input, given that there can be exact values throughout a season. The PV power output solely depends on solar irradiance, with temperature, and the PV module characteristics. The solar irradiance is modelled as a beta distribution function [133, 134], which is shown as

$$f_b(s) = \begin{cases} \frac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} s^{(p-1)}(1-s)^{(q-1)}, & \underset{p,q\geqslant 0}{0 \leqslant s \leqslant 1} \\ 0, & \text{else} \end{cases}, \tag{4.1}$$

where $f_b(s)$ is the beta distribution function of solar irradiance, s. The input parameters are p and q are calculated using the mean, μ and variance, σ of the solar irradiance data, and are defined as

$$q = (1-\mu)\left(\frac{\mu(1+\mu)}{\sigma^2} - 1\right), \tag{4.2}$$

$$p = \frac{\mu \times \beta}{1-\mu}, \tag{4.3}$$

where

$$\rho_s^y = \int_{s_y}^{s_{y+1}} f_b(s)\,\mathrm{d}\,s \tag{4.4}$$

is the probability of occurrence from the boundaries of solar irradiance at states s_y and s_{y+1}. The PV output power is evaluated as [62]

$$P_t^{pv} \;=\; N \times FF \times V_t \times I_t \quad , \tag{4.5}$$

given that

$$FF \;=\; \frac{V_{mpp} \times I_{mpp}}{V_{oc} \times I_{sc}}, \tag{4.6}$$

$$V_t \;=\; V_{oc} - K_v \times T_t^c, \tag{4.7}$$

$$I_t \;=\; s_t \left[I_{sc} - K_I \times (T_t^c - 25)\right], \tag{4.8}$$

and

$$T_t^c \;=\; T_a + s_t \left(\frac{T_{nom} - 20}{0.8}\right). \tag{4.9}$$

The PV power output, P_t^{pv} at time t, is a factor of the fill factor, FF, the output voltage V_t and the output current I_t. The FF is defined in (4.6) where V_{mpp} and I_{mpp} represent the voltage and current at maximum power point, respectively, V_{oc} represents the open circuit voltage and I_{sc} is the short circuit current. Equations (4.7) and (4.8) define V_t and I_t, respectively and K_v is the voltage temperature coefficient, K_I is the current temperature coefficient, and T_t^c is the cell temperature in *celcius* which is defined in (4.9); s_t is the solar irradiance at time t, T_a is the ambient temperature, T_{nom} is the nominal operating temperature. The electricity prices are modelled as a log-normal distribution function to characterize the tariff at each hour. It is expressed as

$$f_b(P) = \frac{1}{P\sigma\sqrt{2\pi}} exp\left(-\frac{(\ln P - \mu)^2}{2\sigma^2}\right), \tag{4.10}$$

where the μ and σ represent the mean and standard deviation values, and P is the distribution function parameter. The Probability Density Functions (PDFs) are sliced into multiple intervals such that each interval produces a probability of occurrence and a mean value.

The backward technique is used to eliminate duplicate scenarios to reduce the number of scenarios generated. This technique also helps to reduce the computational burden of the whole algorithm [135].

4.3.2 Objective Functions

The considered collective objectives of the study are expressed by the following objectives

4.3.2.1 Power Loss Index

This objective is based on the power loss of the distribution network, before and after DG unit allocation, expressed in Equations (2.9) to (2.11).

4.3.2.2 Voltage Deviation

Voltage regulation and monitoring are a primary, yet important task of the distribution network operator, which is also a concern for the consumer given that appliances and meters. It is therefore essential to measure the voltage deviation while injecting the DG and BESS units. It is defined as [12]

$$VD = \sum_{i=2}^{N} |V_i^t - V_{ref}|, \tag{4.11}$$

where the reference voltage, V_{ref} is set at one and V_i represents the voltage at each bus after the addition of DG or BESS units.

4.3.2.3 Voltage Stability Index

Voltage collapse is a phenomenon that is a consequence of random load increase in distribution networks. While integrating DG units, the VSI is applied to monitor the degree of voltage collapse of the system. The VSI needs to be maximized and is defined in Equations (2.12) to (2.14).

4.3.2.4 Installation Cost

The cost generated while sizing the DGs is very important. Therefore, there is a need to minimize it simultaneously with the sizing objective [136–138], which is defined as

$$C_{\text{inst}} = \sum_{i=1}^{N} (n_{\text{PV}} \times c_{\text{PV}} + n_{\text{BESS}} \times c_{\text{BESS}}), \tag{4.12}$$

where n_{PV} and n_{BESS} are the unit number of solar PV and BESS units respectively, and c_{PV} and c_{PV} are the unit cost of solar PV and BESS units respectively.

4.3.2.5 Operational Cost

The operational cost includes the cost of maintaining DG and BESS units and the cost of power from the grid. It is formulated as [62, 139]

$$C_{\text{op}} = \sum_{y=1}^{Y} \sum_{t=1}^{24} \sum_{s=1}^{N_s} \rho_s (C_{t,s}^{\text{ss}} \times P_{t,s}^{\text{ss}} + PV_{t,s}^{OM}) \times \left(\frac{1 + inf}{1 + int} \right)^{y-1}, \tag{4.13}$$

where $C^{\text{ss}}_{t,s}$ represents the cost of power from the substation, $P^{\text{ss}}_{t,s}$ indicates the power from the substation, $PV^{OM}_{t,s}$ is the operation and maintenance cost of the PV-DG units, and ρ_s is the probability of scenario s. The inf and int respectively represents the inflation and interest rates over a 10-year period.

4.3.2.6 Emission Cost

The emission cost objective is defined in (2.22).

4.3.3 Constraints

$$P_i^t = \sum_{j=1, j\neq i}^{N} Y_{ij} V_i^t V_j^t \cos(\theta_{ij} + \delta_j - \delta_i) \tag{4.14}$$

and

$$Q_i^t = \sum_{j=1, j\neq i}^{N} Y_{ij} V_i^t V_j^t \sin(\theta_{ij} + \delta_j - \delta_i). \tag{4.15}$$

Although there was no injection of reactive power, it is necessary to monitor boundaries during the injection of real power. The operating voltage at every bus must satisfy the range at all buses. The admittance on branch is represented as Y_{ij}. The bus voltage limit is formulated as

$$V_i^{min} \leq V_i \leq V_i^{max} \quad i = 1, 2, ..., N, \tag{4.16}$$

where V_i is the current voltage at bus i. Then V_i^{min} and V_i^{max} are 0.98 and 1.01 respectively.

The power flow balance is also considered. The total real power generation (from all DG and BESS units) must be equal to the total real load, total real power loss, and the BESS charging and discharging power [140]. Therefore, a balance of the power flow is calculated as

$$\sum_{i=1}^{N} P_i^{\text{DG}} + \sum_{j=1}^{J} P_j^{\text{Dis}} = \sum_{i=1}^{N} P_i^{\text{LOSS}} + \sum_{i=1}^{N} P_i^{\text{LOAD}} + \sum_{j=1}^{J} P_j^{\text{Ch}}, \tag{4.17}$$

where the P_j^{Dis} and P_j^{Ch} represent the BESS discharging and charging power to and from the grid from bus j.

4.3.4 BESS Operation Constraints

Given that BESS's performance in any application depends on the BESS technology, this work selected the Lead-acid battery technology. Lead-acid batteries are reliable, economically viable, and can be left on a float charge for more extended periods; hence their overcharging tolerance. These characteristics are well suited for the ESS integration in distribution networks.

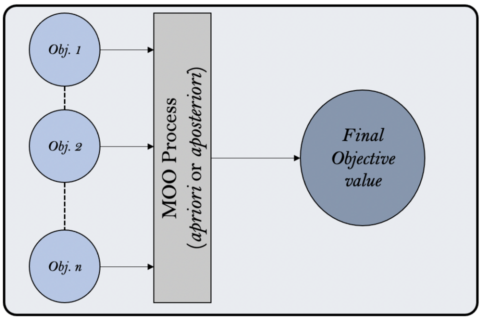

FIGURE 4.1: Conventional approach to handle multiple objectives.

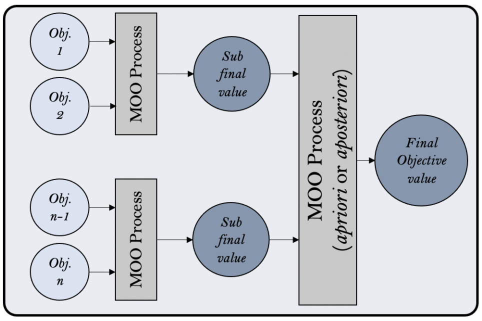

FIGURE 4.2: Proposed categorical approach to handle multiple objectives.

For a practical scenario, the BESS model is subject to certain constraints such as SOC limit prevents excessive charging or discharging from the battery, and defined as [141]

$$SOC^{min} < \frac{E_t^B}{E_t^{BA}} < SOC^{max}, \tag{4.18}$$

where the SOC^{min} and SOC^{max} are 0.2 and 0.9 respectively. The charging and discharging power are specified as [66, 142]

$$E_{t+1}^B = \begin{cases} E_t^B - P_t^B \triangle t \eta_{Bc} & P_t^B \leqslant 0 \\ E_t^B - \frac{P_t^B \triangle t}{\eta_{Bd}} & P_t^B > 0 \end{cases}, \tag{4.19}$$

where E_t^B is the energy of the BESS unit at time t, P_t^B is the charging power of the BESS unit at time t, $\triangle t$ is the time interval, η_{Bd} and η_{Bc} are the discharging and charging efficiency of the BESS unit respectively, the battery power is limited by

$$E^{\min} \leqslant E_{i,t}^B \leqslant E^{\max}, \tag{4.20}$$

where $E_{i,t}$ is the energy of the i^{th} BESS unit at time t.

4.4 Optimization Strategy

4.4.1 Multistage Multiobjective Framework in an Optimal Integration Problem in Distribution Networks

In the optimal integration problem, objective functions are categorized into three collective objectives: grid performance (or technical benefits), economic benefits, and environmental benefits. Each of these collective objectives can consist of many objective functions except for the environmental benefits, which only deals with the greenhouse gas emission cost. The proposed framework categorically handles the adopted objectives according to their respective collective objectives. Figure 4.1 shows the conventional and proposed method for handling multiple objectives.

As seen in Figure 4.1, the conventional approach, irrespective of the approach, the objectives are fed into the MOO framework without considering the collective objectives. Figure 4.2 illustrates the initial handling of categorized objectives, followed by the final handling of the collective objectives. The first stage of optimization adopts the apriori approach, which implements the Weighted Sum Aggregate method (WSA) to all concerned objectives to get subfinal values. The subfinal values represent the value for each collective objective, which are handled using a TOPSIS approach.

4.4.2 Multiobjective Framework using the TOPSIS Approach

This process is merged with the multistage multiobjective framework to produce non-dominating solutions. The TOPSIS method is used to solve the multiobjective optimal integration problem in distribution networks. This method applies the Euclidean geometry between positive ideal solutions (P^{+ve}) and the negative ideal solutions (P^{-ve}). The shortest distance from $P^{+ve}$and longest from P^{-ve} helps identify the best compromise solution from the Pareto optimal set. The following steps explain the process of the TOPSIS method.

Step 1 all objectives are transformed into a nondimensional entity and stored in a normalized decision matrix. The normalization is defined as

$$D_{ij} = \frac{F_{ij}}{\sqrt{\sum_{i \in M, j \in N} F_{ij}^2}}, \tag{4.21}$$

where M represents the number of alternatives and F_{ij} is the i^{th} alternative value of the j^{th} objective.

Step 2 as an option, weights are assigned to determine the importance level of all objectives. The element in the decision matrix are determined as

$$WD_{ij} = W_j D, \tag{4.22}$$

where the sum of weight W_j of the j^{th} objective is equals to one.

Step 3: The values of P^{+ve} and P^{-ve} which represents the best and worst solutions of the objective functions. They are expressed as

$$P^{+ve} = B_1^+, B_2^+, ..., B_M^+, \tag{4.23}$$

$$P^{-ve} = B_1^-, B_2^-, ..., B_M^-, \tag{4.24}$$

where

$$B_j^+ = \begin{cases} max(B_{ij}), & \textit{if objectives are benefits} \\ min(B_{ij}), & \textit{if objectives are cost-wise} \end{cases}$$

$$B_j^- = \begin{cases} max(B_{ij}), & \textit{if objectives are cost-wise} \\ min(B_{ij}), & \textit{if objectives are benefits} \end{cases}.$$

Step 4 Find the Euclidean distance from the ideal solutions of P^{+ve} and P^{-ve} to their alternative solutions, P_i. It is represented as

$$d_i^+ = \sqrt{\sum_{J=1}^{N}(B_{ij}^2 - {B_j^+}^2)} \tag{4.25}$$

$$d_i^- = \sqrt{\sum_{J=1}^{N}(B_{ij}^2 - {B_j^-}^2)} \tag{4.26}$$

Step 5 Calculate the relative closeness index, ζ based on the Euclidean distance from step 4, and expressed as

$$\zeta = \frac{d_i^-}{d_i^+ + d_i^-} \tag{4.27}$$

Step 6 Select the best solution based on the highest value of ζ.

4.4.3 Proposed Algorithm

4.4.3.1 Overview of the Whale Optimization Algorithm

The WOA was developed by Mirjalili [143] and has been applied successfully to many optimization problems, including the optimal sizing problem. The algorithm involves the feeding nature of whales (specifically humpback whales). According to whales' intelligent behavioural nature, they use a specific technique to target small fish that are close to the sea surface. This technique is called the bubble net feeding, where whales swim round a school of fish (prey) to form a 9-shaped bubble trail. In this algorithm, an initial solution is termed as the objective prey and assumed as the current best solution. During iterations, other whales update their positions towards the best whale position. The WOA is mathematically modelled in three sections. (i) encircling prey (ii) bubble net hunting method and (iii) search the prey.

Encircling prey This form of hunting is based on a circular positioning around a prey. The position of the whale moves towards the prey in a step-wise manner. It can be modelled as

$$\overrightarrow{X}_{t+1} = \overrightarrow{X}_t^* - A \cdot \overrightarrow{D}, \tag{4.28}$$

where $A = 2a \cdot r - a$ and a is linearly reduced from 2 to 0, and $r \in [0, 1]$ where r can take up random in 0 and 1 interval.
$\overrightarrow{D} = |C \cdot \overrightarrow{X_t^*} - \overrightarrow{X_t}|$, is the distance between the current whale position and the best whale position where $C = 2 \cdot r$ is a random parameter that is updated at every round of iteration. The current iteration is denoted by subscript t and $t+1$ for the next iteration. $\overrightarrow{X}$ represents the position vector and $\overrightarrow{X}^*$ represents the current best solution.

Bubble net hunting method This method is the exploitative phase of the algorithm. This behaviour is attained by decreasing the value of a, as explained in Section 4.4.3.1. This behaviour is modelled as shown in (4.28). The spiral equation is created as follows:

$$\overrightarrow{X}_{t+1} = \overrightarrow{D}' \cdot e^{bl} \cdot cos(2\pi l) + \overrightarrow{X}^{*}. \tag{4.29}$$

The component $cos(2\pi l)$ simulates the spiral shape of the whale's path, l takes a value between [-1,1], and b is a constant (usually 1) that gives the spiral shape regular definition. Since the whales can be shrink towards a prey or move spirally, there is a need to model this behaviour. A probability of 50% is chosen for both feeding mechanisms. The model is as follows:

$$\overrightarrow{X}_{t+1} = \begin{cases} \overrightarrow{X}^{*}_{t} - A \cdot \overrightarrow{D}, & p < 0.5 \\ \overrightarrow{D} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X}^{*}_{t} & p \geqslant 0.5 \end{cases}, \tag{4.30}$$

where p is a random number between $[0, 1]$.

Search for prey The WOA uses this technique to overcome a possible local optimum mainly. This is called the exploration phase, where whales search randomly according to check other possible solutions. If the best solution is not global, the search agent can still find other better solutions in the global space. The use of this approach is dependent on the value of A. If the value of A is lesser than 1, (4.28) is triggered, else (4.31) is triggered, as shown below.

$$\overrightarrow{X}_{t+1} = \overrightarrow{X}_{rand} - A \cdot \overrightarrow{D}, \tag{4.31}$$

where
$\overrightarrow{D} = \left| C \cdot \overrightarrow{X}_{rand} - \overrightarrow{X}_{t} \right|$, $\overrightarrow{X}_{rand}$ represents the random whales' position in current iteration, $\overrightarrow{D}$ is the distance between current whale position, $\overrightarrow{X}_{t}$ and the randomly selected whales' position while C is a random parameter generated anew in every round of iteration.

4.4.3.2 Proposed Hybrid WOA-GA Approach

The WOA-GA is a hybrid method to find improved solutions from the optimal integration of DG and BESS units. The optimal integration of units in distribution networks is a combinatorial problem due to the discrete nature of finding optimal locations, and a non-convex problem due to the nonlinear nature of power constraints while finding optimal DG unit sizes. The WOA-GA exploits the GA's binary encoding attribute and the fast convergence attribute of the WOA, which is excellent for solving the complex and large iterative computations. Figure 4.3 shows how the problem is structured in the WOA-GA algorithm.

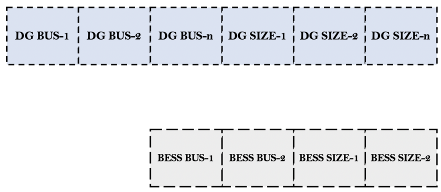

FIGURE 4.3: Structure of a whale chromosome for each population

Firstly, the WOA mechanism finds the optimal sizes for DG units for pre-selected bus locations. The WOA possesses a fast convergence capability, which is an excellent attribute for solving the complex and large iterative computations.

The second stage uses the GA to find the optimal locations of the DG and BESS units, through an integer-based technique. The GA deploys the crossover and mutation operators to generate a child for each parent in a population. A condition is set for each offspring to replace their parent if they have a better fitness value. Otherwise, the parent is rolled over to the next generation. The tournament selection process is used to select the parents in the current generation while a heuristic crossover operator is adopted as applied in [144], is used to produce new whales solution. Lastly, a vectorized mutation operator, as in [145], is used to improve the health of each whale. For the crossover rate (as in [146]), we consider a pair of parent $x^1 = \{x_1^1, x_2^1, ..., x_n^1\}$ and $x^2 = \{x_1^2, x_2^2, ..., x_n^2\}$ to produce an offspring $u^1 = \{u_1, u_2, ..., u_n\}$, therefore

$$u_i = \sigma(x_i^2 - x_i^1) + x_i^2, \tag{4.32}$$

where σ is a uniformly distributed value in the range [0,1] and parent x^2 would have a better fitness value than parent x^1. This kind of crossover operator utilizes parents' fitness value to produce offsprings; hence, the crossover probability is relatively proportional to the fitness value. The mutation operator is adopted from the differential evolution algorithm and expressed as

$$\overrightarrow{V}_i^G = \overrightarrow{X}_{r_1^i}^j + F \times (\overrightarrow{X}_{r_2^i}^G - \overrightarrow{x}_{r_3^i}^G)\ , \tag{4.33}$$

where $\overrightarrow{V}_i^G$ is the donor vector created from the target vector $\overrightarrow{X}_i^G$ and F is the scaling parameter for controlling the difference vectors. The notations r_1^i, r_2^i, and r_3^i are random integers in the range [1, N_{var}], where N_{var} is the number of decision variables.

4.4.3.3 Implementation of the Multiobjective WOA-GA

This section discusses the implementation of the proposed multi-stage multiobjective WOA-GA framework in the optimal integration of DG and BESS units in a distribution network. The variables and parameters of the WOA-GA are presented in Table 4.1. To solve the integration problem using the proposed framework, a pod of whales is modelled as a set of solutions. Each whale has a chromosome representing their fitness in terms of DG and BESS units locations and their sizes. Figure 4.3 illustrates the structure of each whales' chromosomes. The first part of the whales' chromosome represents the DG or BESS location and the second part represents the DG or BESS sizes, which are used as the decision variables. The whales' population is illustrated as

$$\overrightarrow{X}_{\text{pop}} = \begin{pmatrix} L_1^1 & \cdots & L_N^1 & S_1^1 & \cdots & S_N^1 \\ L_1^2 & \cdots & L_N^2 & S_1^2 & \cdots & S_N^2 \\ \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ L_1^M & \cdots & L_N^M & S_1^M & \cdots & S_N^M \end{pmatrix}, \tag{4.34}$$

where L_N^M is the total N number of DG or BESS unit location for M number of whales, and S_N^M represents the sizes of the proposed DG or BESS units.

The following steps are involved in the implementation of the hybrid WOA-GA.

1. Read the distribution network data; Power at each bus, Load at each bus, Resistance on each branch, Reactance on each branch.
2. Generate an initial population of whales with chromosomes representing DG locations and sizes.
3. Update the distribution network by injecting the DG sizes (corresponding to their rated power) in the suggested bus locations.
4. Run the backward/forward load flow algorithm to determine the new voltage magnitude and real power at each bus.
5. Calculate the objective functions using the new parameters obtained from step 4.
6. Update the chromosomes of all whales in the population (i.e. the DG sizes) according to steps 3 and 4.
7. Select the whale with the best chromosome for the second phase.
8. Use the GA to update the DG location.
   - Choose the best two whales as parents.
   - Perform the crossover operation to generate offspring from the parent.
   - Perform the mutation operation to obtain offsprings with better chromosomes.
   - Stop when sub-criteria is reached.
9. Generate another population of whales with chromosomes representing BESS locations and sizes.
10. Inject the BESS units into the updated distribution network (with the DG units).
11. Run the load flow algorithm to determine the new voltage magnitude and real power generated at each bus.
12. Update the distribution network according to steps 4 to 8.

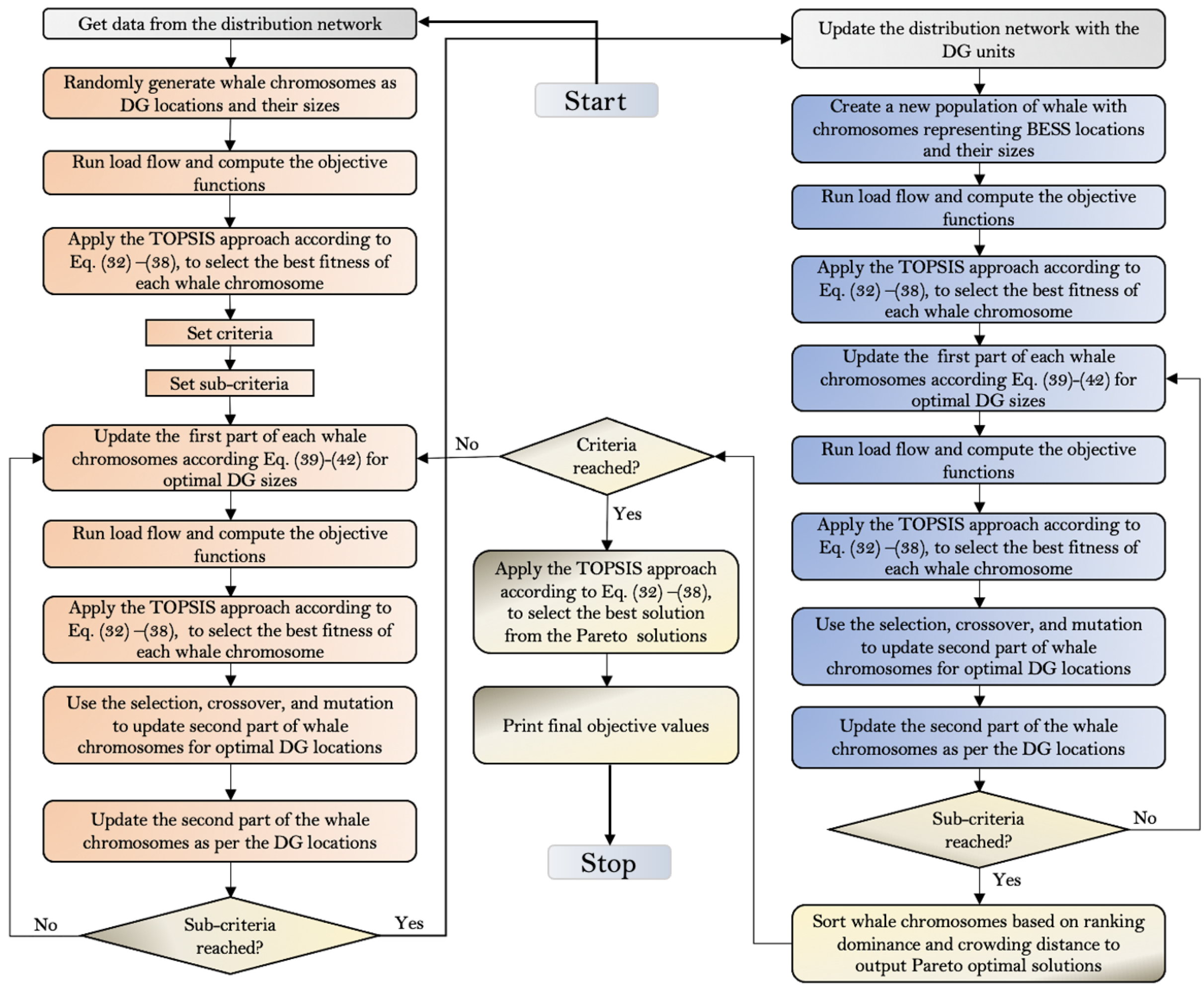

FIGURE 4.4: Flowchart of the proposed MOWOAGA implementation to the optimal DG and BESS unit integration

13. Stop if criteria are reached.

14. Print out final objective values.

These steps are illustrated as a flowchart in Figure 4.4.

4.5 Numerical Results

The proposed algorithm is evaluated on the IEEE 33-bus distribution test network (See Figure 4.5), with a total real and reactive power of 3.72 MW and 2.3 MVaR respectively. The voltage and apparent power are 12.66 KV and 100 MVA respectively. All buses are feasible for installing PV-DG or BESS units except the first bus reserved for the substation. The real power from PV-DG units is based on the PV module characteristics, temperature, and solar irradiance, which is considered as an uncertainty; hence modelled as a beta Probability Density Function (PDF).

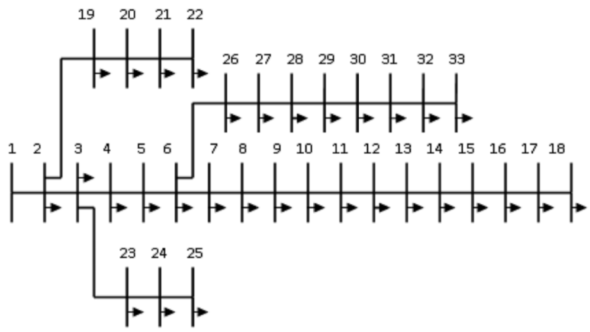

FIGURE 4.5: A single line diagram of the IEEE 33-bus test distribution network

TABLE 4.1: Parameters of the WOAGA

Parameters	**Value/Type**
Population size	100
Generations	200
F	0.75
Selection type	Tournament
Crossover type	Heuristic
Mutation type	Vectorized

The WOAGA is compared to its primary variants; WOA and GA, using the relative parameters shown in Table 4.1. This chapter proposes a new sub-framework for handling multiple objectives across different collective objectives in an optimal integration problem. As discussed in Section 4.4.1, there is a need to always consider objectives in the sense of the technical aspect, economic aspect, and due to the rise in reducing carbon emission, environmental aspects. The Pareto front for the collective objectives in a feasible region is shown in Figure 4.6. Theoretically, all Pareto optimal solutions, even in a constrained space, should follow a uniform distribution in a multiobjective projection. The combination of TOPSIS and crowding distance substantially projects this characteristic. The TOPSIS approach was also used to select the best trade-off solution among the Pareto optimal solutions. It is to note that the final compromise solution is neutral to any collective objective; hence no weights have been applied in step 3 of the TOPSIS approach (See Section 4.4.2). However, weights can be applied at the request of the decision-maker to show other alternative results.

Further Pareto projections can be seen in Figures 4.7 and 4.8, where the economic/environmental and technical/economic objectives are projected on a two-dimensional plane respectively. It is seen that to focus more on the technical objectives will be a trade-off for the economic objective. In the same vein, improving the environmental objective, that is reducing carbon emissions, will require more cost; hence a proportional increase in the economic objective.

Table 4.2 shows the comparison of the final objective values from the conventional direct method and the proposed categorical method. Both approaches are compared based on the MOWOAGA technique, which produces a final fitness value by selecting the best compromise from Pareto optimal solutions. It can be seen that the direct approach produces lesser power loss and voltage deviation values than the

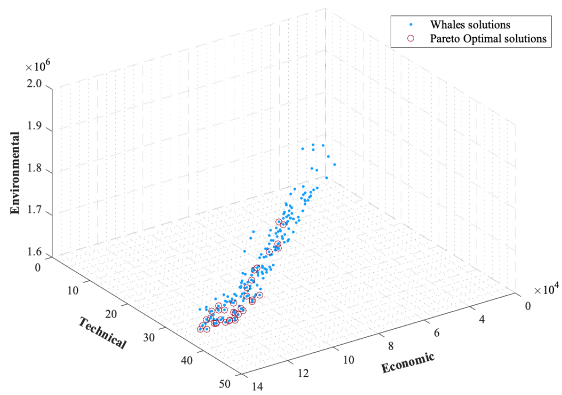

FIGURE 4.6: Pareto optimal solutions and final whale solutions.

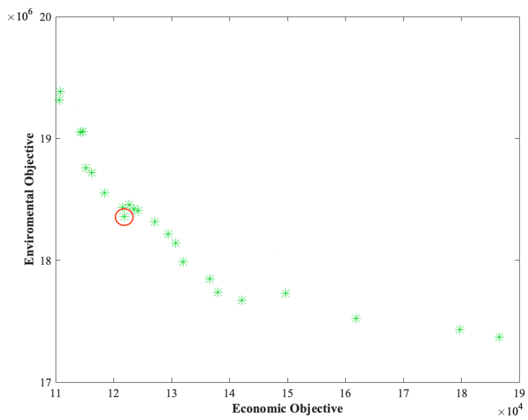

FIGURE 4.7: Pareto optimal front the economic and environmental objective.

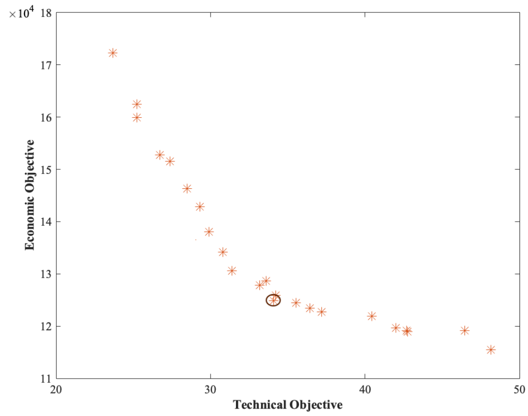

FIGURE 4.8: Pareto optimal front the economic and technical objective.

categorical approach. The better technical objective values may be influenced by the higher number of (related) technical objectives. Although not on the same scale, the objective values are factored by related parameters, such as voltage, power, and current. On the other hand, the categorical approach produces a more reduced installation, operational cost, and emission cost. A practical scenario like the DG planning problem should consider closely related and conflicting objective functions in producing Pareto optimal solutions; else, a higher number of closely related objectives than other objectives may cause a bias even without applying a preference method. The obtained results are shown in Table 4.3 where each collective objective values are displayed. The WOAGA is the spotlight as it optimizes all collective objectives better than the WOA and GA. According to the table, the WOAGA yields the technical, economic, and environmental objectives as 33.853, 12954.31, and 1823457, respectively.

Table 4.2: Final objective values for optimal location and sizing of PV-DG and BESS units

Approach	PL	VS	VD	IC	OC	EC
Direct	101.2	0.9610	0.0022	61976.97	75749.63	1876211
Categorized	101.6	0.9610	0.0023	58294.39	71248.71	1823457

Table 4.3: Comparison of algorithms performance on collective objectives

Algorithm	**Collective Objectives**		
	Technical	**Economic**	**Environmental**
	PL, VS, VD	**IC, OC**	**EC**
WOAGA	33.853	12954.31	1823457
WOA	35.005	13217.78	1873441
GA	35.239	13291.24	1865168

Table 4.4 shows the optimal DG and BESS unit locations, their sizes, and the effect on power loss (PL), voltage deviation (VD), and voltage stability (VS). It is seen that the WOAGA produces an optimal location at bus 11, 19, 26, and 32, with their power capacity as 914.2 kW, 865.1 kW, 959.7 kW, and 990.8 kW respectively, and BESS location 6, 26 with their sizes as 791.2 kW and 831.4 kW respectively, which produces favourable technical objective values than the WOA and GA. The GA binary operation's effect can also be seen through the suggested BESS location from the WOAGA and the GA. Compared to the study in [81] where the total power loss is lower without PV-DG integration than with PV-DG units, the total power loss is further reduced when the PV and BESS are integrated simultaneously into the distribution network.

Figure 4.9 shows the comparison of mean voltage profile of a full day for three cases; the base case, when DG unit is integrated, and when DG and BESS units are integrated. It can be seen that the integration of DG and BESS units improves the distribution networks' voltage profile.

Different statistical methods are used to understand the proposed algorithm's performance for solving the optimal integration of DG and BESS units in a distribution network. Figure 4.10 shows the box plot for the voltage deviation outputs when each algorithm are run 50 times. It is seen that the performance of

Table 4.4: Comparison results for optimal location and sizing of PV-DG and BESS units

Algorithm	DG location	Sizes (KW)	BESS location	Sizes (KW)	PL	VS	VD
WOAGA	11	914.2	6	791.2	101.6	0.9610	0.0023
	19	865.1	26	831.4			
	26	959.7					
	32	990.8					
WOA	11	896.3	12	679.9	105.1	0.9511	0.0112
	20	711.1	31	834.1			
	25	1064.6					
	30	839.6					
GA	6	951.4	6	804.2	105.8	0.9524	0.0216
	13	560.6	26	812.1			
	25	1087.6					
	31	779.7					

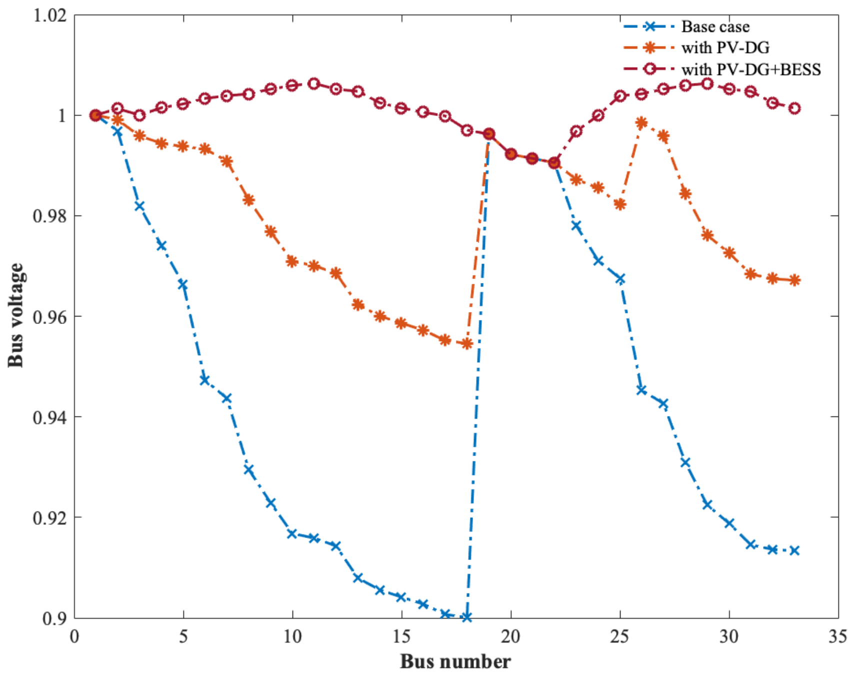

Figure 4.9: A 24-hour mean voltage profile for different cases

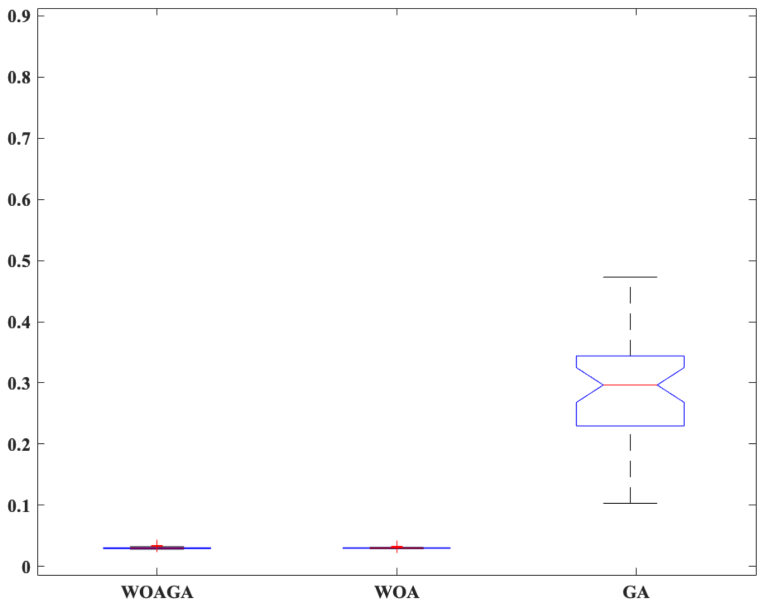

Figure 4.10: Performance of the each algorithm in obtaining the minimum voltage deviation of the distribution network

the WOAGA and WOA are very consistent in producing the optimal values while the GA has a lower consistency with a larger interquartile range.

The convergence characteristics of each algorithm are displayed in Figure 4.11. It is observed that the WOAGA, although not faster than the WOA to converge, converges faster than the GA and eventually produces the best value at the 78^{th} iteration. This outcome is attributed to the shared attribute from the WOA and the GA.

Each algorithm was run 50 times, and a Kruskal Wallis rank-sum test was used to confirm a statistically significant result and a box plot to visualize the performance from each algorithm. Table 4.5 shows the mean and standard deviation with their p-values. It is also noticed that, unlike some hybrid algorithms where time complexity is traded-off with performance, the WOAGA uses the unique features of the WOA and GA to produce better trade-off solutions; hence the better computational time from Table 4.5.

Table 4.5: Statistics for the grid performance of the distribution network

	Technical Objective				
Algorithm	**Mean**	**Best**	**Worst**	**Std.**	**C.T.**
WOAGA	34.446	33.853	36.004	0.976	204
WOA	35.257	35.005	36.242	1.22	254
GA	35.342	35.239	36.211	1.03	241
	rank-sum test				
p-value	0.01				

Furthermore, the performance of the multiobjective methods is analyzed to observe the uniform spread of Pareto solutions. In context, the single objective analysis is similar to the multiobjective space since they

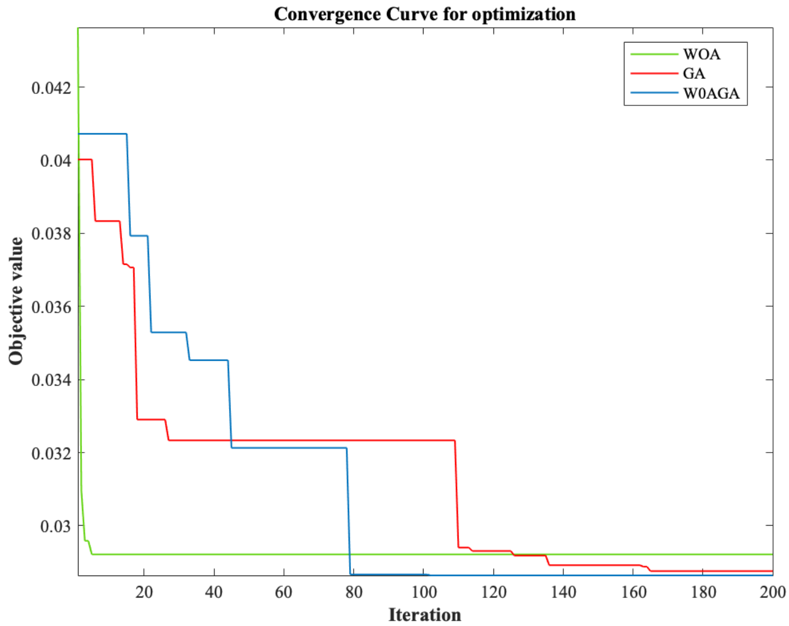

Figure 4.11: Convergence characteristics of each algorithm

both involve the understudy of the change in the distribution of solutions in relation to different techniques. The multiobjective analysis tends to reveal the quality of non-dominated solutions, which is determined mostly by their spatial nature. Since this study proposed a new multiobjective framework that involves a double production of Pareto optimal solution selection, it is necessary to measure the quality of the solutions; hence, the spacing matric (SP-metric) is adopted for this purpose. SP-metric is the progressive distance between each solution and its closest neighbour. The computed SP-metric for each algorithm is displayed as a box plot in Figure 4.12. It can be seen that the MOWOAGA is the centerline of the boxes are almost in line with each other, which shows that the median is similar; hence, the techniques follow the same distribution pattern. The box plot validates the proposed approach as it is observed that the MOWOAGA box has the shortest height, which means a better SP metric than other algorithms. In other words, the MOWOAGA produces non-dominating solutions that are uniformly distributed and close to each other. The TOPSIS approach is responsible for this even and compact distribution due to its consideration of best and worst solutions for final decision value, making it easier for the crowding distance to sort the Pareto optimal solutions at the final stage.

4.6 Summary

This chapter developed a novel approach to seamlessly coordinate the interaction between the allocation of the PV-DG and BESS units in a distribution network and developed the MOWOAGA, a new multiobjective metaheuristic algorithm, to decompose the discrete and nonconvex optimal DG and BESS unit integration problem. In addition to the algorithm, a new multi-stage framework is proposed for handling multiple objectives in a collective manner. The MOWOAGA is validated by applying it to the simultaneous

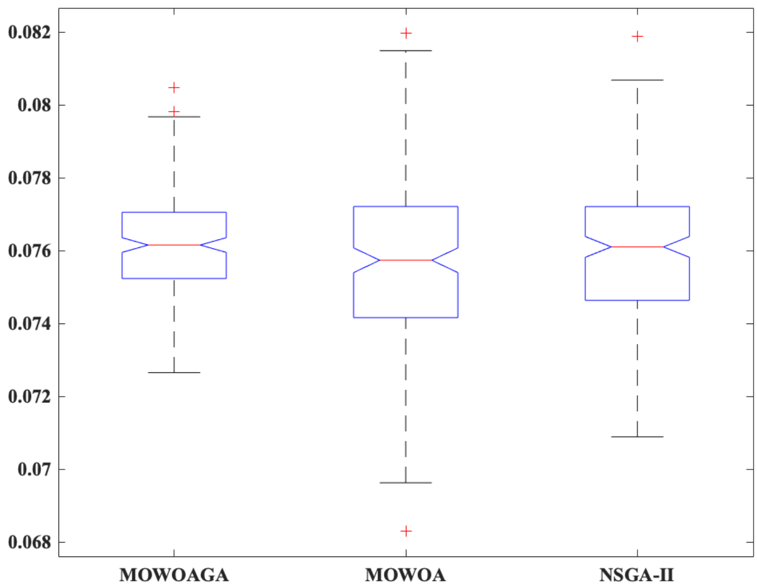

FIGURE 4.12: Distribution of Pareto optimal solutions for each algorithm

integration of PV-DG and BESS units in the IEEE 33-bus test network, which compares favourably with other variants of the algorithm, such as WOA and GA. The proposed algorithm utilizes the GA's powerful binary operation to manoeuvre the optimization problem's discrete nature and inherits this approach and uses the WOAs' mechanism to produce a faster convergence. The effect is seen in the convergence curve where it converges better than the GA and produces a better fitness value than the WOA. The quality of the non-dominating solutions produced by the MOWOAGA is measured using the SP metric, which shows superiority than the WOA and GA.

The different variation of weights assignment to all objectives in a multi-stage multiobjective optimization framework could be studied in future works. Future work could also implement Pareto optimal solutions in the first and second stage of the multi-stage framework. It will be interesting to see the interactions between the two stages.

The next chapter discusses the development of a game-based MOO for managing two decision-makers in an EV charging model.

Chapter 5

A Game-based Multiobjective Technique for a Coordinated Charging Model for Electric Vehicles in a Smart Grid

This chapter is based on the following publication:

This chapter is based on the following publication: *K.E. Adetunji, I. Hofsajer, and L. Cheng*, "A Coordinated Charging Model for Electric Vehicles in a Smart Grid using Whale Optimization Algorithm", *In IEEE 23rd International Conference on Information Fusion (FUSION), July 2020*

The author of this thesis conceptualized this work, partook in the formal analysis, developed the models and algorithms, and wrote the original draft of the paper.

5.1 Introduction

With the increase in the clamour for reducing carbon emissions, several means have been used to combat its potential disruption to the earth's climate. Adding to it, the rapid increase of load demand also calls for subtle methods for efficiently utilizing energy, which in some cases forces research towards other carbon emission-prone technologies. The transportation sector takes a large share in the utilization of greenhouse gases, ranking second behind the power sector [147]. Therefore, as a direct substitute for conventional combustion-based engines, electric vehicles (EVs) are the potential solution to tackle the problem, as mentioned earlier.

EVs are used as energy storage systems or real-time on-demand electricity sources for powering the utility grid [148]. EVs have been used in topologies such as Vehicle to Vehicle (V2G), Grid to Vehicle (G2V), and Vehicle to Grid (V2G) [45]. V2V is a system where vehicles power each other according to a demand-response approach, while G2V is where the utility grid provides power for EVs. The last configuration, V2G is the latest configuration where EVs can power the grid. The V2G topology can provide economic viability to integrate additional charging loads into the grid network [45], especially with the costumers' incentives that come with the implementation. However, the benefits of the implementation of EVs come with a major drawback: the disruption of the electric grid. The uncoordinated charging of EVs can cause a grid breakdown, especially during peak periods. In light of this, researchers have found it necessary to develop an optimization algorithm for a coordinated charging system.

The studies done over time can be categorized into two major approaches. The first is the Load Frequency Control (LFC) technique, which uses the deviation of frequency signal to coordinate the charging/discharging rate. The LFC technique is easy to implement since it considers EV a systematic demand response device [149, 150]. The second approach uses optimization programming to dynamically find the optimal charging and discharging schedules. This approach is categorized into centralized and decentralized methods. With this approach, charging/discharging of EVs can be optimally scheduled under different constraints and uncertainties. While both categories include the mathematical modelling of objective functions (examples are power losses, charging cost, load variance, and voltage stability) to mimic the system's behavior, the major difference is the singular scheduling of EVs. The decentralized category is based on a single-user information scheme.

An EV user is expected to make a schedule based on price signals. Xing et al [151] developed a decentralized algorithm for the optimal scheduling of EVs. The V2G configuration was assumed to be bidirectional. The centralized category allows for a unified schedule for all EV users while maintaining a goal. Unfortunately, many EV scheduling problems are so far NP-complete [152]. Hence, metaheuristic optimization algorithms have been applied to counter the problem's nature by finding sub-optimal results.

Tong, Zhao, Yang, and Zhang [153] used the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to solve an EV scheduling problem, with a multi-objective function for charging cost minimization and load variance minimization. The algorithm was validated on the IEEE 33-bus distribution network.

In the quest to solve the MOO space, Singh and Tiwari [154] implemented the Grey Wolf Optimization (GWO) algorithm for optimal EV scheduling considering a multi-objective framework. They compared the multi-objective function to a single objective and was evaluated using a 38-node distribution feeder. Jiang and Zhen [155] used an Improved Binary GWO (IBGWO) for a real-time EV charging schedule, considering cost minimization. The algorithm was compared to the Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Binary GWO. Singh and Tiwari [58] also implemented the GWO alongside a distribution feeder reconfiguration approach for optimal EV charging in smart grids, while considering real power loss minimization.

In the quest to easily solve the MOO space, Mehta, Verma, and Yang [156] developed a bi-level optimization framework for energy management. The first level considers minimizing the daily cost incurred by the real power manager, while the second level minimizes the real power loss from the reactive power manager.

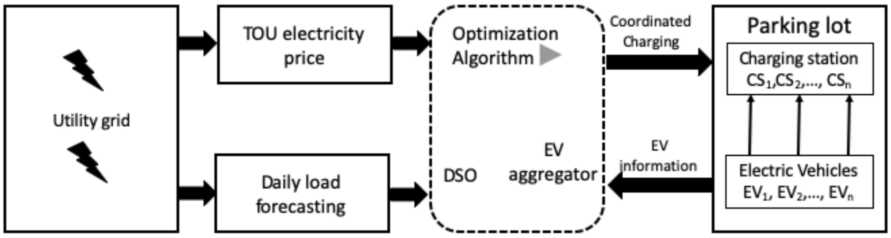

FIGURE 5.1: Centralized coordinated EV charging model

Due to various factors, EV drivers can arrive late for charging. This setback can cause the disorganization of a calculated system. Therefore, there is a need to coordinate the charging process within a required schedule. [67] implemented the Ant Colony Optimization (ACO) algorithm to optimize EV scheduling problems, intending to reduce total tardiness. Alvarez et al. [157] also minimized the total tardiness for a community-based parking lot by using a GA-enhanced Artificial Bee Colony (ABC) algorithm.

This chapter formulates the multi-objective optimization framework based on current electricity pricing and implements the WOA as the proposed strategy to solve the optimal EV charging scheduling problem in a smart grid. A centralized, coordinated model in a smart grid was considered. The chapter contribution is based on the specially formulated multi-objective framework, which encourages more participation of EV users in a centralized coordinated model. The objectives are charging cost minimization, load variance minimization, and power loss minimization.

The rest of the chapter is organized as follows: Section 5.2 discusses the proposed EV model and the multi-objective handling; Section 5.3 discusses the problem overview, which involves the formulation of the objective function. The WOA is presented in Section 5.4, while Section 5.5 discusses the numerical results. Finally, Section 5.6 presents the conclusions from the study.

5.2 Multi-Objective Optimization Modelling

This section discusses the MOO modelling, especially with Optimal EV charging. Firstly, a realistic scenario is created based on the model shown in Figure 5.1 [158]. It is presumed that customers can own a maximum of 500 electric cars in a grid network. The model is based on a centralized system, where an overall charging cost is optimally calculated based on the current grid status. The model involves an EV aggregator and a Distribution Network Operator (DNO). The EV aggregator takes account of EV users driving time, energy demand, and charging demand from EV users. The DNO monitors the grid performance at certain intervals.

A single EV is modelled to acquire EV data such as hourly demand from parking lots, EV driving time, and waiting time. This task is done by applying a normal distribution, which takes the mean and variance of historical data to produce a Probability Density Function (PDF) for the driven distance and hours. Also, for the DNO to monitor the grid quality, a backward/forward power flow analysis is run to evaluate the potential power loss and voltage deviation on the grid after EV loads.

In summary, the DNO is charged with maintaining good power quality, which involves minimizing power losses and maintaining a good voltage profile, while the EV aggregator is charged with reducing the charging cost for EV users [159]. This realization negates the ranking of objective functions as seen in models such as the Analytical Hierarchical Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). For modularity, it is assumed (realistically) that the load variation is a concern for both stakeholders, given that the EV aggregator will be technically inclined. Therefore, we have a case of equal proportionality in the MOO space. The model is dubbed an intra-progressive form of MOO since it consistently checks for the best objective value through a tournament scheme.

Given that the EV aggregator is the first to send data to the optimization system, an initial preference is given to its concerned objective (the charging cost). The second preference is assigned to the DNOs' objective (which is power loss). The first two results are compared to other assigned permutations. Unlike the Lexicographic or Hierarchical (*rank*) method, the model does not involve the ranking of objective functions due to the *order of importance* [160], rather, through a stipulated set of weights, to form a game using a set of objectives. Figure 5.2 shows an illustration of the workings.

Here is a sequence of steps for the proposed MOO:

Step 1: For a consistent comparison between functions, a normalization technique is applied a priori to the set of objectives for scalarization, expressed as

$$F_i^{norm}(\mathbf{x}) \;=\; \frac{F_i(\mathbf{x}) - F_i^{min}}{F_i^{max} - F_i^{min}}, \tag{5.1}$$

where $\mathbf{x}$ is the vector of decision variables *wrt* the objective function; F_i^{min} is approximated as the utopia point and F_i^{max} is determined by an engineering intuition [160]. In this case, maximum values were determined from the uncoordinated charging system.

Step 2: A vector of weights is assigned *a priori* to each objective function to particularize each decision-making, defined as

$$U_i = \sum_{k \in K} w_k^t [F_i^{norm}(x)], \tag{5.2}$$

where w_k^t is an initial vector of weights in vector K, applied to a set of objective functions at run t. The first and second weighted objectives (U_1 and U_2) will represent the decision-makers.

Step 3: Calculate the Euclidean distance between each stakeholder and other permutated weighted functions. The result of each stakeholder are denoted as DM_1 and DM_2 respectively.

Step 4: Determine the final fitness, U with the condition stated as

$$U \;=\; \begin{cases} U_1^f & \text{if } DM_2 < DM_1 \\ U_2^f & \text{if } DM_2 \geqslant DM_1 \end{cases}, \tag{5.3}$$

where U_1^f and U_2^f represent the final values of each decision-maker.

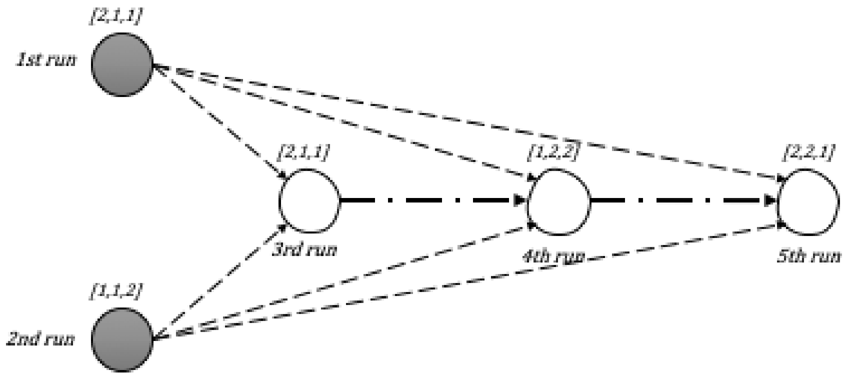

FIGURE 5.2: Illustration of the proposed MOO model process

The circles represent different types of weighted objectives, where the grey circles represent a biased decision of each decision maker, and then individually compared to the white circles, which are other permutated decision.

5.3 Problem Overview

Given that there are many problems faced with the optimal coordination of charging of EVs in a smart distribution network, this section discusses the tackled problems (which are coined as the objective functions). The objective functions are categorized as grid performance and economic benefits and are listed as follows:

5.3.1 Load Variance Minimization

A potential varying of load variance in an EV-present smart grid is almost unavoidable. This is mostly caused by a proposed cost-effective charging time. Equation (2.15) is used to calculate the load variance minimization objective.

5.3.2 Charging Cost Minimization

This objective is an important aspect of a centralized EV charging control, since it can closely determine the acceptance rate of such model. A high charging cost would obviously scare customers away, which can cause an uncoordinated charging system. The objective function is defined in (2.21).

5.3.3 Power Loss Minimization

Power loss minimization is the most common metric to measure the grid performance. The random plugging of EVs for charging will increase power loss, also causing fluctuations on the power grid. This objective is defined as in (2.8)

These three objectives are formulated as a multi-objective model (explained in Section 5.2). The charging model is subject to the following constraints:

$$P^{EV}_{min,n} \leqslant P^{EV}_{t,n} \leqslant P^{EV}_{max,n}, \tag{5.4}$$

$$V_{min,n} \leqslant V_{t,n} \leqslant V_{max,n}, \tag{5.5}$$

where N is the total number of plugged-in EVs; t is the time step; C_t is the current TOU price at time t; $P_{n,t}$ is the n^{th} EV charging power at time t.

and

$$SoC^{EV}_{min,n} \leqslant SoC^{EV}_{t,n} \leqslant SoC^{EV}_{max,n} \tag{5.6}$$

where the desired SoC is defined as [161]

$$SoC^{EV}_{t,n} = min\left\{SoC_{init} + \frac{E_d}{\eta},\ SoC_{init} + \frac{Chr}{\eta} \cdot t_d\right\} \tag{5.7}$$

The charging rate is denoted as Chr while the SoC_{init} represents the initial state of charge. Every EV will possess a battery capacity, η and require an energy demand E_d.

5.4 Optimization using the Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA) is implemented for the smart control of EV charging by assessing the proposed MOO model. The algorithm, developed by Mirjalili and Lewis [143], involves two major methods to find optimal solutions in a search space. The methods are conceptualized from the feeding nature of whales. A probabilistic model is used to switch between these methods. The third form of search is implemented to search outside a confined search space. This method allows for the potential overcoming of local optima.

For the smart charging model, the WOA takes the amount of EVs to be charged per time slot as the dimension. Each slot represents a solution in a solution space, where the whales would have to search for sub-optimal solutions. The maximum power of each EV bounds this search to the upper limit.

Each whales' fitness is evaluated through the MOO model and the best whale (final objective value) is updated as the leader, while the position of the best whale is also updated. The positions are further updated with the WOA mechanism.

The update uses the probabilistic model, which s defined as

$$\overrightarrow{X}_{t+1} = \begin{cases} \overrightarrow{X}_t^* - A \cdot \overrightarrow{D}, & p < 0.5 \\ \overrightarrow{D} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X}_t^* & p \geqslant 0.5 \end{cases}, \tag{5.8}$$

where p is a random number between $[0, 1]$. Also, $\overrightarrow{X}_{t+1}$ and $\overrightarrow{X}_t^*$ represents the next EV time slot and current best EV time slot respectively.

The upper subequation in (5.8) represents the shrinking mechanism while the lower represents the spiral mechanism. Using the shrinking mechanism, the best EV time slot is achieved by applying a random vector $\overrightarrow{r}$. This can be seen in the definition of $\overrightarrow{A}$ and $\overrightarrow{C}$. They are defined as $\overrightarrow{A} = 2\overrightarrow{a} \cdot \overrightarrow{r}$ and $\overrightarrow{C} = 2 \cdot \overrightarrow{r}$. The spiral search is obtained through a similar but with an additional $2\pi l$ factor to mimic a spiral shape.

While these two forms of search are utilized, the WOA also tries to explore a search space to check for better solutions. This additional search is to avoid getting stuck in local optima. The behaviour is formed as

$$\overrightarrow{X_{t+1}} = \overrightarrow{X_{rand}} - A \cdot \overrightarrow{D}, \tag{5.9}$$

where

$$\overrightarrow{D} = \left| C \cdot \overrightarrow{X_{rand}} - \overrightarrow{X_t} \right|. \tag{5.10}$$

Here, $\overrightarrow{X_{rand}}$ and X_t represent the random EV time slot and the current EV time slot respectively, and $\overrightarrow{D}$ is the distance between current EV time slot $\overrightarrow{X_t}$ and the randomly selected EV time slot. The reader is referred to [143] for a deeper understanding of the WOA. The implementation of the algorithm to the centralized coordinated EV model is shown in Algorithm 1.

5.5 Numerical Results and Discussion

In this chapter, the proposed model was applied to an IEEE 33-bus distribution network, with a total of 3.72 MW and 2.3 MVaR. The base case values for the voltage and the apparent power are 12.66 KV and 100 MVA respectively (See Fig. 5.3 [162]). The capacity of the smart parking lot is assumed to accommodate a maximum of 500 EVs, while considering a maximum power of 8.90 KW.

From Fig. 5.3, it is noticed that the charging stations (CS) are allocated to specific buses through a pre-computed sensitivity analysis.

In this Chapter, the optimization algorithm is based on a probabilistic density function from historical load profile. Fig. 5.4 illustrates the difference in load demand curve when EVs are introduced to the grid network. It is seen that there is a sharp increase in load demand during the late hours of the day.

Algorithm 1 WOA Implementation (adapted from [133])

Generate data for the load profile, indicating winter and summer seasons.
Run a pdf to generate the EV load profile, driving time, and parking time.
Generate a TOU price per the season, during peak and off-peak hours
Implement the backward/forward algorithm to calculate the initial *power loss* and *voltage profile* before and after the addition of EV load

Set the whales' positions (which is the EV time slot), X_i using the maximum power of each EV as the maximum limit.
The dimension of the search is the total number of EVs per the time stamps
while $t < maxIter$ **do**
  Evaluate the MOO space U for each EV time slot X_i at run k
  Obtain the best objective value, U^* and update the EV time slot accordingly.
  if $U > U^*$ **then**
    $U^* \leftarrow U$
    $X^* \leftarrow X$
  end if
  for each run, k **do**
    for Each particle i **do**
      if $p < 0.5$ **then**
        if $|A| < 1$ **then**
          Update the position of the current EV time (from Equation (5.8)) slot.
        else if $|A| \geqslant 1$ **then**
          Choose a random EV time slot outside of the present set of EV time slots (using Equation (5.9)).
        end if
      else if $p \geqslant 0.5$ **then**
        Update the position of the current EV time slot (from Equation (5.8)).
      end if
    end for
  end for
  $t++$
end while
return $\vec{X}^*, U^*$

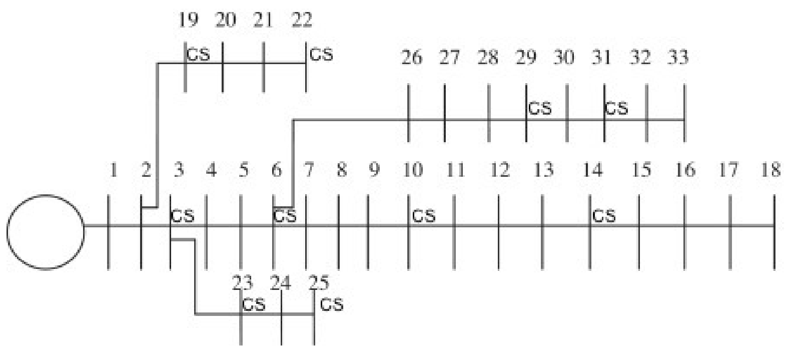

FIGURE 5.3: The IEEE 33-bus test distribution system (adapted from [161])

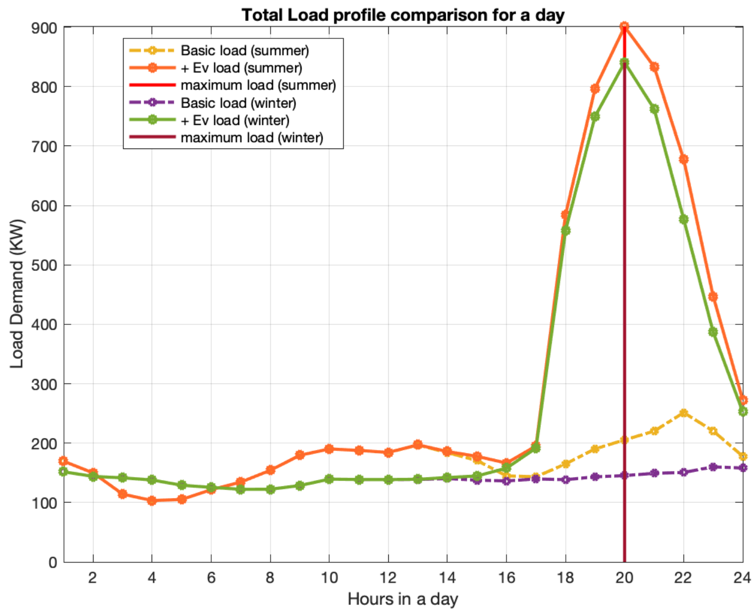

FIGURE 5.4: Comparison of the normal and the EV-based load profile

A centralized coordinated charging system can substantially reduce this curve. The WOA, GWO, BAT, PSOGWO, and GWOCS are compared for performance test.

TABLE 5.1: Comparison for summer load values and charging cost

	Optimization Algorithms					
Summer	**Uncoordinated**	**GWO**	**GWOCS**	**PSOGWO**	**BAT**	**WOA**
Load variance	912970	627700	1033200	1406700	267360	220880
Peak Load (KW)	442.67	297.81	329.48	360.22	260.07	254.39
Charging cost	2.44	1.99	4.45	5.39	0.28	0.19

TABLE 5.2: Comparison for winter load values and charging cost

	Optimization Algorithms					
Winter	**Uncoordinated**	**GWO**	**GWOCS**	**PSOGWO**	**BAT**	**WOA**
Load variance	691470	361040	584510	181110	128210	75768
Peak Load (KW)	480.35	229.75	265.01	257.76	169.18	161.66
Charging cost	2.36	1.12	4.65	3.47	1.59	0.19

The uncoordinated EV charging system is 912970 with a peak load of 442.67 KW at 22h00. This system is best improved by the WOA, with a load variance of 220880 and a peak load of 254.39 KW at 22h00. The WOA also performed better in the charging cost of EV charging, with a value of 0.19. The BAT algorithm came close with a value of 0.28. During winter, the uncoordinated EV charging system is 691470, with a peak load of 480.35 KW at 22h00. This is most improved by the WOA, with a load variance of 75768 and a peak load of 161.66 KW at 22h00.

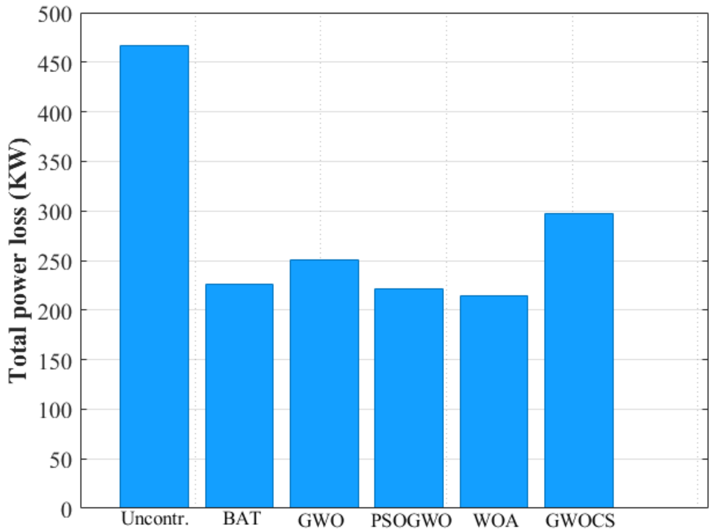

FIGURE 5.5: Real power loss on the IEEE 33-bus test distribution system

The total real power loss of the system is recorded in Figure 5.5. The uncoordinated charging of EVs (represented as "Uncontrolled") shows a high total power loss on the distribution network. The optimization algorithms substantially minimized the total real power loss on the distribution network. The WOA performs better than all benchmarked algorithms, with the lowest power loss value of 216.93 KW. Furthermore, Figure 5.6 shows the performance of each algorithm on individual buses.

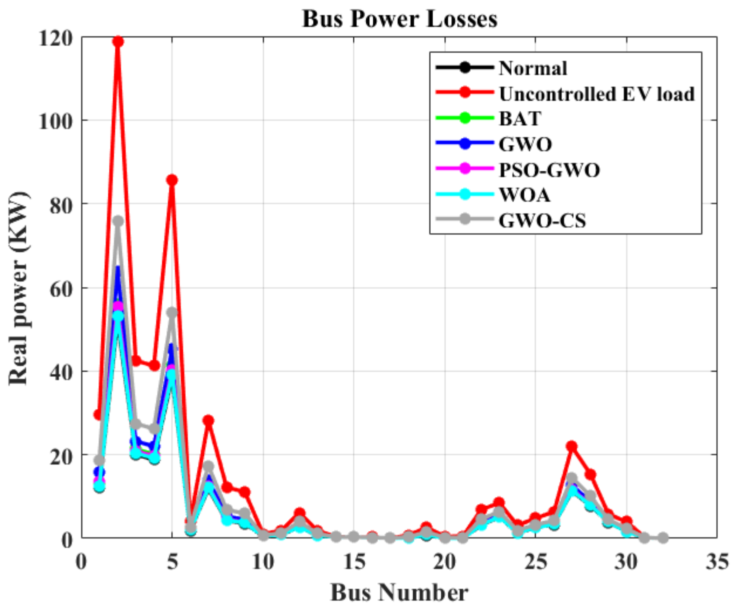

FIGURE 5.6: Total real power loss on each bus

As evident in the literature, the minimization of power loss should improve the voltage profile of the distribution network. Fig. 5.7 shows the performance of each algorithm. It is observed that there is a huge difference between the normal case (where there is an EV charging system) and the uncontrolled case of EV charging. The WOA and the BAT algorithm have the most improved profile. It is noteworthy that the goal is to improve the voltage profile beyond the normal case.

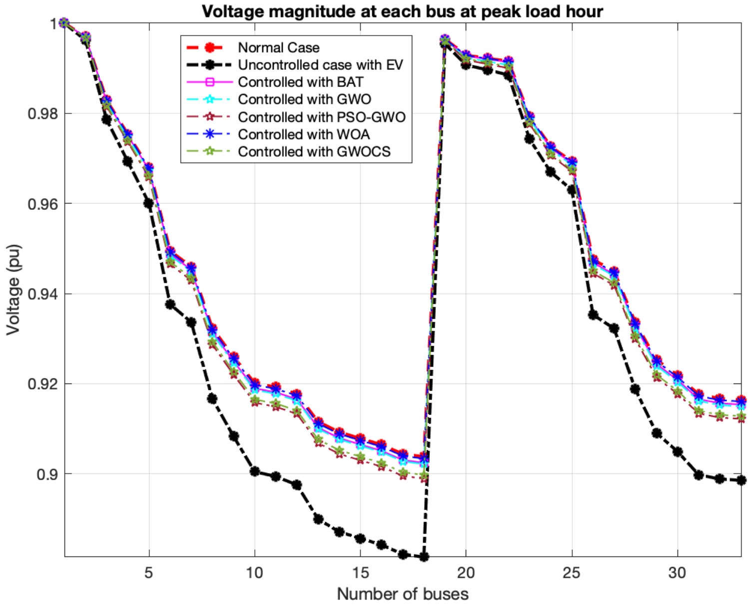

FIGURE 5.7: Voltage profile

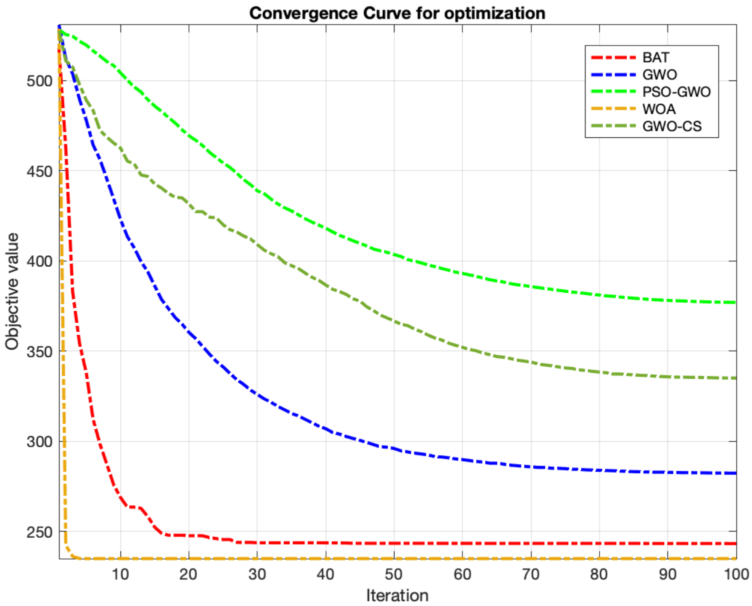

FIGURE 5.8: Convergence curve of all algorithms

All algorithms had an equal number of search agents (which is 20) and were run on 100 iterations. The BAT and the WOA perform better than other algorithms in the group. This is evident in the previous results. Fig. 5.8 shows the convergence curve of each algorithm.

5.6 Summary

This chapter proposes a game-based multi-objective WOA for the optimal centralized EV charging coordination in a smart grid network. The chapter aims to maximize grid performance and economic benefits. The framework did not consider a step-wise EV penetration; only a maximum EV penetration was considered. The proposed model has been tested on the IEEE 33-bus distribution network to illustrate the effectiveness of the proposed algorithm.

The results obtained were compared with other algorithms such as GWO, BAT, GWOCS, and PSOGWO. The special handling of MOO produces a minimized charging cost, which encourages a coordinated EV charging system. The result will also improve the grid performance. Also, a good convergence characteristic of the WOA was noticed.

The next chapter discusses the development of an extensive smart grid planning framework, focusing on implementing the dynamic planning mechanism in an efficient manner. The chapter also discusses the allocation of EV charging stations using reinforcement learning.

Chapter 6

An Optimization Planning Framework for Allocating Multiple Distributed Energy Resources and Electric Vehicle Charging Stations in Distribution Networks

This chapter is based on the following publication:

K.E. Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng, "An optimization planning framework for allocating multiple distributed energy resources and electric vehicle charging stations in distribution networks". *Applied Energy, vol. 322, p. 119513, doi: 10.1016/j.apenergy.2022.119513.*

The author of this thesis conceptualized this work, partook in the formal analysis, developed the models and algorithms, and wrote the original draft of the paper.

6.1 Introduction

6.1.1 Background

In the quest to improve power systems while reducing greenhouse gas emissions, research works have focused on developing smart grids, serving as a one-step, multiple-stream potential solution to tackle problems in power transmission, energy efficiency, and power generation sustainability. The European Union Commission [163] defines a smart grid as "an electricity network that can cost-efficiently integrate the behaviour and actions of all users connected to it – generators, consumers and those that do both – in order to ensure economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety". A fundamental for developing smart grids is allocating Distributed Energy Resources (DERs) into a distribution network. Integrating DER units are proven to improve grid performance, reducing power loss and improving voltage profile [164].

The use of Renewable Energy Source (RES)-based DER units is also advantageous since it reduces the carbon footprints from energy generation (alternative to coal or diesel) [165]. However, the intermittency and high variability of RES can cause a grid collapse. Distribution networks, in particular, are susceptible to breakdown due to their vulnerable radial topology [2]. To solve this problem, other units like Battery Energy Storage Systems (BESS) and capacitors banks or other FACTS devices can be integrated to cushion the adverse effects of RES integration in the distribution network [4, 5]. However, this method can be expensive and can increase the time complexity of the model through the additional modelling of BESS operation (also known as scheduling) [166]. Therefore, there is a need to apply efficient optimization algorithms to find optimal solutions - units' locations and sizes within a considerable amount of time.

Electric Vehicles (EVs), on the other hand, are another component of the smart grid and are becoming popular due to their eco-friendly features. While EVs are essential to the transportation and energy industry due to their capability to supply power to the grid, they threaten regular grid operation as intense random charging can spike peak load at a particular time window [167]. For instance, the EV charger capacity can be as high as the Renault's ZOE 43kW fast charger [168] and the Tesla's 120kW supercharger [169]. Hence, coordinated EV charging research has been carried out to develop control strategies to shift load through peak shaving and valley filling. Another type of study is the optimal allocation of EV Charging Stations (EVCS), where EVCS are allocated to buses in distribution networks while considering objective functions such as power loss and voltage stability.

Looking at the dynamics of developing smart grids, this chapter goes beyond existing literature by proposing a comprehensive planning model that allocates PV-DG, BESS and EVCS facilities in a distribution network while considering the technical, economic, and environmental benefits.

6.1.2 Motivation

Smart grid planning remains a difficult task in the era of transforming distribution networks into smart grids. What is more? The planning model's complexity is due to the combinatorial nature of finding optimal units' locations, making it a mixed-integer non-linear problem; hence, it is called an NP-hard problem. In addition, integrating the RES comes with the challenge of intermittency and variability that could cause reverse power flows and unwanted voltage sags and swells [170, 171]. There is, therefore, a need to process RES power output as uncertainties. As a result, the process adds to the time complexity of the planning model.

Furthermore, most planning or allocation models require multiple DER types, e.g. PV-DG, BESS, WT, for developing smart grids. Another essential concern is the EVCS integration into the grid. Many previous studies have carried out this task separately using range anxiety or optimal allocation strategies. However, the planning of smart grids should be robust as best as possible, making it cost-effective to implement. Unfortunately, these processes add to the model's complexity.

To circumvent this drawback, previous studies have used a static approach, where the distribution network comes with preallocated units while the other unit (e.g. BESS) is optimally allocated to the distribution network. Another form of static approach is to solve the multiple unit allocation problems is to use a sequential method where one unit is allocated before the other. These methods are indeed effective to reduce the time complexity but have a drawback of a limited solution space.

To address these issues, a dynamic mechanism can be implemented using a recombination technique to alternate between different combinations of solutions in one iteration, hence increasing the solution space for potentially better solutions. Section 6.4 discusses the procedure of the mechanism. Considering that the suggested approach will increase the framework's complexity, an efficient optimization scheme can be developed to overcome the drawback. Using a hybrid heuristic scheme and a decomposition procedure can help reduce the model's complexity while solving for optimal solutions. A well implemented hybrid optimization algorithm is also essential to efficiently handle complex model such as smart grid planning. Some previous studies have directly merged two or more algorithms together to produce more optimal results but to the detriment of efficiency [126]. As seen in [10, 11, 82, 172, 173], the algorithms are implemented to perform better in optimality of solutions but not considering the computational time complexity. Some studies [10, 26] have reported a high computational time due to the complexity of the proposed hybrid algorithms. Nonetheless, most previous studies on hybrid algorithms do not report the computational efficiency.

Furthermore, the main concept of planning smart grids does not only focus on achieving better grid performance. Another focus is to minimize the investment costs to encourage potential investors and reduce carbon emissions, promoting environmental cleanliness [4,174]. Most studies on smart grid planning or optimal allocation of units have focused on optimizing a category of objectives to avoid bias in the final results. Li et. al [8] explains the uncontrollable bias in optimization results when closely related objectives are adopted in the MOO space. For example, recent studies [14,175] considered only the technical benefits (e.g. power loss, voltage stability, voltage deviation, reliability cost) in the optimization space. However, the case may not represent a robust planning model where objectives other than the technical benefits are essential for optimization.

Another issue discussed in [9, 126] is the difficulty in representing more than three objectives in the MOO space. Even further, optimizing more than three objectives increases the Pareto optimal solutions, shooting up the computational burden of the optimization model [127, 128]. Given the mentioned setbacks regarding multiple objectives for planning models, there is a need to cautiously optimize all related objective functions simultaneously. Therefore, a multi-category multi-objective optimisation (MCMOO) framework is developed to adequately represent all objective functions in the final solutions, adopting the crowding distance and the TOPSIS approach.

6.1.3 Contributions

The optimal allocation of multiple units is vital to enhance grid operation. Developing such planning models with the allocation of different units - DG, BESS, capacitors in distribution networks can help understand the effects of each unit on the grid. However, while planning models exist for the above units, little to no study has been carried out on the integration of EVCS with other units. Hence, the contribution of the chapter is as follows:

- A new methodological optimization framework for cooperative, smart grid planning of integrating PV-DG, BESS, and EVCS in a distribution network has been proposed, considering uncertainties from solar irradiance, load consumption, and electricity prices. A multiphase approach coupled with a recombination method is formulated to increase the solution space for more potential optimal solutions. This methodology is contrary to previous studies [66, 81, 176] that apply a static approach to integrate multiple DER types in distribution.
- To deal with the spatially varying nature of the planning framework, where units' locations change at every iteration, a reinforcement learning (RL) technique is introduced to solve optimum EVCS locations. The RL technique is suitable for a dynamic model such as the proposed planning framework, using an agent to take actions according to the varying state of the distribution network and finding an optimum policy that corresponds to an improved grid performance.
- Using the proposed planning framework, a category-based multiobjective framework is introduced to simultaneously handle many objectives, which is a practical case of planning a smart grid network. The following objectives were considered: technical benefit - power loss minimization, voltage stability improvement, voltage deviation minimization; economic benefit - installation cost reduction, operational cost reduction; and environmental benefit - carbon emission reduction in the smart grid planning framework.

6.2 Literature Review

Several methodologies have been proposed to solve optimal integration, such as the analytical (or mathematical) approaches and metaheuristic (or stochastic) techniques. The combined combinatorial and non-convex nature of the placing and sizing problem has influenced the frequent use of metaheuristic algorithms which is major because of its better computational time and efficiency rate [123].

Sharma et al. [132] hybridized the PSO and Artificial Bee Colony (ABC) to optimally size capacitor banks while reducing power loss in a 34-node and 69-bus distribution system. A summation method was used to handle the objectives, which may not produce accurate results for real-world scenarios. Jeddi et al. [10] hybridized a Harmony Search Algorithm (HSA) and the Firefly Algorithm (FA) to maximize profits of distribution network companies by reducing operational costs and increasing income in a distribution network. The proposed algorithm uses the HSA mechanism to search towards the best objective values in the harmony memory and uses the FA mechanism for a random search, which was validated on a 38-bus distribution network and reported to converge faster than the HSA.

Pamshetti and Singh [65] integrated BESS and soft open points units in a distribution network, using demand response and conservative voltage reduction schemes in a two-stage optimization framework. The PSO and GAMS MINLP solver is used to optimize the total installation cost for the planning stage and total operating cost for the operation stage, respectively.

While stochastic optimization algorithms have been developed to be effective for the integration problem, multi-objective optimization (MOO) frameworks is another problem faced by researchers. Handling multiple is a tricky one, given that when not handled appropriately, it can yield unrealistic results. This problem has birthed different forms of MOO approaches and frameworks, considering complexity and practicality. The Analytical Hierarchical Process (AHP) was used by [86] and [89] weight assignment in a multi-objective integration of DG and BESS units in distribution networks. The AHP technique douses the effect of weight input bias in the optimization process by increasing the number of alternatives to each objective, followed by a pairwise matrix to compute the final weights for the problem's objectives. Adetunji et al. [44] also applied a game-based approach to reduce the effect of direct weight assignment. The approach is based on assigning different weight vectors to the objectives at different runs, followed by calculating final objective values after the run is complete. The highest value becomes the utility value at every iteration. The *aposteriori* method proves to overcome the bias problem since objective functions are assigned their preference after the optimization process. Sharma et al. [100] used the Non-dominated Sorting Genetic Algorithm (NSGA-II) to minimize power loss and grid demand cost in a BESS integration problem. The uses a crowding distance technique to generate the non-dominating solutions, and the Technique for Order Preference by Similarity (TOPSIS) is used to choose the compromise solution.

Selim et al. [99] applied the Grey Relational Projection (GRP) method in a MOO framework to select compromise solutions from a Pareto optimal set. The MOO framework uses an improved Harris Hawks Optimization (IHHO) algorithm to allocate and size DG units in a multi-objective framework, which adopted power loss minimization, voltage deviation reduction, and voltage stability improvement. The GRP method is computationally efficient, but it works better when handling closely related objectives; hence, only the technical objectives are considered. In [177], a fuzzy decision model is applied to find the compromise solution from a set of non-dominating solutions.

Adetunji et al. [113] developed a planning methodology that integrates PV-DG and BESS units in the IEEE 33-bus distribution network. First, they developed an MOO framework that handles many objectives - real power loss, voltage stability improvement, voltage deviation reduction, installation cost reduction, operational cost reduction, and emission reduction, categorizing objectives according to technical, economic or environmental characteristics. Then, the framework is carefully phased to find the final utility values using a hybrid algorithm - WOA and GA, and a TOPSIS approach. Singh et. al [175] also used the TOPSIS approach to find the most compromise alternative from a set of Pareto solutions generated from a multi-objective DER allocation problem. Five objectives were considered in the MOO space and the approach was evaluated on an IEEE 33-bus distribution network.

Given that an uncoordinated charging of EVs can disrupt the grid, EV charging control strategies have been developed to control the adverse effect on the grid by recommending charging time slots for EV owners, providing incentives and applying load shifting techniques while monitoring the grid performance. Adetunji et al. [177] used a hybrid chaotic WOA and Gravitational search algorithm optimization technique to suggest time slots for optimal EV charging in the IEEE 33-bus distribution network, considering power loss minimization, voltage stability improvement, and emission cost reduction. The authors split the network into the different load profiles motivating for a better energy management system. Reinforcement Learning (RL) techniques have been used to suggest EVCS to EV drivers on request. This control scheme also follows the load shifting technique but applies it as a policy control over a time horizon. Wang et al. [178] use the RL technique with real-time pricing to generate a scheduling control strategy for EV charging. The focus was to maximize the profit of EVCS. Qian et al. [179] used a deep RL to generate optimal navigation routes to EVCS while minimizing the charging cost.

Other studies focused on the allocation of EVCS in distribution networks, knowing that the EV varying load profile can affect the operation of the grid. Zeb et al. [46], in the presence of PV-based DG units, integrated EVCS into a real distribution network in a university in Pakistan, using the PSO algorithm to minimize installation cost, power losses, and regulate transformer loading. Erdinc et al. [115] developed a comprehensive optimization model for siting and sizing solar and wind-based DG units, BESS, EVCS in a real distribution network in Turkey, minimizing real power losses and maximizing the BESS penetration.

As seen in literature, most planning models involving the allocation of multiple DER or FACTS device types are optimized either using a preallocated or a consecutive one. A unit type is defined herein as different units according to their mode of operation. Some unit types are DG, BESS, EVCS, capacitors, and voltage regulators. It is to note that all forms of DG units, such as PV-DG, wind DG, diesel generator, are categorized as a DG unit. To summarize previous works related to allocating multiple DER types or FACTS units in distribution networks, Table 6.1 shows a summary of published papers in the field of smart grid planning.

6.3 Model Formulation

The planning framework involves the optimal integration of PV-DG, BESS, and EVCS in a distribution network, culminating objective functions to serve as the indicator to suggest optimal solutions - unit locations and sizes. The process is to be discussed in Section 6.3.4. Figure 6.1 illustrates the planning model showing the allocation of the units. The general modelling of a distribution network involving the objective functions, constraints, and uncertainties is discussed herein.

6.3.1 Stochastic Parameter Decision Module

A stochastic decision module is introduced in the planning framework to model uncertainties of parameters, such as solar irradiance, load consumption, and electricity prices. This work employs the beta, normal, and

Table 6.1: Summary of previous studies in smart grid planning problem

Ref.	**Mechanism type**	**Algorithm**	**Objectives**	**DG**	**BESS**	**CB**	**EVCS**
[87]	Consecutive	Grasshopper optimization algorithm	Power loss minimization Voltage profile improvement	✓		✓	✓
[115]	Consecutive	Second order conic programming	Power loss minimization BESS maximization	✓	✓		✓
[180]	Preallocated	Coyote optimization algorithm	Power loss minimization	✓	✓		
[181]	Consecutive	Chaotic BAT	Power loss minimization Voltage deviation reduction Voltage stability improvement	✓		✓	
[88]	-	Enhanced gray wolf optimizer	Power loss minimization Voltage profile improvement Total investment cost reduction	✓		✓	
[86]	Consecutive	Particle swarm optimizer	Power loss minimization Line loading improvement	✓	✓		
[66]	Preallocated	Fitness-scaled chaotic artificial bee colony algorithm	Power loss minimization Line loading improvement flicker reduction Voltage profile improvement	✓	✓		
[117]	Consecutive	Henry gas solubility optimizer	Power loss minimization Voltage profile improvement	✓	✓		
[81]	Preallocated	WOA	Power loss minimization	✓	✓		
[129]	Preallocated	Artificial bee colony algorithm	Power loss minimization Line loading improvement flicker reduction Voltage profile improvement	✓	✓		
[100]	-	Genetic algorithm	Power loss minimization Grid demand cost	✓	✓	✓	
[85]	Consecutive	Water cycle algorithm	Power loss minimization Voltage deviation reduction Voltage stability improvement emission cost reduction	✓		✓	

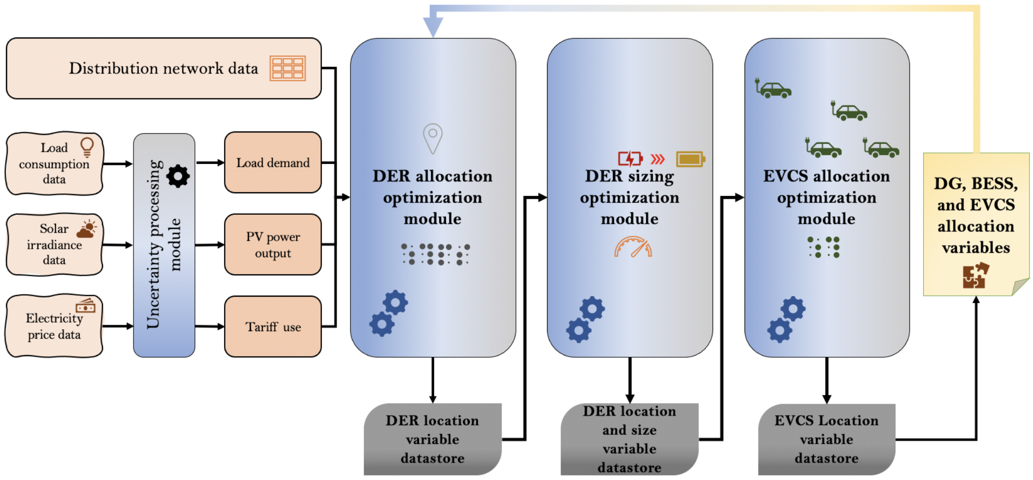

FIGURE 6.1: Planning framework for integrating DG, BESS, and EVCS in a distribution network.

log-normal probability distribution to characterize the uncertainties of solar irradiance, load consumption, and electricity process respectively. Equation (6.1), showing the expression for a beta distribution, is

$$f_b(s) = \begin{cases} \frac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} s^{(p-1)}(1-s)^{(q-1)}, & 0 \leqslant s \leqslant 1 \\ & \scriptstyle p,q \geqslant 0 \\ 0, & \text{else} \end{cases} \tag{6.1}$$

where $f_b(s)$ is the beta distribution function of solar irradiance, s. The input parameters are p and q are calculated using the mean, μ and variance, σ of the solar irradiance data, and are defined as

$$q = (1-\mu)\left(\frac{\mu(1+\mu)}{\sigma^2} - 1\right) \tag{6.2}$$

$$p = \frac{\mu \times \beta}{1-\mu}, \tag{6.3}$$

where

$$\rho_s^y = \int_{s_y}^{s_{y+1}} f_b(s)\, \mathrm{d}\, s \tag{6.4}$$

is the probability of occurrence from the boundaries of solar irradiance at states s_y and s_{y+1}.

The intensity of the real power from the PV is dependent on the following equations.

$$P_t^{pv} \;=\; N \times FF \times V_t \times I_t \quad , \tag{6.5}$$

where

$$FF \;=\; \frac{V \times I}{V_{oc} \times I_{sc}}, \tag{6.6}$$

$$V_t \;=\; V_{oc} - K_v \times T_t^c, \tag{6.7}$$

$$I_t \;=\; s_t \left[I_{sc} - K_I \times (T_t^c - 25)\right], \tag{6.8}$$

and

$$T_t^c = T_a + s_t \left(\frac{T_{nom} - 20}{0.8} \right). \tag{6.9}$$

The PV power output, P_t^{pv} at time t, is a factor of the fill factor, FF, the output voltage V_t and the output current I_t. The FF is defined in (6.6) where V_{mpp} and I_{mpp} represent the voltage and current at maximum power point, respectively, V_{oc} represents the open circuit voltage and I_{sc} is the short circuit current. Equations (6.7) and (6.8) define V_t and I_t, respectively and K_v is the voltage temperature coefficient, K_I is the current temperature coefficient, and T_t^c is the cell temperature in *celcius* which is defined in (6.9); s_t is the solar irradiance at time t, T_a is the ambient temperature, T_{nom} is the nominal operating temperature.

The work also considers the uncertainties from electricity prices, shown in (6.10)

$$f_b(P) = \frac{1}{P\sigma\sqrt{2\pi}} exp \left(-\frac{(\ln P - \mu)^2}{2\sigma^2} \right), \tag{6.10}$$

where the mean and standard deviation values are denoted by μ and σ and P represents the distribution function parameter. The load consumption follows a normal distribution.

6.3.2 Utility Function

The utility function of the proposed planning framework is to optimize the technical, economic, and environmental objective functions, using a dedicated MOO sub-framework to be discussed in Section 6.3.4.

6.3.2.1 Technical Benefit

This benefit relates to improvement of grid performance after the units are allocated. It involves minimizing power loss, improving voltage stability, and minimizing voltage deviation, all expressed as

Power loss: It has a significant impact on distribution networks, and expressed as in (2.9) to (2.11).

Voltage Stability Index: The voltage stability is expressed in (2.12).

$$F_2 = VSI$$

Voltage Deviation: Voltage regulation and monitoring are a primary, yet important task of the distribution network operator, which is also a concern for the consumer given that appliances and meters. It is therefore essential to measure the voltage deviation while injecting the DG and BESS units. It is defined as [12]

$$VD_t = \sum_{m=2}^{M} |V_m^t - V_{ref}|, \tag{6.11}$$

where the reference voltage, V_{ref} is set at one and V_m represents the voltage at each bus after integrating DG or BESS units. Hence,

$$F_3 = VD$$

6.3.2.2 Economic Benefit

This benefit relates to the installation cost and operation cost.

Installation Cost: The cost generated while sizing the DGs is very important. Therefore, there is a need to minimize it simultaneously with the sizing objective [137, 138] which is

$$C_{\text{inst}} = \sum_{d=1}^{D}\sum_{b=1}^{B}(n_d^{\text{PV}} \times c^{\text{PV}} + n_b^{\text{BESS}} \times c^{\text{BESS}}), \tag{6.12}$$

where n_{PV} and n_{BESS} are the unit number of solar PV and BESS units respectively, and c_{PV} and c_{PV} are the unit cost of solar PV and BESS units respectively.

Operational Cost: The operational cost includes the cost of maintaining DG and BESS units and the cost of power from the grid. It is formulated as [62, 139]

$$C_{\text{op}} = \sum_{y=1}^{Y}\sum_{t=1}^{24}\sum_{s=1}^{N_s}\rho_s(C_{t,s}^{\text{ss}} \times P_{t,s}^{\text{ss}} + PV_{t,s}^{OM}) \times \left(\frac{1+inf}{1+int}\right)^{y-1}, \tag{6.13}$$

where $C_{t,s}^{\text{ss}}$ represents the cost of power from the substation, $P_{t,s}^{\text{ss}}$ indicates the power from the substation, $PV_{t,s}^{OM}$ is the operation and maintenance cost of the PV-DG units, and ρ_s is the probability of scenario s. The inf and int respectively represents the inflation and interest rates over a 10-year period.

6.3.2.3 Environmental Benefit

This benefit is the emission cost objective is defined in (2.22).

6.3.3 Constraints

6.3.3.1 Power Balance Constraints

For a more feasible simulation and practical approach, the overall real and reactive power is monitored to avoid exogenous power flowing in or out of the distribution network. Hence, the sum of the power at each bus including the power loss must be equals to zero, represented as

$$\sum_{m=1}^{M}(P_m^{\text{LOSS}} + P_m^{\text{LOAD}} + P_m^{\text{Ch}}) + \sum_{m=1}^{M}\sum_{p\in\mathcal{P}} P_{p,m}^{\text{EV}} = \sum_{m=1}^{M} P_m^{\text{DG}} + \sum_{m=1}^{M} P_m^{\text{Dis}}, \tag{6.14}$$

where the P_m^{Dis} and P_m^{Ch} represent the BESS discharging and charging power to and from the grid from bus m.

6.3.3.2 Nodal Voltage Constraint

The operating voltage at every bus must satisfy the range at all buses. The admittance on branch is represented as Y_{ij}. The bus voltage limit is formulated as

$$V^{\min} \leq V_m \leq V^{\max} \quad m = 1, 2, ..., M, \tag{6.15}$$

where V_m is the current voltage at bus m. Then $V^{\min}$ and $V^{\max}$ are 0.98 and 1.01 respectively.

6.3.3.3 BESS Operation Constraints

To enhance the practicality of the planning framework, the BESS technology is clearly defined, infusing the appropriate parameters. The lead-acid batteries were employed for this work, given their reliability, economic viability, and their tolerance to overcharging. Hence, they are suitable for integrating into distribution networks. Knowing that batteries are very expensive, the BESS units are integrated using small sizes, with the mind that the the DG and EVCS facility will be modelled optimally to improve the grid performance while maintaining a considerable investment cost. Since lead-acid batteries are energy-based, the BESS will be sized in Kilowatts-hour (KWh).

Even with the overcharging tolerance, the model must limit the excessive charging and discharging from the battery, defined as

$$SoC^{min} < \frac{E_t^B}{E_t^{BA}} < SoC^{max}, \tag{6.16}$$

where the maximum SoC, SoC^{max} is set at 0.9 and the minimum SoC, SoC^{min} is 0.2. The batteries' charging and discharging power are represented as

$$E_{t+1}^B = \begin{cases} E_t^B - P_t^B \triangle t \eta_{Bc} & P_t^B \leqslant 0 \\ E_t^B - \frac{P_t^B \triangle t}{\eta_{Bd}} & P_t^B > 0 \end{cases}, \tag{6.17}$$

where E_t^B is the energy of the BESS unit at time t, P_t^B is the charging power of the BESS unit at time t, $\triangle t$ is the time interval, η_{Bd} and η_{Bc} are the discharging and charging efficiency of the BESS unit respectively, the battery power is limited by

$$E^{\min} \leqslant E^{B}_{i,t} \leqslant E^{\max}, \tag{6.18}$$

where $E_{i,t}$ is the energy of the i^{th} BESS unit at time t.

6.3.3.4 EV Model

Each EVCS is modelled as a load, relative to the EVs charging at a certain time. Hence, the total power drawn by the EVs through the chargers in EVCS at a granular time should be in the range of the allowed bus power capacity, represented as

$$P^{EV}_{i,t} = \sum_{k \in B^i_k} n^{EVCS}_{k,i} \cdot P^{EV\_sample}_{k,t}. \tag{6.19}$$

The EVCS capacity should not be exceeded when all EVs are charging in (6.20);

$$P^{\text{EVCS\_CAP}}_{p} \geqslant \sum_{i \in \mathcal{I}} \sum_{p \in \mathcal{P}} P^{EV}_{i,p}. \tag{6.20}$$

Each EVCS facility is modelled to have a constant 50 EV charging units with 11KW power rating each. The daily charging of EVs follows a normal distribution, applied to reduce the ambiguity of deploying EVs to charge from a distribution network.

6.3.4 Proposed MOO Framework

This section discusses the multi-objective framework and the implementation of the integration methodology in the distribution network. The developed framework aims to integrate DERs and EVCS in a distribution network while optimizing many objective functions. In order to generate practical solutions, that is, appropriate locations and capacities of units, there is a need to handle the multiple objectives such that they reflect the quality of the final optimal solutions.

The proposed framework categorically handles the adopted objectives according to their respective collective objectives. Unlike the conventional approach, where all objectives are fed into the MOO framework without considering the collective objectives, the new MCMOO categorizes the objectives before the final handling of the collective objectives. The first optimization phase adopts the apriori approach, assigning weights to all concerned objectives to get subfinal values. The subfinal values represent the value for each collective objective, which are processed using the TOPSIS decision-making technique. This technique applies the Euclidean geometry between positive ideal solutions (P^{+ve}) and the negative ideal solutions (P^{-ve}). The shortest distance from $P^{+ve}$and longest from P^{-ve} helps identify the best compromise solution from the Pareto optimal set. Section 4.4.2 discusses the steps involved to achieve compromise solutions using TOPSIS.

Step 1 all objectives are transformed into a non-dimensional entity and stored in a normalized decision matrix. The normalization is defined as

$$D_{ij} = \frac{F_{ij}}{\sqrt{\sum_{i\in M, j\in N} F_{ij}^2}}, \tag{6.21}$$

where M represents the number of alternatives and F_{ij} is the i^{th} alternative value of the j^{th} objective.

Step 2 as an option, weights are assigned to determine the importance level of all objectives. The element in the decision matrix is determined as

$$WD_{ij} = W_j D, \tag{6.22}$$

where the sum of weight W_j of the j^{th} objective is equals to one.

Step 3: The values of P^{+ve} and P^{-ve} which represents the best and worst solutions of the objective functions. They are expressed as

$$P^{+ve} = B_1^+, B_2^+, ..., B_M^+, \tag{6.23}$$

$$P^{-ve} = B_1^-, B_2^-, ..., B_M^-, \tag{6.24}$$

where B_j^+ and B_j^+ represent the objectives as benefits or cost, respectively.

Step 4 Compute the Euclidean distance from the ideal solutions of P^{+ve} and P^{-ve} to their alternative solutions, P_i. It is represented as

$$d_i^+ = \sqrt{\sum_{J=1}^{N} (B_{ij}^2 - B_j^{+2})}, \tag{6.25}$$

$$d_i^- = \sqrt{\sum_{J=1}^{N} (B_{ij}^2 - B_j^{-2})}. \tag{6.26}$$

Step 5 Calculate the relative closeness index, ζ based on the Euclidean distance from step 4, and expressed as

$$\zeta = \frac{d_i^-}{d_i^+ + d_i^-}. \tag{6.27}$$

Step 6 Select the best solution based on the highest value of ζ.

According to this approach, the population (whales) are sorted with respect to the first objective function to yield dominating solutions according to the number of objective functions. After that, the crowding distance technique is adopted from the NSGA-II to sieve out the non-dominating solutions from the population. Besides eliminating excess solutions, the crowding distance technique also handles the duplication of solutions in the Pareto front.

6.4 Dynamic Planning Mechanism

The formulated problem in Section 6.3 is a large-scale mixed-integer linear problem, difficult to solve using traditional optimization techniques. The proposed dynamic mechanism adds to the time complexity, given its iterative approach over sub-iterations of individual unit type allocation. This approach is different from the traditional static mechanism. The static mechanism is defined herein as the passive allocation of units in a distribution network, either consecutively or preallocatedly. A consecutive form of unit allocation is a step-by-step approach where each unit type is allocated one after the other, while a preallocated unit type involves the optimal allocation of a particular unit type into a grid network earmarked with one or more unit types. The drawback of the static mechanism is its inability to check for other possible scenarios of different unit type locations. A recombination technique is adequate for exploring such scenarios, hence a dynamic mechanism is proposed.

The proposed planning mechanism is based on a global optimization scheme where multiple unit types are optimized consequential to one another. The mechanism uses a recombination technique to ensure a larger solution space, achieved through the permutations of different unit locations. As seen in Figure 6.2, the PV-DG locations are checked against the BESS and EVCS facilities in the second round of iterations, using the memory block to guide the optimization for lesser time complexity. The memory block contains the best configuration for each unit/facility, used for referencing to achieve a new optima during each sub-iteration of the each allocation phase. This mechanism saves the computational time, hence reducing the computational time complexity.

The dynamic planning mechanism follows a sequential, iterative approach to reach a global optima. It is noteworthy that the sequential pattern should not be mistaken for a multi-stage approach where each stage optimizes different objective functions or a sequential programming where multiple objective functions are optimized one after the other. Rather, in the dynamic planning mechanism, each stage in the proposed approach optimizes a common utility function (a function of MCMOO) to find optimal variables.

6.5 Proposed Solution Methodology

This section focus on how to update the planning model under the proposed dynamic mechanism framework to obtain optimal solutions for the problem discussed in Section 6.3.2. The problem expands since it is being solved in n number of iterations. To obviate this problem, the planning model is decomposed into two problems; an integer- and a continuous-based problem. As discussed in Section 6.1.2, the major difference between this dual-stage and other works is that the two stages work together to optimize a common set of objectives. The first phase uses the GA to handle discrete decision variables, while the second phase uses the WOA to handle the continuous variables, solving the same problem. As shown in Figure 6.2, the RL technique is used as a subroutine to find optimal EVCS locations with respect to the DG and BESS locations.

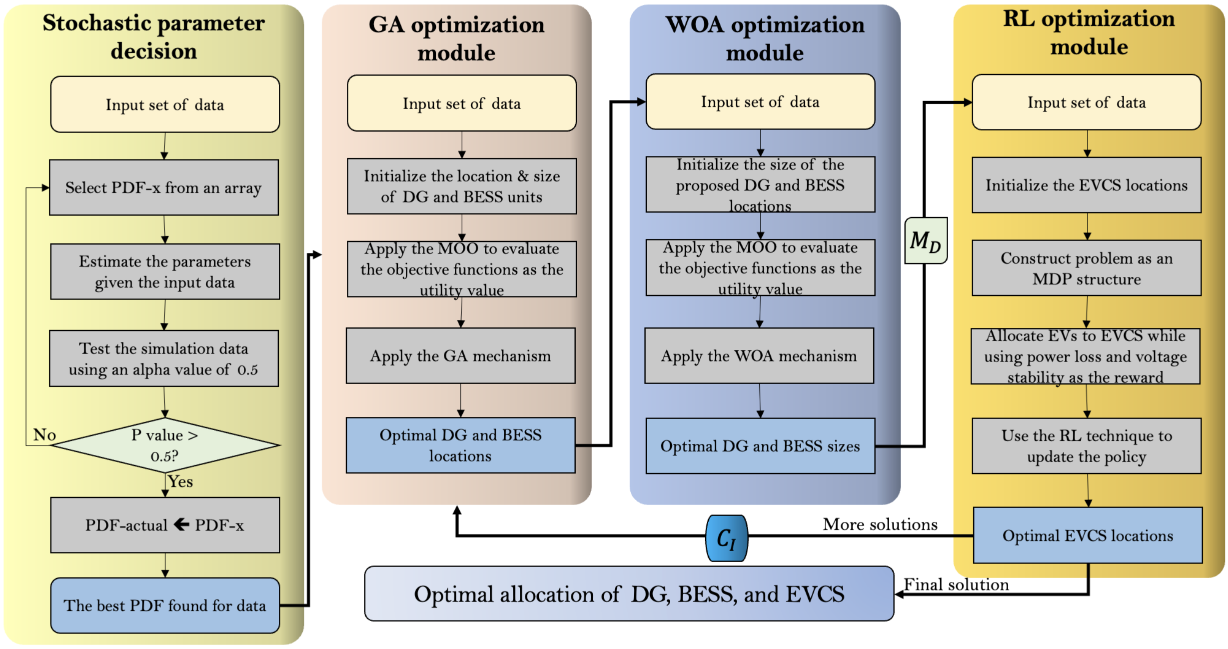

FIGURE 6.2: Multi-phase planning optimization model.

Figure 6.2 illustrates the whole mechanism of the proposed methodological planning framework using a cooperative Whale Optimization Algorithm-Genetic Algorithm (WOAGA-RL) optimization scheme as the core. In each episode of the planning framework, the first phase uses the GA to generate optimal DG and BESS locations with fixed sizes, stops at a certain criterion, and transfers the location variables to the next phase. Each variable serves as an input to WOA in the second phase to find optimal locations for them. The utility function is a common denominator for both phases, suggesting the optimal allocation of DG and BESS units. The end of the second phase triggers a subroutine that takes effect using the RL technique to choose the optimal EVCS locations according to the acquired variables from previous phases. These processes are repeated until a stopping criterion is met. The memory block, M_D serves as a reservoir for preserving the best location for each iteration, which is called at intervals during the optimization process at every iterations. The converging indicator block, C_I is a differential component that measures the variation of utility values, implemented to define the iteration intervals for managing the memory block. Overall, M_D and C_c is used to circumvent the complexity of running all iterations. Algorithm 2, referred to as Co-operative WOAGA-RL shows the overall mechanism to achieve optimal solutions. In one iteration, the WOA and GA optimizer, shown in Algorithms 3 and 4, is called alternately at each step, to find optimal solutions for PV-DG and BESS units, locations and sizes. Still in one iteration, the Q-Learning is applied to find optimal EVCS locations using the optimal policy for EV control strategy for each potential solution. Algorithm 5 shows the procedure for selecting the optimal EVCS locations.

6.5.1 EVCS Allocation using Reinforcement Learning

The sub-problem of allocating EVCS in the distribution network is achieved by finding policies for recommending EVs to charge at different EVCS locations. The optimal policies are selected based on the most

Algorithm 2 Cooperative WOAGA-RL Algorithm

Initialize number of maximum iterations for planning framework, $maxIter$, maximum number of iterations for WOA, It_{max}, maximum number of generations for GA, G_{max}, $t, g \leftarrow 0$.
Create population P_1, P_2, P_3 containing pools of solutions S_1, S_2, S_3, respectively
Initialize objectives as a set, ϕ and accord to each solution $S_i \in P_k$
while $t < maxIter$ **do**
  Update the first part of S_1 (DG sizes) in P_1
  procedure $S_1(1 : {}^{size(S_1)}/2)^* \leftarrow \mathbf{WOA}(P_1, \phi)$
  Update the second part of S_1 (DG location) in P_1;
  procedure $S_1({}^{size(S_1)}/2 : end)^* \leftarrow \mathbf{GA}(P_1, \phi)$
  Update the distribution network with solution, S_1^*
  Initialize population P_2 of solutions, S_2 representing BESS locations and sizes
  Update the first part of S_2 (BESS sizes) in P_2
  procedure $S_2(1 : {}^{size(S_2)}/2)^* \leftarrow \mathbf{WOA}(P_2, \phi)$
  Update the second part of S_2 (BESS location) in P_2;
  procedure $S_2({}^{size(S_2)}/2 : end)^* \leftarrow \mathbf{GA}(P_2, \phi)$
  Update the distribution network with solution, S_2
  Store optimal DG and BESS allocation variables, $V_t \leftarrow [S_1\ S_2]$ and U into memory block, M_D
  Initialize population P_3 of solutions S_3 representing EVCS allocation
  Update EVCS locations in distribution network
  procedure $S_3^* \leftarrow \mathbf{QLearning}(P_3, \phi)$
  $S \leftarrow [S_1^*\ S_2^*\ S_3^*]$
  $t++$
end while
return S

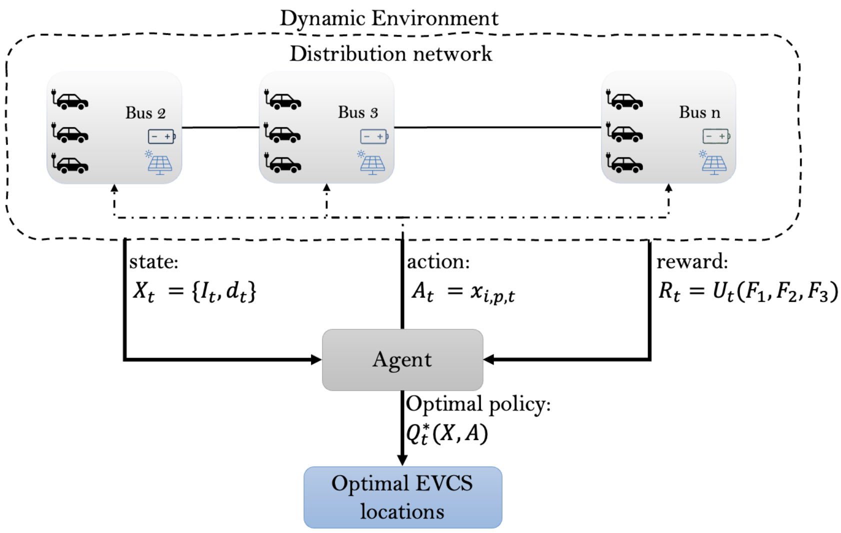

FIGURE 6.3: EVCS allocation model

favourable objective function values, for which the bus location with the best policy indicates the optimal EVCS location. The RL approach is implemented herein, to find the policies at different bus locations. Figure 6.3 shows the EVCS allocation model.

The agent is used to find optimal charging schedule suitable for a set of EVCS locations in the distribution network. The agent's actions are dependent on the locations and sizes of the PV-DG and BESS units. The completion of all iterations produces the optimal policy that represents the optimal EVCS locations.

Algorithm 3 WOA Optimizer

procedure WOA(P, ϕ, It_{max})
while $t < It_{max}$ **do**
for each $S_i \in P$ **do**
if $|A| < 1$ **then**

$$S_{i+1} = \begin{cases} S_t^* - A \cdot D, & p < 0.5 \\ D \cdot e^{bl} \cdot \cos(2\pi l) + S_t^* & p \geqslant 0.5 \end{cases},$$

else if $|A| \geqslant 1$ **then**
$S_{i+1} = S_{rand} - A \cdot D$
end if
end for
Optimize the objective space, ϕ for each solution, S in population, P
Obtain the best utility value, $U(S)^*$ in relation to each solution S.
$U(S) \leftarrow MCMOO(\phi, S)$
if $U(S)^* < U(S)$ **then**
$U(S) \leftarrow U(S)^*$
$S \leftarrow S^*$
end if
$t++$
end while
return S and U

Algorithm 4 GA Optimizer

procedure GA(P, ϕ, G_{max})
Optimize the objective space, ϕ for each solution, S in population, P
while $g < G_{max}$ **do**
for each $S \in P$ **do**
$U \leftarrow MCMOO(\phi, S)$
$Smut \leftarrow Mutate(S)$
$S^{trial} \leftarrow Crossover(S, S^{\mathbf{mut}})$
$U \leftarrow MCMOO(\phi, S, S^{\mathbf{mut}})$
Select better solution according to U^*
$S^* \leftarrow best(S, S^{\mathbf{trial}})$
end for
$g++$
end while
return S and U

To allocate EVCS location in this manner, the problem must be modelled as a Markov Decision Process (MDP).

The sub-problem is formed into an MDP-based problem such that it comprises states, actions, transition function, and discount factor. The Q-learning technique is then adopted to find optimal policies. Q-learning uses the current state of the distribution network to perform actions while a reward is offered according to the quality of the action taken. The terminologies are discussed in the following.

State: The distribution network state at time t is represented as $X_t = \{I_t, d_t\}$, where I_t is the set of EVs charging at time t, and d^t represents the EV charging demand at time t. The charging demand is assumed to be proportional to the parking or charging time; hence the charging time is ignored, with the assumption that all EVs must complete their charging based on their approved charging demand.

Action: An agent recommends an EV charging station based on the current state X_t at time t. Therefore, the action taken by a central aggregator agent is described as $\mathcal{A}_t = x_{i,p,t}$, representing the index p of EVCS at bus i.

Transition function This function is responsible for moving the distribution network environment from a current state X_t to the next state X_{t+1}, influenced by the current state and immediate action. Hence, the transition function can be represented as

$$X_{t+1} := f(X_t, \mathcal{A}_t, L_t) \tag{6.28}$$

Reward Since the focus is on the grid performance, the reward is calculated according to the grid performance of the distribution network. The reward given to the agent is closely related to the environment's objective, which is to minimize load variance and improve voltage stability. The reward is therefore defined as the normalized weighted sum of the technical objectives when a round of horizon is completed, expressed as

$$R(X_t, \mathcal{A}_t) = \max \left[\sum U_t(F_1, F_2, F_3) \right]. \tag{6.29}$$

Algorithm 5 SARSA-Learning Algorithm

Initialize number of episodes, $\mathbb{E}$
Initialize the EVCS locations as S_3
Initialize EVCS location selection as action A
Initialize voltage stability as reward r
  for each $S_3 \in P$ **do**
    while $\mathfrak{e} < \mathbb{E}$ **do**
      Collect distribution network and EVCS features to realize state, X
      Select action $\mathcal{A}$ from X
      Receive reward r, receive new data, and generate next state X'
      Update $Q(X, \mathcal{A})$ using 6.30
      $X \leftarrow X'$
      Terminate at desired state $e++$
    end while
  end for
  Choose best solution S in P as S^*
  $S \leftarrow S^*$
  return S

6.5.2 SARSA-Learning Technique

Given the MDP structure of the problem, the technique produces an optimal policy that follows the good actions taken, determined by the reward at each state. The policy is updated. The effect of choosing action $\mathcal{A}_t$ in state S_t, following policy π is calculated using the state-action function and represented as

$$Q^{\pi}(X_t, \mathcal{A}_t) = \mathcal{E}\left[R(X_t, \mathcal{A}_t) + \gamma Q^{\pi}(X_{t+1}, \mathcal{A}_{t+1})\right]. \tag{6.30}$$

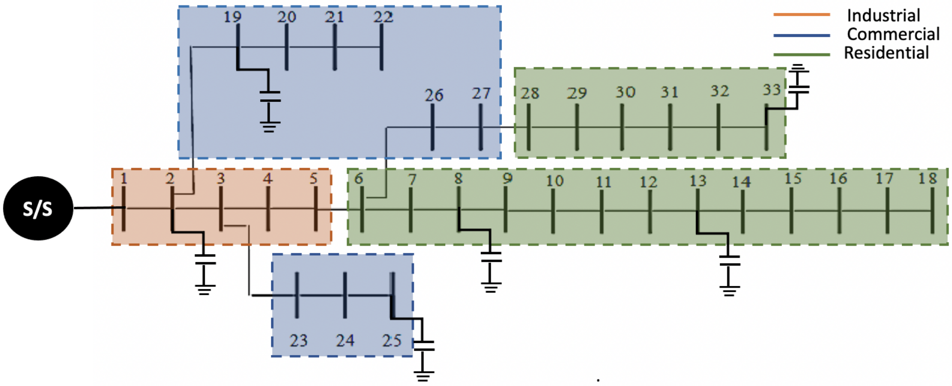

Figure 6.4: Modified IEEE 33-bus distribution network.

The discount factor γ proffers a balance of rewards over an expectation $\mathcal{E}$ in a horizon, T. Hence the SARSA technique finds the optimal policy that maximizes the grid operation performance, expressed as

$$Q^*(X, \mathcal{A}) = \max_{\pi} Q^{\pi}(X_t, \mathcal{A}_t). \tag{6.31}$$

Knowing this, good policies can be learned according to state-actions pairs by recursively updating the state-action function, using

$$Q(X_t, \mathcal{A}_t) = (1-\alpha)Q(X_t, A_t) + \alpha_t \left[R_t(X_t, \mathcal{A}_t) + \gamma[Q(X_{t+1}, \mathcal{A}_{t+1})]\right]. \tag{6.32}$$

The α symbol represents the learning rate factor that controls the decision to either choose a previous state-action value or the updated state-action value.

6.6 Tests and Results

6.6.1 Input Data

The proposed planning framework is initially evaluated on a modified IEEE 33-bus distribution network, and was later evaluated on a large scale 118-bus distribution network. The IEEE 33-bus network, displayed in Figure 6.4, is a radial type with a 12.6kV nominal voltage, 100MVA base voltage, and 3.715 MW and 2.300 MVar as the real and reactive power demand of the network. Four DG units and two BESS units are considered to augment the distribution network. The load profile is sectionalized into three profiles - residential, commercial, industrial load. To account for irregularities, the load profile, solar irradiance, and electricity prices are processed as uncertainties, using the MCS consisting of different PDFs. The DG and BESS cost and other parameters are adapted from [113], displayed in Table 6.2.

Table 6.2: Parameters of the system model

Parameters	**Value**
PV-DG installation cost	1.287
PV-DG O&M cost	0.013
BESS installation cost	1.161
BESS O&M cost	0.625
BESS SoC_{min}, SoC_{max}	0.2, 0.9
Duration of project (yr)	10
Voltage deviation tolerance	0.05%
Interest rate	3.6
Inflation rate	3.2
Carbon emissions (Kg/Kwh)	0.55428

Table 6.3: Different case scenario adopted for analysis

Case Scenario	**PV-DG**	**BESS**	**EVCS**
Case I	✓	✗	✗
Case II	✓	✓	✗
Case III	✗	✗	✓
Case IV	✓	✗	✓
Case V	✓	✓	✓

6.6.2 Simulation and results

The developed planning framework is solved considering five cases, detailed in Table 6.3. Case I corresponds to a scenario where there is no consideration of BESS scheduling and EVCS load but only PV-DG. Case II considers the PV-DG with the support from the BESS but no EVCS load. It is to note that the EVCS load still exists but is not controlled in its operation. Cases I and II are chosen to show the effect of uncoordinated charging in EVCS even with augmented units. The third case (Case III) considers the controlled operation of EVCS but with no PV-DG and BESS support. Case IV however considers the controlled operation of EVCS with the support of PV-DG while the last case (Case V) considers a scenario where a distribution network is modelled to have a controlled operation of EVCS with the support of both PV-DG and BESS. Cases III, IV, and V focus on the significance of augmented support when the EVCS operation is controlled in a distribution network. It is to note that the PV-DG units are implemented to serve real power to the distribution network, according to the stochastic parameter model in Section 6.3.1. With the PV and BESS units allocated, the EV charging strategy is proposed considering the availability of PV power and BESS operation, which is then used to allocate the EVCS facilities.

Table 6.4 shows the technical variables - power loss, voltage stability, and voltage deviation. It is to note that this variable is dimensionless, given the normalization of its components at the first stage of the MCMOO. A lower technical value means a better grid performance. The results for Cases I and II show an almost insignificant impact of BESS in the distribution network given that the EVCS operation is not controlled. The results from Case V show the importance of augmenting the distribution, with

DG & BESS integration and EVCS allocation using EV charging control strategy. For example, the case produces a 160.5 power loss, with an improvement of 27.2 %, 17.5%, 19.3%, and 7.3% for cases I to IV respectively.

It is also seen that in Case V in tandem with Case IV, the addition of BESS in the distribution network minimizes the voltage deviation with a 79.5% improvement for Case V compared to Case IV, and a 53.3% improvement for Case II compared to Case I. This result does not only show the importance of BESS integration, it also uncovers the significance of optimally allocating EVCS, seeing that the BESS unit minimizes the voltage better when EVCS are allocated optimally, as in Case V. The evidence of the significance of optimally allocating EVCS facilities is also seen from the results of Case III. The power loss is more improved (i.e minimized) compared to Case II that has PV-DG and BESS units but no EVCS allocation planning.

Table 6.4: Grid performance values from the IEEE 33-bus distribution network under different cases

Indices	**Case I**	**Case II**	**Case III**	**Case IV**	**Case V**
Power loss (KW)	220.1	194.7	198.9	173.2	160.5
Voltage Stability	0.8891	0.9024	0.9512	0.9666	0.9672
Voltage deviation	0.2511	0.1172	0.0173	0.0083	0.0017

Table 6.5 shows a summary of the optimal allocation variables for the PV-DG, BESS, and EVCS for all cases. It is to note that only the technical benefits of optimally allocating EVCS facilities are considered to feed from buses in the distribution network, but no consideration of the cost of allocating the EVCS facilities. Cases IV and V are the highlight, as they show promising results related to the allocation of EVCS facilities. The technical benefits are improved compared to other cases, and with the economic benefits on the high side, it is compensated with a reduced emission cost compared to Cases I to III.

6.6.3 Extensive Analysis on the Effect of Different Cases on Grid Performance

Figures 6.5 and 6.6 illustrate the total real power loss and the individual real power loss on each bus in the distribution network. It can be observed that there are similarities in Cases I and II given that. It is observed in Figure 6.6 that there is no overcompensation of reducing power loss on a bus to offset other buses, reducing the total real power loss. The voltage profile of the distribution network is depicted in Figure 6.7. All of the buses in the distribution are seen to be better regulated in Case V scenario.

While technical benefits seem to be crucial to the success of planning smart grids, investment costs are important due to the fact that exorbitant costs can sway the process of planning. It is therefore important to do a trade-off between economic and technical benefits. Figure 6.8 shows the Pareto optimal solutions for technical and economic objectives. The environmental benefits are very important for the planning being the major pioneer for developing smart grid networks, hence Figure 6.9 depicts the Pareto optimal solutions for trade-off between environmental and technical benefits.

TABLE 6.5: Optimal allocation variables for integrating PV-DG, BESS, and EVCS facilities in a 33-bus distribution network

Cases	**PV-DG** **Location**	**Size (KW)**	**BESS** **Location**	**Size (KWh)**	**EVCS Location**	**Tech.**	**Eco.**	**Env. (Kg/KWh)**
Case I	6	1200	-	-	-			
	14	1212	-	-	-	39.1414	5693.17	1991632
	24	812.5						
	31	1601						
Case II	6	931.1	6	692.8	-			
	14	657.2	18	892.3	-	38.3221	13011.33	1822473
	23	623.2						
	32	862.7						
Case III					8, 17, 19			
					22, 28, 33	38.631	-	-
Case IV	3	965.2	-	-				
	12	910.1	-	-	8, 17, 21	34.712	4277.12	1916321
	19	852.3			23, 28, 32			
	29	901.4						
Case V	3	1323	6	1331	8, 16, 19			
	12	831.3	26	917.4	23, 27, 32	33.2849	13032.51	1822473
	19	1225						
	31	844.4						

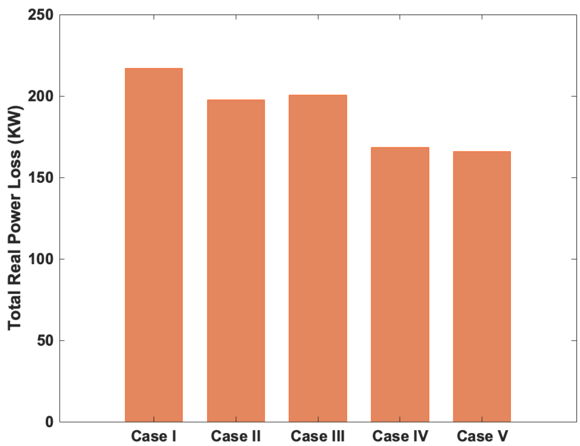

FIGURE 6.5: Total real power loss in a 33-bus distribution network for all cases.

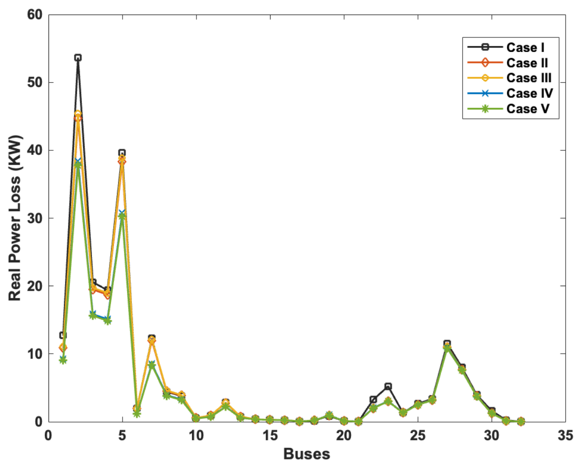

FIGURE 6.6: Bus power loss in a 33-bus distribution network for all cases.

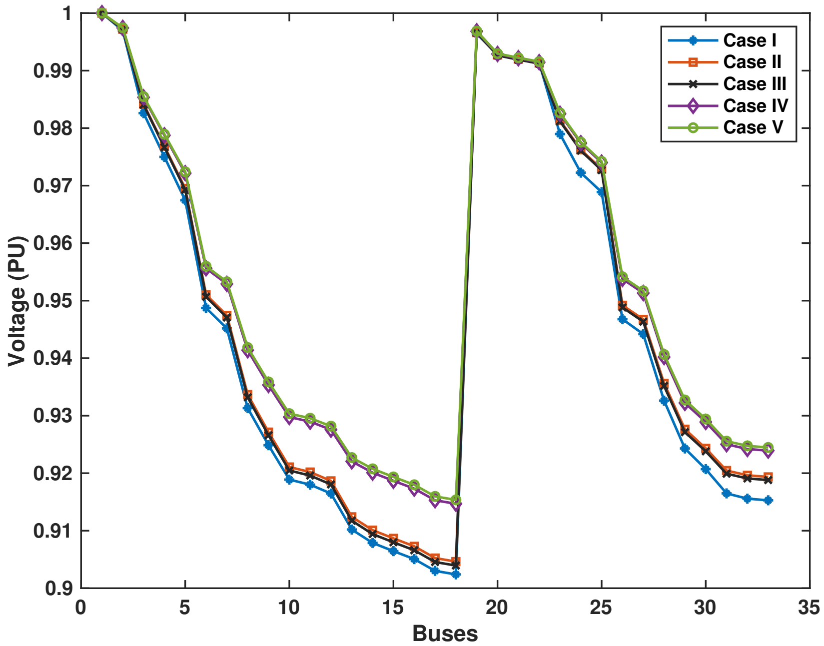

FIGURE 6.7: Bus voltage profile in the IEEE 33-bus distribution network for different cases.

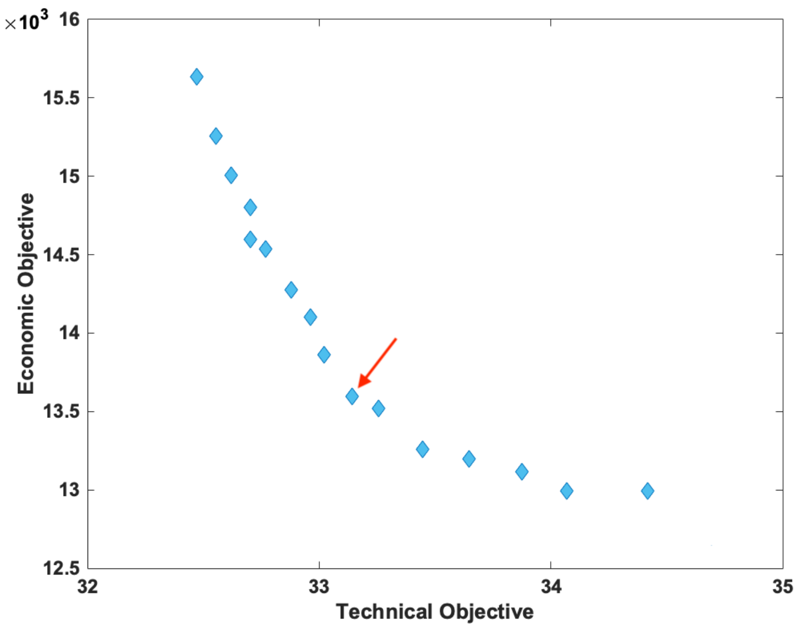

FIGURE 6.8: Two-dimensional Pareto front for technical and economic benefit for Case V.

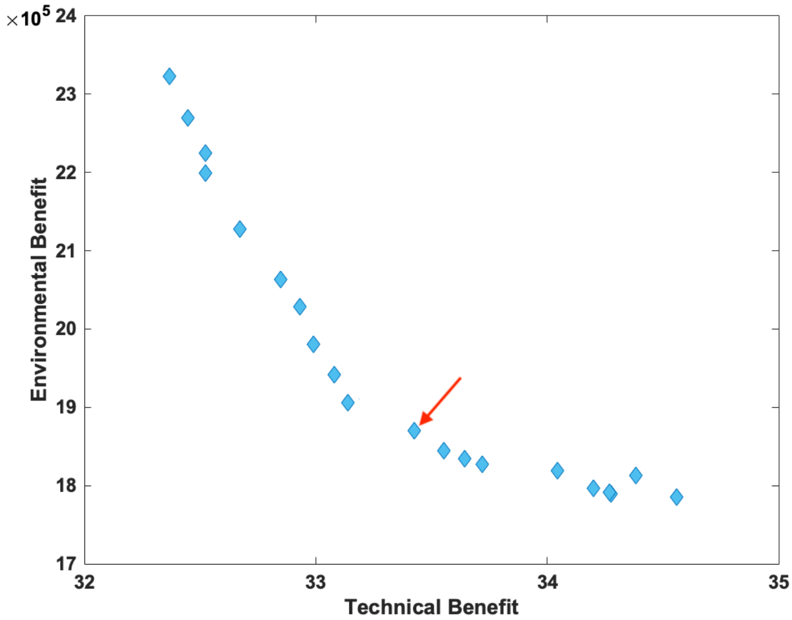

FIGURE 6.9: Two-dimensional Pareto front for technical and environmental benefit for Case V.

6.6.4 Performance of the Proposed Hybrid WOAGA-RL Optimizer

In this section, the efficiency of the proposed hybrid optimizer has been evaluated and compared with the PSO, WOA, and BAT for case V. The optimizers' efficiency is based on the convergence characteristic, computational time, and solution distribution quality. The major parameters; population size and iteration number are the same - 50 and 100 respectively. The simulations are run 50 times, taking the average for each adopted metric, and for generating a population of solutions, in which its distribution will be evaluated. Figure 6.10 shows the convergence characteristics of all adopted algorithms. It is observed that the WOA-RL converges faster than other optimization schemes, a peculiarity of the WOA (seen in [81,182,183]. However, the WOAGA-RL converges with a better power loss value than the all algorithms. The convergence of the proposed optimization scheme, WOAGA-RL follows the discrete, gradual pattern of the GA and the WOA's steep attribute.

Another performance analysis is the evaluation of solution distribution quality. Each optimizer produces a number of solutions according to the number of simulation runs, which will always follow a distribution that is to be evaluated. Figure 6.11 shows a boxplot that illustrates the spread of the distribution. It is observed that the WOAGA-RL produces the most compact, even distribution of solutions, given that it has the shortest box height and the most central median line.

A statistical analysis is carried out using a Kruskal-Wallis rank-sum test to test the significance among all optimizer's population of soultions. The mean, best, worst, and standard deviation values are computed and displayed in Table 6.7. It is seen that the WOAGA-RL has the best mean and standard deviation values from the population of solutions produced. It is to note that the computational time is high for all

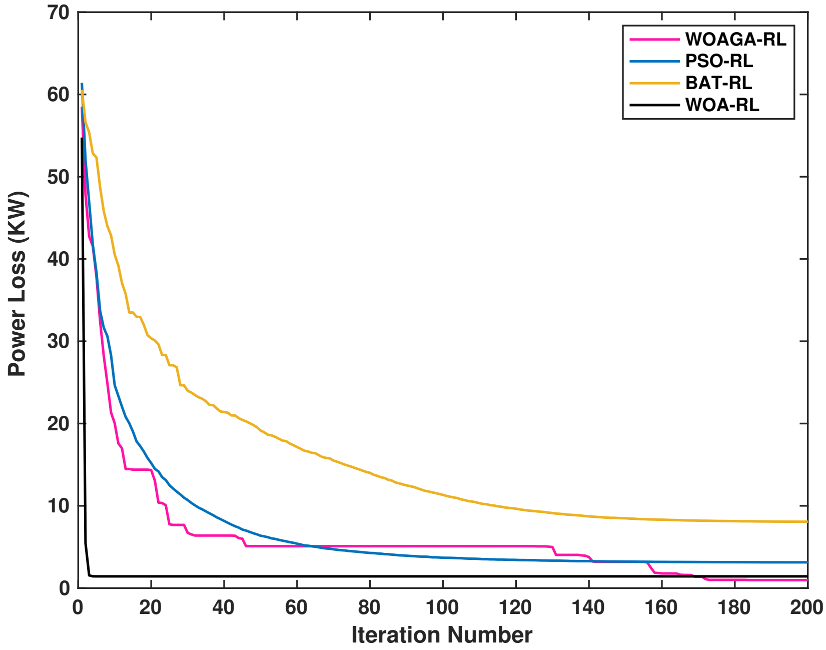

FIGURE 6.10: Convergence characteristics of each algorithm.

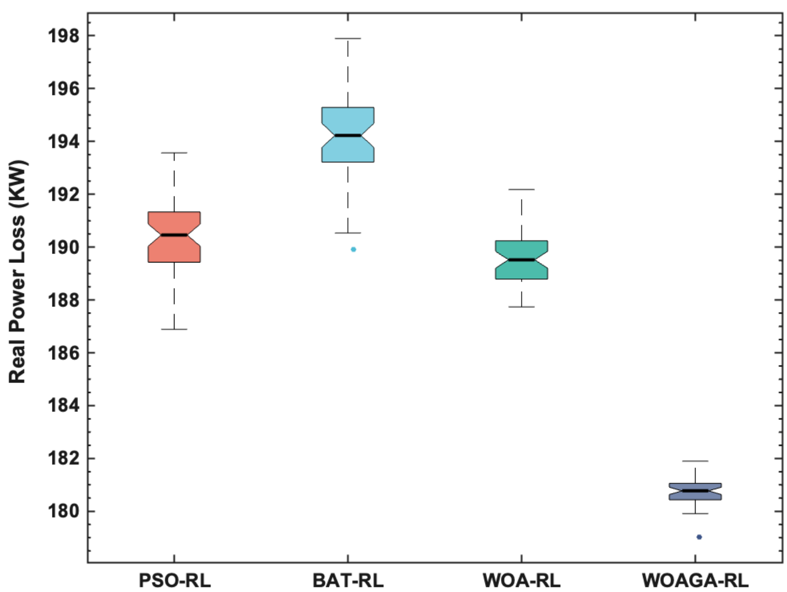

FIGURE 6.11: Performance of each algorithm in generating real power losses under Case V.

optmization scheme, considering the fact that a recombination method is implemented to produce a larger solution space.

6.6.5 Performance of the Proposed Dynamic Mechanism

In this section, the robustness and time complexity of the dynamic mechanism is evaluated and compared with the conventional mechanism for Case V. Using the WOAGA-RL, a statistical analysis was carrried out for three mechanisms, using 50 simulation runs. The mean, best, worst, and standard deviation values were derived for this purpose, shown in Table 6.6. The computational time is derived using an average time taken to run one iteration. The preallocated from of mechanism is implemented by earmarking the distribution network with PV and BESS allocations while the consecutive follows the step-by-step process of allocating each unit/facility.

Few observations were made: *(i)* The standard deviation for all mechanisms shows a fair deviation across the distribution of solutions. *(ii)* There is a small difference in benefit value for the preallocated and consecutive mechanisms. This is quite understandable since the preallocated form of mechanism uses a fairly optimal allocation. *(iii)* The dynamic mechanism performs better than the two mechanisms. *(iv)* The dynamic mechanism takes the most computational time, hence more complex. Looking at the values relatively, the dynamic mechanism uses lesser time given that it completes an iteration for all unit types with the memory block assistance in reducing the number of iterations. The consecutive mechanism uses an addition of each step for its cummulative time while the preallocated performs only one step for a unit type since other unit type(s) are already earmarked with the distribution network.

TABLE 6.6: Performance of planning model mechanisms using Case V

Metric	**Stat.**	**Preallocated**	**Consecutive**	**Dynamic**
Technical	Mean	37.5331	37.1717	33.912
	Best	35.9284	36.4674	33.285
	Worst	39.4832	38.1121	34.674
	Std. dev.	0.545	0.364	0.213
Economic	Mean	15351.5	15342.3	13039.3
	Best	15350.5	15341.7	13032.5
	Worst	15352.6	15343.1	13055.2
	Std. dev.	0.331	0.289	0.221
Environ.	Mean	2201145	2201077	1822511
	Best	2201144	2201076	1822473
	Worst	2201145	2201077	1822598
	Std. dev.	0.255	0.257	0.221
Comp. Time (s)		92	198	362

Table 6.7: Statistics for the grid performance of the distribution network for Case V.

	Technical Objective				
Algorithm	**Mean**	**Best**	**Worst**	**Std.**	**C.T.**
WOAGA-RL	33.9121	33.2849	34.6742	0.213	362
WOA-RL	34.6572	33.3919	34.6572	0.543	369
BAT-RL	35.4311	33.6989	37.7865	0.810	481
PSO-RL	34.8113	33.6183	36.4062	0.617	397
	rank-sum test				
p-value	0.01				

6.6.6 Validation of the Proposed on the IEEE 118-bus Distribution Network

To verify the scalability of applying the proposed planning framework to large scale distribution networks, the IEEE 118-bus is adopted to test distribution network. The details, taken from [184], has an 11 kV nominal voltage and a 100 MVA nominal power, with real and and reactive power demand of 22.709 MW and 17.041 Mvar, respectively. Eight DG units and four BESS units (with high capacity) are considered to augment the network. The same number of cases from validation of the IEEE 33-bus distribution network are considered.

Table 6.8 shows the summary of the technical benefits while applying the proposed planning framework for different cases. Quite similar to the inference drawn earlier in Section 6.6.2, integrating the BESS will have a significant effect on the voltage stability only when EV charging are controlled. Case III results confirms this argument, showing a voltage stability and deviation balance even without the DG and BESS support. Table 6.9 displays the suggested optimal allocation variables in the 118-bus network. It is also seen that the BESS unit integration is beneficial to the distribution network in Cases II and V, where the technical benefit is improved by 0.4% and 5.8% for Cases I and IV, respectively. It can be inferred that the proposed planning framework works well across different network scales.

Table 6.8: Grid performance values from the IEEE 118-bus distribution network under different cases

Indices	**Case I**	**Case II**	**Case III**	**Case IV**	**Case V**
Power loss (KW)	1034.7	928.4	941.2	708.3	681.2
Voltage Stability (PU)	0.7122	0.7513	0.8233	0.9178	0.9481
Voltage deviation (PU)	0.223	0.0873	0.0691	0.0347	0.0219

6.6.7 Performance of the Proposed Multiobjective Sub-framework

To verify the performance of the proposed MOO framework, the SP-metric is adopted to measure the quality of the Pareto optimal solutions. The computed SP-metric is the progressive distance between each solution, measuring the uniformity and consistency of all solutions. Figure 6.12 depicts the computed metric as a boxplot for each algorithm. The boxplot's height shows a good distribution of Pareto optimal solutions and its centerline depicts the median of the distribution, showing the quality of the distribution. As seen in Figure 6.12, the proposed multiobjective implementation has the shortest box, portraying

Table 6.9: Optimal allocation variables for integrating PV-DG, BESS, and EVCS facilities in a 118-bus distribution network for different cases

Cases	PV-DG		BESS		EVCS	Tech.	Economic	Environ.
	Location	Size (KW)	Location	Size (KWh)	Location			(Kg/KWh)
Case I	23, 48	2027, 2734						
	75, 83	2621, 3364				60.2302	18895.34	123579
	92, 110	3193, 2074						
Case II	20, 41	1152, 1320	45	1422				
	50, 74	1072, 971.1	51	2065		59.8916	41543.67	2341242
	83, 116	1076, 1849	82	2101				
			116	1862				
Case III	-	-	-	-	8, 17, 25			
					53, 63, 88	59.9745	-	
					95, 103, 117			
Case IV	23, 49	2531, 3134	-	-				
	75, 83	3072, 2533	-	-	8, 18, 27	51.7191	20790.42	154233
	95, 110	2792, 3557			54, 63, 85			
					97, 110, 116			
Case V	22, 45	1167, 2058	45	2125	8, 18, 30			
	50, 78	1873, 2109	50	1754	71, 85, 91	48.7231	52234.38	171345
	91, 110	983.3, 2649	91	1721	99, 101, 116			
			113	2283				

the production of the Pareto optimal solutions as close to each other and uniformly distributed. The implementation of the multiobjective approach for all algorithms proves to be valid as it is seen that the centerline of all approaches' boxes are almost in line with one another.

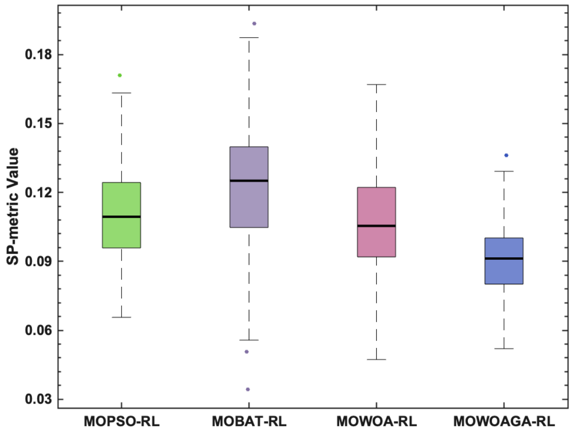

FIGURE 6.12: Spread values for Pareto optimal solutions for different multiobjective optimization algorithms under Case V.

6.7 Summary

This chapter proposes a novel multi-phase planning framework for allocating PV-DG, BESS and EVCS facilities in distribution networks, using a recombination technique to find optimal locations while considering power loss reduction, voltage stability improvement, voltage deviation reduction, installation cost reduction, operational cost reduction, and emission cost reduction. A category-based mulitobjective approach is developed to simultaneously optimize the multiple objectives, grouping each objective according to their benefit. The proposed planning framework applies a reinforcement learning technique for controlling EV charging to determine the optimal EVCS locations according to the suggested optimal PV-DG and BESS locations and sizes in one round of iteration, contrary to previous works that only considers EVCS allocation as a separate study.

The framework is validated on the IEEE 33- and 118-bus distribution network adopting different case scenarios. The results show that the proposed planning framework is capable of allocating multiple units/facilities in a distribution network. It is therefore concluded that the proposed optimization scheme can be applied to almost any network scale without deterring its efficient process. Furthermore, the multitobjective approach is validated and compared to other approaches. The results depicts that the proposed approach is effective generating Pareto optimal solutions. Future works will consider extending the EV charging strategy, improving the reinforcement learning technique and adding more constraints and objectives in the EV charging model while maintaining a considerable level of time complexity.

The next chapter investigates planning mechanisms and discusses the improvement of the dynamic planning mechanism in a smart grid planning framework.

Chapter 7

A Novel Dynamic Planning Mechanism for Allocating Electric Vehicle Charging Stations Considering Distributed Generation and Electronic Units

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This chapter is based on the following publication:

K.E. Adetunji, I. Hofsajer, A.M. Abu-Mahfouz, and L. Cheng, "A novel dynamic planning mechanism for allocating electric vehicle charging stations considering distributed generation and electronic units". *Energy Reports.* - Under Review

The author of this thesis conceptualized this work, partook in the formal analysis, developed the models and algorithms, and wrote the original draft of the paper.

7.1 Introduction

The growing interest in the decarbonization and stabilization of utility grids have birthed research in transforming the traditional power grid into an efficient smart grid. To this course, different studies have integrated different distributed energy resource (DERs) units into the distribution networks. Renewable energy sources (RES) have been the main focus, to aid a sustainable power grid while reducing carbon footprints. While RES is known for its' setback in continuous power supply, such as variability and intermittency, battery energy storage systems (BESS) are deployed to counter the effects, storing energy for downtime use and regulating the voltage fluctuations [185, 186]. However, these systems are very expensive to install and maintain [187], and even more, they add to the time complexity of the distribution networks, starting from the simulation software modelling to the implementation.

Furthermore, an inappropriate installation of these units can be counter-intuitive to the expected results [188, 189], hence, previous studies have developed planning framework to allocate multiple unit types in power system networks. These unit types include energy sources and power electronic devices, such as photovoltaic distributed generators (PV-DG) units, wind turbines (WT-DG) units, microturbines, BESS, capacitors, voltage regulators, static compensators, and fault detectors.

More recently, electric vehicles (EVs) are the promising technologies to support sustainability and efficiency in modern power system networks, due to their combustion-free energy and capability to feed in real and reactive power into an electrical grid [45]. However, their natural charging pattern may cause potential grid collapse [190]. Therefore, there is a need to strategically coordinate these charging, either by assigning time slots or recommending charging stations. Hence, there is a need to consider the optimal allocation of electric vehicle charging stations (EVCS) in the smart grid planning models.

7.1.1 Contributions

In this chapter, we develop a planning framework by optimally allocating multiple unit types to a distribution network. The framework consists of various objectives, therefore adopting a MOO technique to find compromise solutions that represent all adopted objectives in the view of a decision-maker. The chapter contributions are

- *Dynamic Planning Mechanism*: We design a novel adaptive-dynamic planning mechanism as an underlying blueprint for use by an optimization scheme to solve the planning problem. Unlike other conventional mechanisms, the dynamic mechanism uses a recombination technique that considers the feedback of other unit types to expand the solution space.
- *Hybrid Evolutionary Optimization Scheme*: We develop a hybrid cooperative spiral-based genetic algorithm and differential evolution optimization scheme based on the newly designed planning mechanism. The scheme adopts a decomposition system that helps split the whole problem into sub-problems, using each algorithm at different stages of the optimization process. The CoSGADE is implemented in two forms, hoping to solve the complex model in a considerably reasonable computational time.
- *EVCS Allocation*: We introduce a reinforcement learning-based allocation scheme, using the results from the EV charging strategy to suggest optimal EVCS locations in distribution networks. A reinforcement learning technique is introduced to find the optimal EV charging strategy for different bus locations.

7.1.2 Chapter Outline

The rest of the chapter follows the structure - Section 7.2 discusses the integration model and the problem description, entailing the objective functions, constraints, and the MOO technique. Next, Section 7.3 discusses the solution methodology, entailing the proposed dynamic planning mechanism and the new optimization technique, the CoSGADE. Finally, Section 7.4 discusses the numerical results, while Section 7.5 presents the conclusions from the study.

7.2 Problem Description and Modelling

In this section, a multiobjective optimal allocation problem consists of multiple different DER technologies and FACTS devices aiming to optimize adopted objective functions in a smart grid planning framework. In addition, some terminologies are predefined in the planning framework. The adopted objectives and constraints are discussed in the following subsections.

7.2.1 Objective Functions

The objective of the planning model is to improve grid performance which has been formalized by adopting three objective functions - power loss minimization, voltage stability improvement, and voltage deviation reduction. The objective functions are defined as follows.

7.2.1.1 Power Loss Minimization

One of the primary objectives of a utility grid is to deliver maximum power from the source to all nodes in a power system network. To achieve maximum power delivery, power loss within the network has to be minimized as best as possible. We, therefore, consider the power loss minimization as one of the objectives, defined as in (2.9)

7.2.1.2 Voltage Deviation Reduction

Delivery of power also comes with the assurance of quality. Power quality is affected by the deviation of voltage from the tolerance range, which can be aggravated by newly installed units. Hence, the second objective is to reduce the voltage deviation at each bus and described as in (4.11)

7.2.1.3 Voltage Stability Improvement

The voltage stability is indexed as (2.12) to (2.14)

7.2.2 Constraints

A power system network has many constraints that guide its smooth operation. Therefore, there is a need to formulate necessary constraints to improve the practicality of the optimal unit allocation model.

$$P_i^t = \sum_{j=1, j\neq i}^{N} Y_{ij} V_i^t V_j^t \cos(\theta_{ij} + \delta_j - \delta_i), \tag{7.1}$$

and

$$Q_i^t = \sum_{j=1, j\neq i}^{N} Y_{ij} V_i^t V_j^t \sin(\theta_{ij} + \delta_j - \delta_i). \tag{7.2}$$

Although there was no injection of reactive power from PV-DG unis, it is necessary to monitor boundaries during the injection of real power.

The operating voltage at every bus must satisfy the range at all buses. The admittance on a branch is represented as Y_{ij}. The bus voltage limit is formulated as

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad i = 1, 2, ..., N, \tag{7.3}$$

where V_i is the current voltage at bus i. Then V_i^{min} and V_i^{max} are 0.98 and 1.01 respectively.

The power flow balance is also considered. The total real power generation (from all DG and BESS units) must equal the total real load, total real power loss, and the BESS charging and discharging power [140]. Therefore, a balance of the power flow is calculated as

$$\sum_{i=1}^{N} P_i^{\mathrm{DG}} + \sum_{j=1}^{J} P_j^{\mathrm{Dis}} = \sum_{i=1}^{N} P_i^{\mathrm{LOSS}} + \sum_{i=1}^{N} P_i^{\mathrm{LOAD}} + \sum_{j=1}^{J} P_j^{\mathrm{Ch}}, \tag{7.4}$$

where the P_j^{Dis} and P_j^{Ch} represent the BESS discharging and charging power to and from the grid from bus j.

7.2.2.1 BESS Constraints

This chapter selected the Lead-acid battery technology due to its economic viability and reliability since they have a considerably high tolerance for overcharging. For a practical scenario, the BESS model is subject to *state of charge SoC* limit, which prevents excessive charging or discharging from the battery and defined as [141]

$$SoC^{min} < \frac{E_t^B}{E_t^{BA}} < SoC^{max}, \tag{7.5}$$

where the SoC^{min} and SoC^{max} are 0.2 and 0.9 respectively. The charging and discharging power are specified as [66, 142]

$$E_{t+1}^{B} = \begin{cases} E_t^B - P_t^B \triangle t \eta_{Bc} & P_t^B \leqslant 0 \\ E_t^B - \frac{P_t^B \triangle t}{\eta_{Bd}} & P_t^B > 0 \end{cases}, \tag{7.6}$$

where E_t^B is the energy of the BESS unit at time t, P_t^B is the charging power of the BESS unit at time t, $\triangle t$ is the time interval, η_{Bd} and η_{Bc} are the discharging and charging efficiency of the BESS unit respectively, the battery power is limited by

$$E^{\min} \leqslant E_{i,t}^{B} \leqslant E^{\max}, \tag{7.7}$$

where $E_{i,t}$ is the energy of the i^{th} BESS unit at time t.

Given that most EVs use a lithium-ion battery, this work modelled a lithium-ion battery, which injects current to a bus at a given time. The current is expressed as

$$I_i = \frac{(P_i^t + Q_i^t)}{V_i^t}, \tag{7.8}$$

where P_i and Q_i are the real and reactive power at bus i at time, t. V_i^t is the bus voltage at bus i at time, t. The reactive power Q_i^t will always be zero at every time, t, since only real power will only be considered.

7.2.2.2 Capacitor Constraints

The capacitor banks are also bounded by maximum sizes, given as

$$CAP^{\min} \leqslant CAP_i \leqslant CAP^{\max}. \tag{7.9}$$

7.2.2.3 EVCS Constraints

The EVCS is modelled as a load, according to the EVs roaming to charge in a network. Therefore, EVCS facilities must not exceed the total EV load and distributed evenly across all EVCS facilities, hence having the same capacity. The constraint is represented in (7.10)

$$\sum P_{i,t}^{\mathrm{EV}} \leqslant \sum P_k^{\mathrm{EVCS}} | N(\mu, \sigma), \tag{7.10}$$

where $\sum P_k^{\mathrm{EVCS}}$ is the charging of the k^{th} EVCS that follows a normal distribution of a mean and standard deviation across all EVCS.

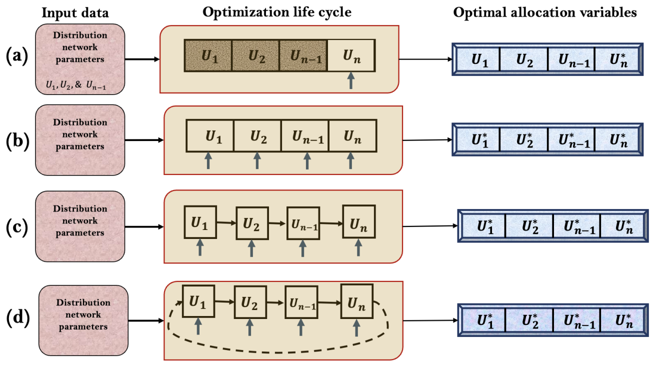

FIGURE 7.1: Mechanisms for smart grid planning models a) preallocated mechanism. b) simultaneous mechanism. c) sequential mechanism. d) dynamic mechanism

7.3 Solution Methodology

7.3.1 Dynamic Mechanism

This section seeks to address the gap observed in the literature by proposing a dynamic mechanism to increase potential solutions for the optimal multiple DER allocation problem.

There are three conventional planning mechanisms for allocating multiple unit types: preallocated, sequential, and simultaneous. The preallocated form of mechanism involves allocating one unit type into a distribution network earmarked with one or more different unit type(s). An example is finding optimal BESS locations and sizes in the presence of PV-DG and capacitor units. The step for allocating PV-DG and capacitors will be skipped, assuming they are optimally allocated, only to focus on allocating the BESS units. This method is very straightforward and less complex, but the assumption that earmarked units are optimally allocated can be costly to derive optimal solutions.

The sequential form of mechanism is allocating multiple unit types in successive order. The first unit, e.g. a capacitor, is singularly allocated, followed by another distinct unit type, e.g., the BESS unit. This mechanism ensures that, within the optimization framework, unit type allocation is dependent on the effect of previously allocated unit type on the distribution network. The simultaneous mechanism allocates all unit types together in one iteration. The location and size of all unit types are manipulated at once, considering the utility value as the fitness value to determine the optimal allocation variable per iteration. The drawback is a limited number of iterations to find the best permutation among unit types. Increasing the number of iterations will be counter-intuitive to the simplicity of the mechanism.

The other form of planning mechanism is the dynamic mechanism, where the permutation of unit location is considered. This mechanism has only been reported in [112] and [113]. Figure 7.1 shows the visual illustration of the proposed mechanisms.

As seen in Figure 7.1, the pre-allocated mechanism involves the most minimal form of manipulating allocation variables, making it the most straightforward approach. The simultaneous form is next in simplicity, as it manipulates all variables in one iteration. Finally, the proposed dynamic mechanism is adapted from the sequential form but adds a cyclic process to involve sub iterations in the main iteration cycle.

In contrast to the planning mechanisms in the literature, we develop a recombination technique with a sub-convergence barometer that simultaneously allocates multiple DER units at a sub-iteration level.

Heuristic proof Using the Big $\mathcal{O}$ notation complexity analysis [191], we show the difference in time complexity for different planning mechanisms (independent of the optimization algorithm) on the mixed-integer linear problem-based smart grid planning problem. Given that we have N_i is the number of variables for a variable type i, T, the number of processes (or iterations), and number of constraints and uncertainties are constant across all planning mechanism modes, the notation for sequential will be $\mathcal{O}(T\frac{N_i}{2} + TN_i)$ which sums to $\mathcal{O}(2T\frac{3}{2}N_i)$. The simultaneous planning mechanism is $\mathcal{O}(TN_i)$, while the dynamic mechanism is $\mathcal{O}(T^2N_i)$. The adaptive form yields $\mathcal{O}((T-p)^2N_i)$, where p, an absolute value always lesser than T, is the remainder of the number of iterations when there is a sub-convergence. A similar approach for calculating time complexity can be found in [192].

7.3.2 Hybrid Optimization Strategy

CoSGADE is a hybrid evolutionary algorithm developed to handle large scale optimization problems, such as the optimal planning of smart grid networks. The high-level approach is to divide the planning framework into sub-iterations of different unit allocations, shown in Figure 7.2

As seen in Figure 7.2, the first vector contains DG locations and sizes while the second and third vectors accommodates the BESS units (BU) and capacitor banks (CB) respectively. Each of these vectors are solved at a sub-iteration level. The lower level of the optimization scheme uses two evolutionary algorithms, namely the DE and GA, to solve the planning problem cooperatively. The problem is split into two sub-problems: i) discrete variable, which handles the location of units, and ii) continuous variables, which involve the sizing of the units. Given its effective capability to manipulate discrete variables, the GA is dedicated to solving optimal unit locations. The DE, on the other hand, uses a similar approach but with some extra parameters that make it efficient for manipulating continuous variables. The DE also models

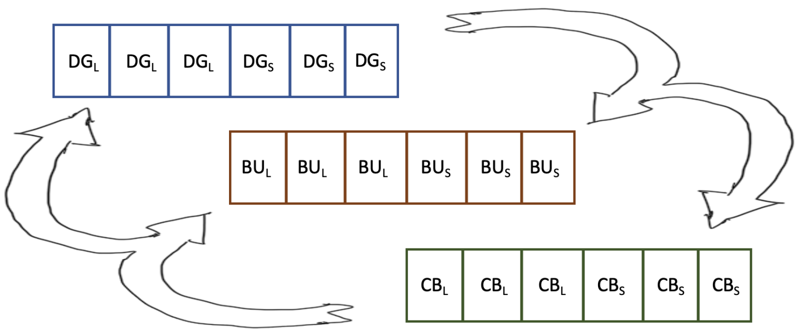

Figure 7.2: High-level process of the planning optimization scheme.

the solution variables as chromosomes, with each gene representing a unit type size. Finally, the DE uses a scaling factor to ensure positive integers during the mutation process in addition to the GA's operator.

The DE's mutation operator also differs from the traditional GA because it uses the difference of parent vector (or chromosome). While the DE is effective, simple, and less complex to implement, it often suffers from stagnation due to the time complexity of manipulating continuous large-scale optimization problems [145, 193]. Stagnation is a common drawback in stochastic search algorithms, where results are no longer improved during the iteration process, even when there are better solutions in the solution space. A spiral mechanism is adopted to overcome this drawback, adapted from the WOA [143] due to its effective finding of optimal solutions in a relatively quick manner. The CoSGADE's search operator is then maintained by implementing a probabilistic roulette wheel that controls the switch between the DE's search and the spiral search for every new generation. Equation (7.11) shows the illustration of the CoSGADE's search mechanism.

$$X_{i,G+1} = \begin{cases} X^{\mathrm{DE}}, & p < 0.5 \\ \\ X^{\mathrm{rand}} - D \cdot \, e^{bl} \cdot \cos(2\pi l) & p \geqslant 0.5 \end{cases}, \tag{7.11}$$

where $[X_{i,G+1} | \forall x^d_{i,G} \in x^D_{i,G}]$ is i^{th} vector solution for the next generation, $G+1$ and d is the variable (gene) in the vector (chromosome). The randomly spiralled phase occurs when the roulette wheel produces a $\geqslant 0.5$ probability value. This phase diversifies the search away from local optima, using the X_{rand}. The D parameter represents the distance between the current vector solution and the best vector solution, expressed as $D = \ |C \cdot X^*_G - X_G|$, where $C = 2 \cdot r$ is a random parameter that is updated at every generation.

The DE's manipulation process starts with the mutation process, creating a donor vector, represented as

$$V_{i,G} = X^*_G + F(X_{r^1_{i,G}} - X_{r^2_{i,G}}), \tag{7.12}$$

which corresponds to each target vector, $X_{i,G}$. The r^i_1 and r^i_2 are mutually exclusive random integers peculiar to every iteration; the scaling factor, F, is a control parameter to ensure positive integers while calculating the difference donor vector. The crossover operator is performed on $V_{i,G}$, manipulating its solution variables to form a trial vector, $U_{i,G} | \forall u^d_{i,G} \in u^D_{i,G}$. The vector is determined using

$$U^d_{i,G} = \begin{cases} v^d_{i,G}, & \text{if } z \leqslant Cr \\ x^d_{i,G}, & \text{otherwise} \end{cases}, \tag{7.13}$$

where z is a uniformly distributed random parameter between 0 and 1, called anew for manipulation of each d_{th} variable of the i_{th} vector of population in generation G. The z parameter also ensures that $U_{i,G}$ gets at least one solution variable from $X_{i,G}$. Finally, the selection process determines the surviving vector

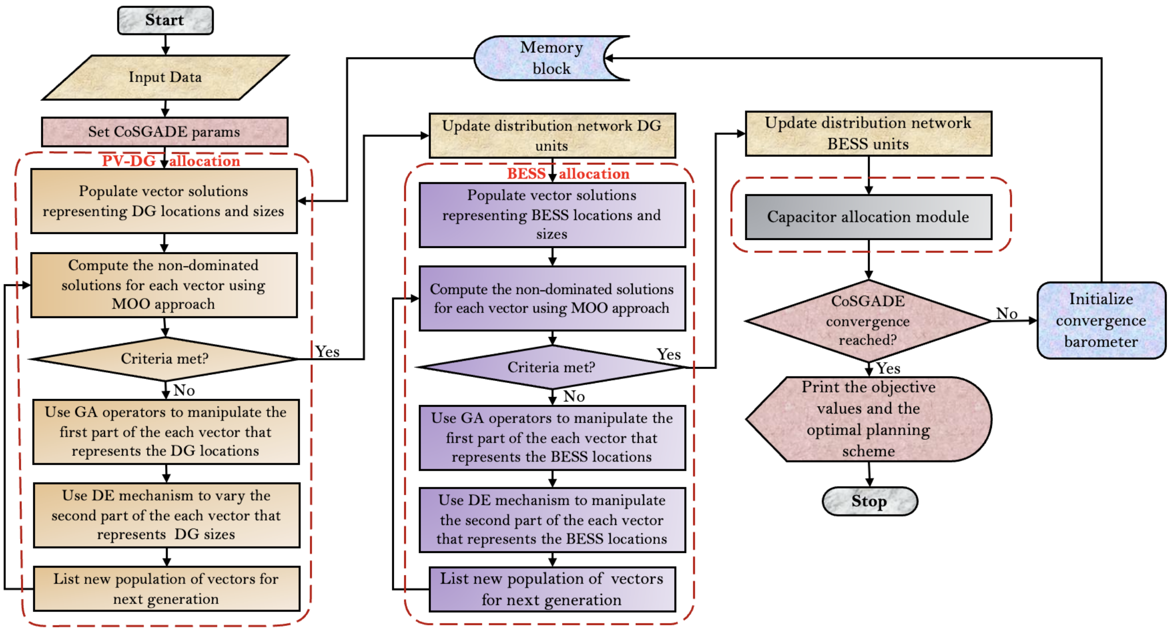

FIGURE 7.3: Flowchart of the first implementation of the CoSGADE optimization scheme

to the next generation, $G+1$, shown as

$$X_{i,G+1} = \begin{cases} U_{i,G}, & \text{if } f\left(U_{i,G}\right) \leqslant f(X_{i,G}) \\ X_{i,G}, & \text{if } f\left(U_{i,G}\right) > f(X_{i,G}) \end{cases}, \tag{7.14}$$

where $f(\cdot)$ is the utility function value for a known vector of allocation variables.

Having explained the CoSGADE mechanism and the dynamic modelling, the optimization scheme will obviously suffer a high time complexity. Firstly, the recombination technique uses more iterations to converge. Secondly, the operation or effect of the units to be allocated has to be carried at T number of iterations. Hence, we propose two implementations for applying the CoSGADE optimizer to mitigate this setback.

CoSGADE-I Here, the process involves the optimization of each unit type in a sub-iteration. This process indeed requires a high computational time which increases drastically according to the number of unit types to be allocated. To overcome the limitation, the CoSGADE is incorporated with a convergence barometer and a memory block. Figure 7.3 illustrates the process. As seen in Figure 7.3, the memory block is initialized after the first round of iterations, beginning the storage of utility values. Then, the convergence barometer is implemented to utilize the memory block, computing the difference in utility values across every ten iterations. A nominal value terminates the current sub-iteration, i.e., suspending the optimizer to use optimal unit type allocation solutions in the memory block. This process significantly reduces computational time. The capacitor allocation module involves an optimization process similar to PV-DG and BESS allocation process.

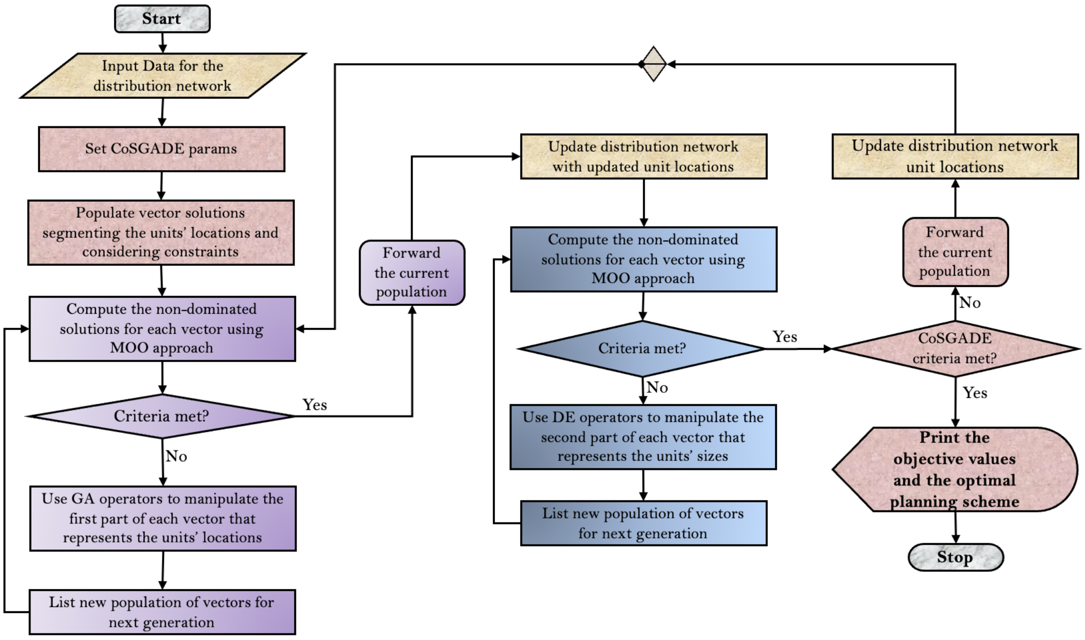

FIGURE 7.4: Flowchart of the second implementation of the CoSGADE optimization scheme

It is to note that other unit types, e.g., EVCS, can easily be replaced or added to the optimization scheme.

CoSGADE-II To achieve the control mechanism that checks different unit type allocation against each other, it is proposed to have one vector representing all the allocation variables, but arranging the vector such that the location and size of all unit types are categorized. The mechanism uses each algorithm for a sub-iteration, containing distinct variable types. Here, the location is first optimized by the GA then the final solution of the sub-iteration is pushed to DE for the size to be optimized. The process is repeated until convergence is reached. Figure 7.4 illustrates the procedure.

It is observed in Figure 7.4 that there are fewer steps, which translates to a faster computational time. Compared to CoSGADE-I, the unit locations are checked against their sizes at every iteration. The solution vectors in a population are represented as follows.

$$\overrightarrow{X}_{\mathrm{G}} = \begin{pmatrix} x^{\mathrm{L}}_{1,1} & \cdots & x^{\mathrm{L}}_{D,1} & x^{\mathrm{S}}_{1,1} & \cdots & x^{\mathrm{S}}_{D,1} \\ x^{\mathrm{L}}_{1,2} & \cdots & x^{\mathrm{L}}_{D,2} & x^{\mathrm{S}}_{1,2} & \cdots & x^{\mathrm{S}}_{D,2} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ x^{\mathrm{L}}_{1,M} & \cdots & x^{\mathrm{L}}_{D,M} & x^{\mathrm{S}}_{1,M} & \cdots & x^{\mathrm{S}}_{D,M} \end{pmatrix}, \tag{7.15}$$

where $x^{\mathrm{L}}_{1,1}$ is the first unit type location of the first chromosome, given a total number of D unit types sizes in M number of population. $x^{\mathrm{S}}_{1,1}$ represents the sizes in the same context.

7.3.3 Reinforcement Learning-based Optimal Control Strategy

This section discusses the allocation of the EVCS facilities into distribution networks. The problem is formed based on an EV charging control strategy. The EVCS location set with the optimal strategy with the best performing grid performance index emerges as the optimal EVCS location. The Markov decision process (MDP) is adopted to model this problem effectively, given the action taken in a specific state to give accumulated rewards that forms a policy. Algorithm 6 shows the procedure of the EVCS allocation scheme.

Algorithm 6 EVCS Allocation Scheme

Initialize maximum number of generations G
Initialize a population P of chromosomes, $V = \{v_1, v_2, \dots, v_n\}$, as the EVCS locations
Set voltage stability as the fitness value of each chromosomes
  while $g < \mathbb{G}_{max}$ **do**
    for each $V \in P$ **do**
      procedure EV_Charge_control(V)
      Sort best chromosome, V^* in the current generation $g++$
    end for
  end while
  Print chromosome with best fitness from the control strategy
  $V \leftarrow V^*$
  return V

The MDP structure is depicted as $\mathcal{M} = \langle \mathcal{S}_t, \mathcal{A}_t, \mathcal{R}_t, T, \gamma \rangle$, where state $\mathcal{S}_t = \langle \mathcal{I}_t, d_s \rangle$ given $\mathcal{I}_t$ is the set of EV chargers drawing power from the distribution network, d_s is the power demand in the network. The action, $\mathcal{A}_t = \langle a_{\text{EVCS}} \rangle$, where a_{EVCS} is the set of EVCS allocated to EV drivers. The reward, $\mathcal{R}_t$ offered to the agent that takes action $\mathcal{A}$ in state $\mathcal{S}$ is measured using (7.16), to be used for the next state, $\mathcal{S}+1$. The probability of transitioning from state $\mathcal{S}$ to the next state, $\mathcal{S}+1$ is expressed as

$$T = f(\mathcal{S}, \mathcal{A}, L_t). \tag{7.16}$$

Therefore, the outcome of carrying out all actions in different states yielding rewards will follow policies π , represented as

$$Q^\pi(\mathcal{S}_t, \mathcal{A}_t) = \mathcal{E}[\mathcal{R}_t(\mathcal{S}_t, \mathcal{A}_t) + \gamma Q^\pi p(\mathcal{S}_{t+1}, \mathcal{A}_{t+1})], \tag{7.17}$$

where $\gamma = \{0, 1\}$ is the discount factor that offers rewards for actions over an expectation $\mathcal{E}$ given a time horizon, T. Given Equation (7.17), an optimal policy which maximizes the grid performance the most is expressed as

$$Q^*(\mathcal{S}, \mathcal{A}) = \max_\pi Q^\pi(\mathcal{S}_t, \mathcal{A}_t). \tag{7.18}$$

This optimal policy is learned using a recursive algorithm to update the state-action pairs, mapped as

$$Q^*(\mathcal{S}_t, \mathcal{A}_t) = (1-\alpha)Q(\mathcal{S}_t, \mathcal{A}_t) + \alpha[Q^\pi(\mathcal{S}_t, \mathcal{A}_t)], \tag{7.19}$$

where α is the learning rate of the algorithm, chosen between 0 and 1. Algorithm 7 shows the SARSA learning procedure for the control problem.

Algorithm 7 Reinforcement Learning for EVCS allocation

Initialize number of episodes, $\mathbb{E}$
Initialize the EV charging demand for set of EVs as state $\mathcal{S}$
Initialize EVCS location selection as action $\mathcal{A}$
Set power loss (2.8) as reward $\mathcal{R}$
while $e < \mathbb{E}$ **do**
  Collect distribution network and EVCS features to realize state, $\mathcal{S}$
  Select action $\mathcal{A}$ from $\mathcal{S}$
  Receive reward $\mathcal{R}$, receive new data, and generate next state $\mathcal{S}+1$
  Update $Q(\mathcal{S},\mathcal{A})$ using (7.17)
  Find the optimal policy using (7.18) and learn this policy using (7.19)
  $\mathcal{S} \leftarrow \mathcal{S}+1$
  Terminate at desired state $e++$
end while
Output the best policy $\boldsymbol{\pi}$

7.4 Numerical Analysis

In order to demonstrate the efficiency and practicality of the proposed planning framework, we evaluate the proposed adaptive-dynamic mechanism and the CoSGADE optimization on a 15-bus, IEEE 69-bus and 118-bus test distribution network. The load consumption is processed as a probability density function, to handle uncertainties from consumers' daily and seasonal behaviour. The same technique is applied to PV power output through the modelling of the solar irradiance and temperature data.

7.4.1 Evaluation of the Planning Optimization Framework

For a robust explanation of the proposed mechanism's efficiency on solving the planning problem, we draft the analysis into 3 cases. Case 1 is the integration of a 2-unit placement - PV-DG and BESS units. Case 2 involves integrating PV-DG, BESS, and capacitor units. In Case 3, an EVCS facility is added to the mix. Each case is analyzed for three study systems - 15-bus, IEEE 69- and 118-bus test distribution network. All cases are analyzed using a single objective framework, with power loss minimization as the objective function. We adopted some conventional optimization algorithms to test the proposed CoSGADE on the study systems using the proposed underlying proposed dynamic mechanism.

7.4.2 Study System I

This study involves the evaluation of the planning model on the IEEE 15-bus distribution network; a 11 kV, 100KVA base KVA, with a real and reactive power of 1226.400 kW and 1251.178 kVAr, respectively. The three cases are implemented for this system, with the results shown in Table 7.1.

TABLE 7.1: Unit allocation variables for Study System I

Case	**Optimizer**	**DG Allocation** *Location (size(KW))*	**BESS Allocation** *Location (size(KW))*	**CB Allocation** *Location (size(KW))*	**EVCS Allocation** *Location*	**% Real PL Min.**
I	GA	10(119.56), 4(131.04)	8(92)	-	-	56.1
	PSO	10(112.11), 11(110.18)	8(84)	-	-	63.2
	PSOGA	11(129.45), 10(92.21)	8(77)	-	-	71.1
	WOAGA	15(158.14), 11(114.28)	10(142)	-	-	72.1
	CoSGADE	11(131.02), 15(128.33)	8(59)	-	-	76.7
II	GA	10(123.56), 4(138.42)	8(91)	4(120), 8(184)	-	68.9
	PSO	10(112.09), 11(108.41)	8(79)	4(136), 9(106)	-	73.9
	PSOGA	11(114.22), 10(94.82)	8(79)	6(186), 12(113)	-	79.8
	WOAGA	15(147.08), 11(112.75)	10(142)	6(177), 12(201)	-	80.7
	CoSGADE	11(130.76), 15(141.38)	8(55)	3(165), 10(189)	-	83.8
III	GA	10(269.23), 4(254.42)	8(105)	4(120), 12(197)	3, 7, 12	39.3
	PSO	10(262.92), 11(275.11)	8(99)	4(166), 9(113)	3, 7, 13	49.7
	PSOGA	11(230.35), 10(184.57)	8(106)	6(242), 12(201)	3, 7, 12	64.7
	WOAGA	15(275.62), 11(217.88)	10(137)	6(297), 12(261)	3, 7, 12	67.2
	CoSGADE	11(272.92), 15(241.38)	8(95)	4(188), 12(222)	3, 6, 12	76.7

From Table 7.1, it is observed that Case 3 has the most power loss and minimum network voltage, given that a multitude of EVs is added to the distribution network model. However, the CoSGADE optimization scheme shows a better performance than the adopted schemes, indicating an improved power loss minimization of 76.7%, 83.8%, and 76.7%, respectively for Cases 1 to 3. The voltage profile is also analyzed, shown in Figure 7.5. It is seen that the CoSGADE produces the best voltage profile for the network.

7.4.3 Study System II

This study involves the evaluation of the planning model on the IEEE 69-bus distribution network; a 12.66 kV network, with a 3.715MW/2.300MVaR as the real and reactive power respectively. To understand the

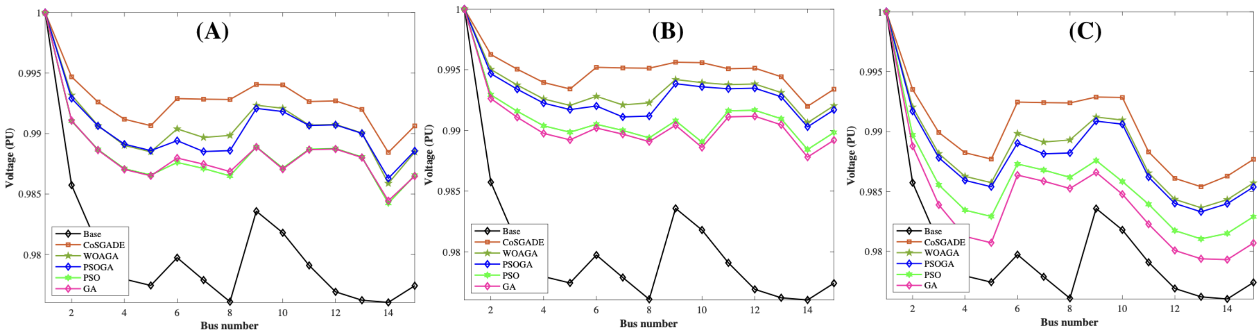

FIGURE 7.5: Study system I voltage profile for all cases (A) PV-DG and BESS allocated to the network. (B) PV-DG, BESS, and Capacitors allocated to the network. (C) PV-DG, BESS, Capacitors, and EVCS allocated to the network.

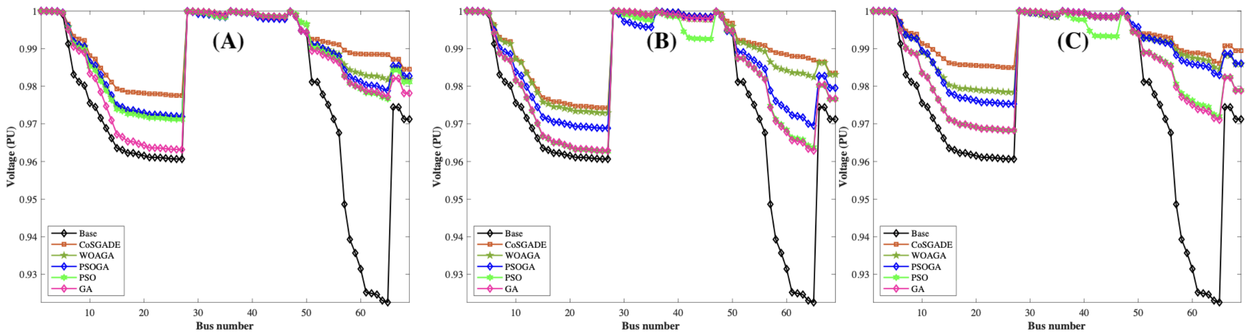

FIGURE 7.6: Study system II voltage profile for all cases (A) PV-DG and BESS allocated to the network. (B) PV-DG, BESS, and Capacitors allocated to the network. (C) PV-DG, BESS, Capacitors, and EVCS allocated to the network.

strength of the proposed mechanism performance, the simulation results are compared to the conventional mechanism.

Table 7.2 depicts a similar scenario to Table 7.1, with Case 3 having the most power loss and minimum network voltage. The CoSGADE optimization scheme also shows a better performance than the adopted schemes, indicating an improved power loss minimization of 78.3%, 86%, and 80.1%, respectively for cases 1 to 3. The voltage profile is also analyzed, shown in Figure 7.6. It is seen that the CoSGADE produces the best voltage profile for the network.

7.4.4 Study System III

This study involves the evaluation of the planning model on the IEEE 118-bus distribution network; a 11 kV network, with a 22.710MW/17.041MVaR as the real and reactive power respectively. To grasp the strength of the proposed mechanism performance, the simulation results are compared to the conventional mechanism.

The CoSGADE optimization scheme in Table 7.3 shows a familiar improvement as in Tables 7.1 and 7.2. An observation is the large scale problem difficulty for the optimization schemes, especially with Case

Table 7.2: Unit allocation variables for Study System II

Case	Optimizer	DG Allocation *Location (size(KW))*	BESS Allocation *Location (size(KW))*	CB Allocation *Location (size(KW))*	EVCS Allocation *Location*	% Real PL Min.
II	GA	12(524.11), 25(509.02), 49(498.12), 62(659.29)	15(382), 63(355)	22(452), 41(376), 60(403)	-	53.7
	PSO	14(535.56), 25(518.33), 45(513.18), 63(661.77)	21(376), 63(352)	22(451), 40(334), 60(412)	-	54.3
	PSOGA	10(555.18), 25(500.83), 49(477.22), 66(650.96)	15(382), 66(377)	20(448), 44(386), 64(411)	-	68.9
	WOAGA	11(592.62), 27(573.92), 52(523.68), 66(689.68)	61(453), 66(468)	22(475), 43(408), 67(442)	-	72.5
	CoSGADE	12(511.24), 21(521.83), 62(518.89), 61(647.47)	21(385), 68(461)	22(464), 48(374), 64(367)	-	89.4
III	GA	02(889.15), 29(814.03), 21(877.42), 61(999.48)	15(552), 65(470)	22(591), 36(415), 65(493)	10, 32, 50, 64	41.1
	PSO	23(902.22), 21(827.63), 60(865.11), 61(998.03)	18(567), 66(478)	22(587), 38(433), 64(497)	08, 21, 55, 64	41
	PSOGA	49(882.54), 21(793.69), 61(863.52), 60(991.48)	31(492), 62(467)	20(495), 39(483), 65(567)	10, 32, 52, 64	66.1
	WOAGA	12(899.75), 50(801.15), 21(831.22), 61(986.59)	62(457), 65(492)	21(492), 37(498), 68(594)	10, 28, 52, 64	65.6
	CoSGADE	12(781.75), 29(834.03), 61(849.52), 21(993.72)	62(452), 61(483)	22(499), 46(558), 69(592)	14, 28, 52, 64	79.3

Table 7.3: Unit allocation variables for study system III

Case	**Optimizer**	**DG Allocation** *Location (size(KW))*	**BESS Allocation** *Location (size(KW))*	**CB Allocation** *Location (size(KW))*	**EVCS Allocation** *Location*	**% Real PL Min.**
III	GA	10(751.29), 35(792.84), 68(799.02), 90(879.71), 105(891.50), 113(778.34)	46(579), 80(650.59), 105(809.05), 113(799.89)	21(457), 45(736), 105(666), 69(733)	3, 9, 25, 47, 58, 84, 96, 115	13.6
	PSO	10(746.24), 34(794.07), 68(783.12), 95(883.72), 105(897.62), 113(779.18)	46(583.88), 83(682.83), 106(811.39), 113(784.27)	30(505), 44(581), 65(622), 105(587)	4, 11, 24, 42, 51, 78, 91, 105	13.5
	PSOGA	10(771.31), 33(798.04), 69(827.41), 86(882.11), 105(897.63), 116(772.92)	33(692), 81(589.43), 102(629.45), 117(554.02)	21(627), 45(730), 105(566), 69(705)	3, 9, 22, 47, 58, 84, 95, 115	29.4
	WOAGA	15(788.11), 38(792.74), 69(885.81), 85(889.59), 103(898.04), 117(789.59)	26(698.95), 83(595.58), 96(643.21), 117(561.72)	21(688), 45(771), 105(575), 69(719)	3, 9, 24, 47, 58, 84, 95, 115	29.8
	CoSGADE	32(675.96), 109(562.22), 113(384.17), 74(899.79), 33(450.05), 79(1015.66)	111(409.61), 110(350.11), 97(578.68), 117(670.99)	28(676), 43(651), 50(700), 64(669)	3, 9, 24, 47, 58, 84, 95, 115	32.3

3, the CoSGADE still outperforms other optimizers in reducing power loss., showing 41.4%, 52.7%, and 32.6% minimization for Cases 1 to 3 respectively. The voltage profile is also analyzed, shown in Figure 7.7. It is seen that the CoSGADE produces the best voltage profile for the network.

7.4.5 Performance Analysis of the CoSGADE Optimization Scheme

This section discusses the performance of the proposed optimization scheme, done by comparing the efficiency of the scheme to other traditional optimization methods. The first check is to evaluate the power loss for each case in the 69-bus and 118-bus systems, shown in Fig. 7.8 and 7.9 respectively.

In Figures 7.8 and 7.9, Cases 4 and 5 are implemented to show the impact of EVCS facilities on the grid operation performance. The uncontrolled case is where EVCS facilities are installed on arbitrary buses,

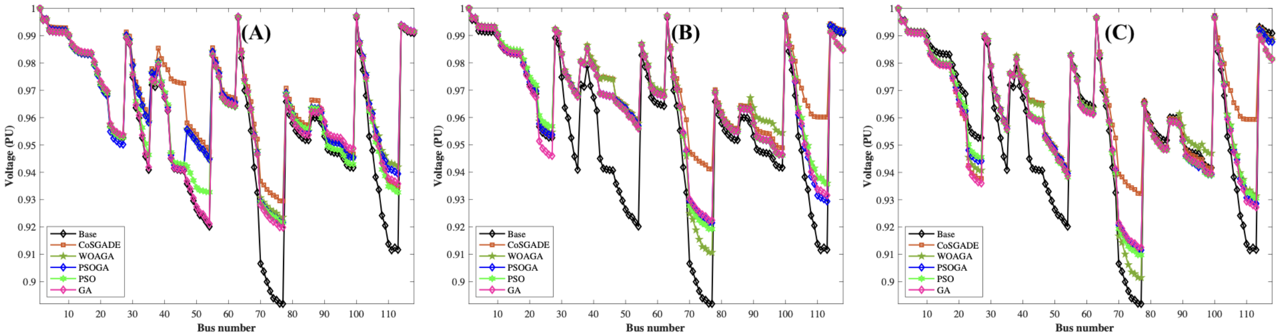

FIGURE 7.7: Study system III voltage profile for all cases (A) PV-DG and BESS allocated to the network. (B) PV-DG, BESS, and Capacitors allocated to the network. (C) PV-DG, BESS, Capacitors, and EVCS allocated to the network.

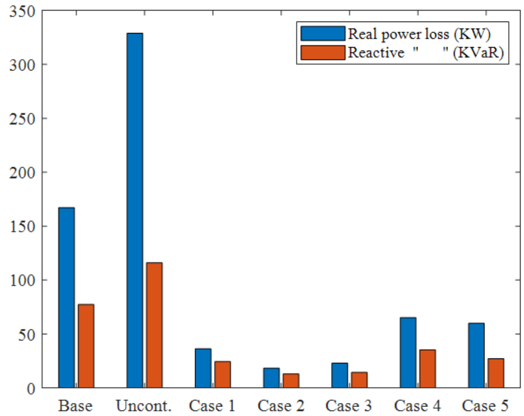

FIGURE 7.8: Power loss profile of the 69-bus system for 5 case scenarios

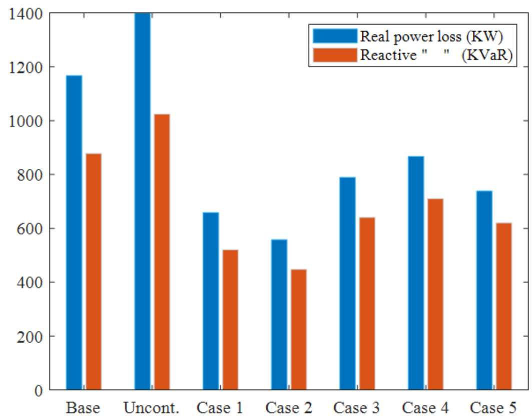

FIGURE 7.9: Power loss profile of the 118-bus system for 5 case scenarios

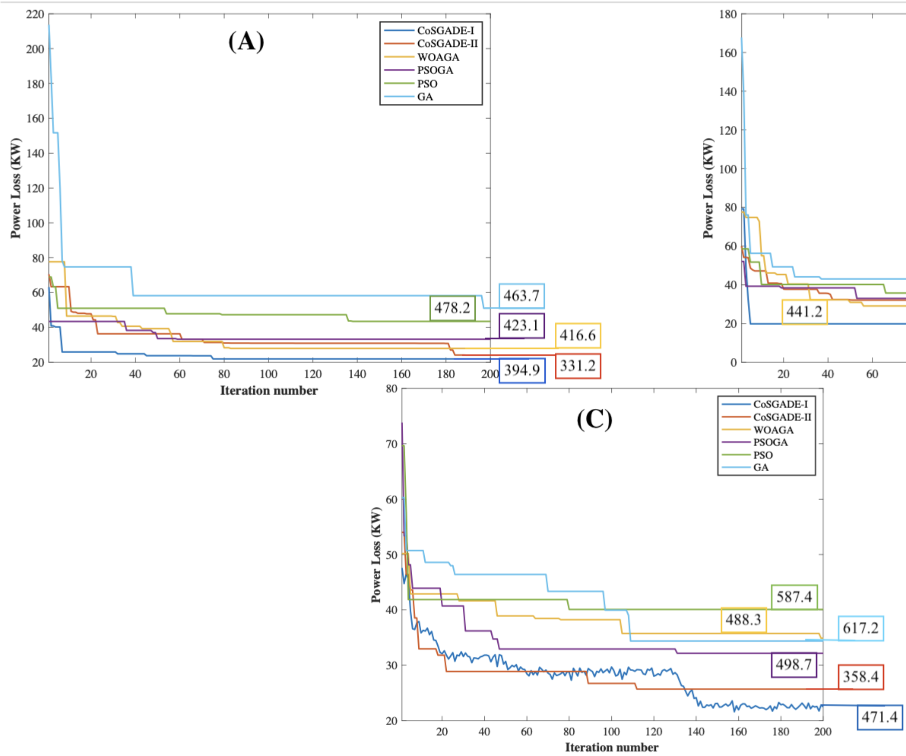

FIGURE 7.10: Convergence and complexity analysis for the 69-bus system

and charging is not coordinated using a control strategy; hence the case shows a high power loss, severely disrupting grid performance.

A second implementation is developed to explore the benefit of the simultaneous planning mechanism, finding a less complex framework, discussed in Section 7.3.2). Like the preceding section, the section analyzes the optimizer's strength in both the single and multiobjective optimization framework.

7.4.5.1 Single Objective Analysis

We adopt the power loss minimization function as the objective function, checking the effect of proposed allocation solutions on the grid's voltage deviation and stability. Firstly, the convergence characteristic and computational time complexity of each optimizer are generated for all study systems, shown in Figures 7.10 and 7.11. The time complexity analysis is generated using the MATLAB profiler software. We used a cumulative calculation of average time spent on all iterations, given that all algorithms uses the same helper functions.

From Figures 7.10 and 7.11, it is observed that the CoSGADE-I converges better than the other optimizers, including the CoSGADE-II. The CoSGADE-II follows a more practical evolutionary algorithm since all unit types are allocated at once for every iteration. Although less computationally complex, as seen from the computational time, its trade-off for optimality is marginally and relatively high. It is also observed that other optimizers use more computational time, given that the optimizers are not tailored for the

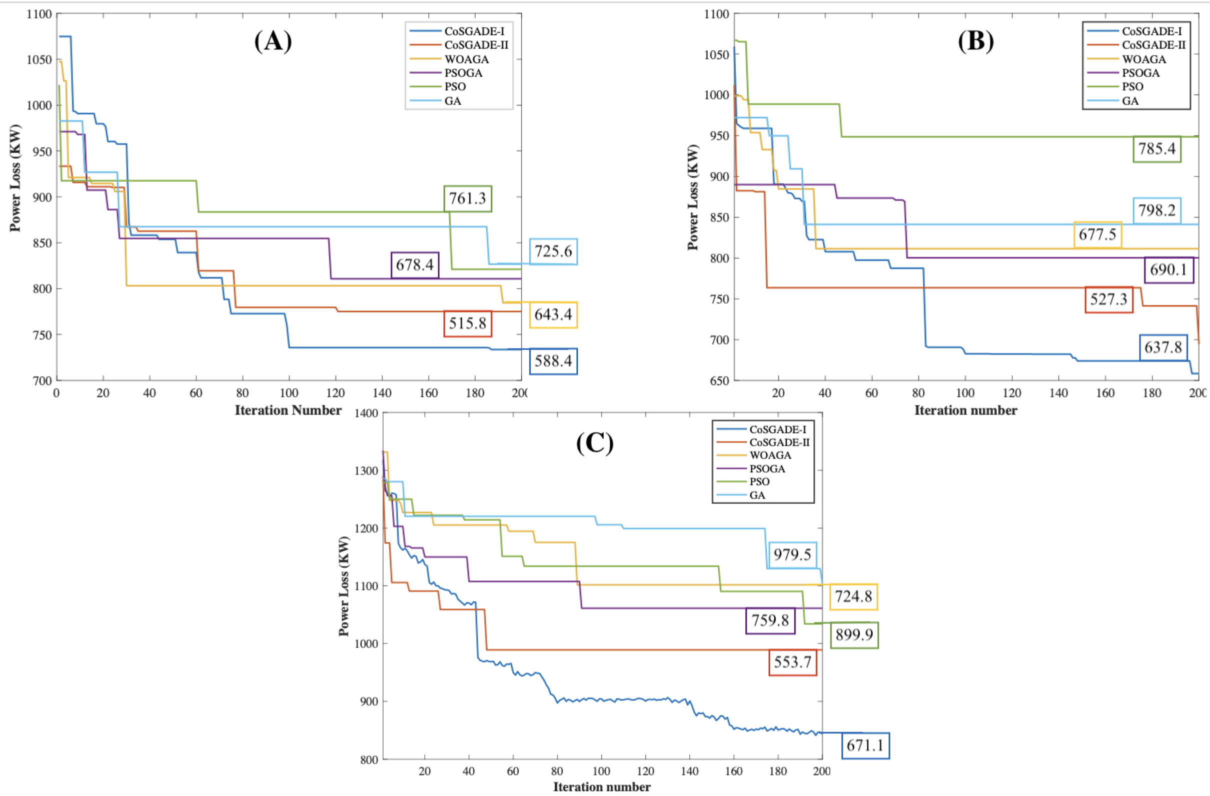

FIGURE 7.11: Convergence and complexity analysis for the 118-bus system

proposed mechanism. Figure 7.12 shows the boxplot that gives more insight into the performance of the algorithms. The boxplot is generated using solutions from 50 runs. The distribution of the solution is analyzed, focusing on the variance to determine the consistency of each optimizer. It is seen from Figure 7.12 that CoSGADE-I and II possess the smallest variance values, which can be determined by measuring the height of the box.

7.4.5.2 Multiobjective Analysis

The performance of multiobjective optimizers is very important for practicality. In real-world scenarios, many objectives are considered when planning a complex project like power system networks. This section provides information on the effect of the proposed optimizer via the proposed adaptive-dynamic planning mechanism in a multiobjective framework. The multiobjective form of the proposed optimizers, which are dubbed M-CoSGADE-I and II - Multiobjective CoSGADE, are formulated using the TOPSIS approach to generate optimal solutions. The MOO techniques are compared with other multiobjective optimizers. A spacing metric (SP-metric) is adopted for measuring the quality of solution distribution, determining the spread of all solutions and understanding the distribution. Table 7.4 shows the metrics for each multiobjective optimizer. It is observed that the proposed frameworks yield a better standard deviation score than other frameworks, interpreted as a compact solution distribution with good confidence in producing reliable, consistent results.

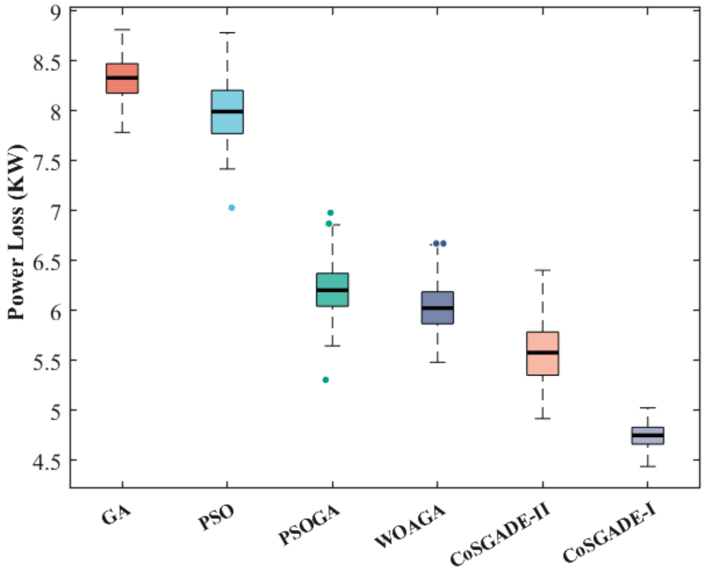

FIGURE 7.12: Box plot analysis of each optimization scheme for the 15-bus system

TABLE 7.4: Performance comparison of multiobjective optimization frameworks

Technique	**Mean**	**Best**	**Worst**	**Std. Dev.**
MOPSO	0.062	0.065	0.081	0.015
NSGA-III	0.061	0.066	0.078	0.016
M-CoSGADE-II	0.053	0.054	0.063	0.012
M-CoSGADE-I	0.051	0.053	0.060	0.012

7.4.6 Validation of the Adaptive-dynamic Planning Mechanism

To verify the efficacy of the proposed mechanism, we analyze its optimality and practicality on single and multiobjective optimization, comparing it with conventional planning mechanisms. Firstly, the CoSGADE optimizer is applied to all mechanisms to produce statistical parameters that determine the performance. Table 7.5 displays the statistical values for all mechanisms, showing a statistical measure of a 50-solution distribution for Case 3 of the 118-bus system, generated by the CoSGADE optimizer via different planning mechanisms.

TABLE 7.5: Statistical comparison of the planning mechanisms

Stat metric	**Planning mechanisms**		
	Sequential	**Simultaneous**	**Dynamic**
Best score	916.12	902.51	789.41
Worst score	931.45	930.67	806.62
Variance	0.41	0.26	0.23
Time (s)	253	126	369

It can be inferred from the table that the dynamic mechanism has a good standard deviation score, varying insignificantly from other schemes. It is to note that the main purpose of this analysis is to validate the

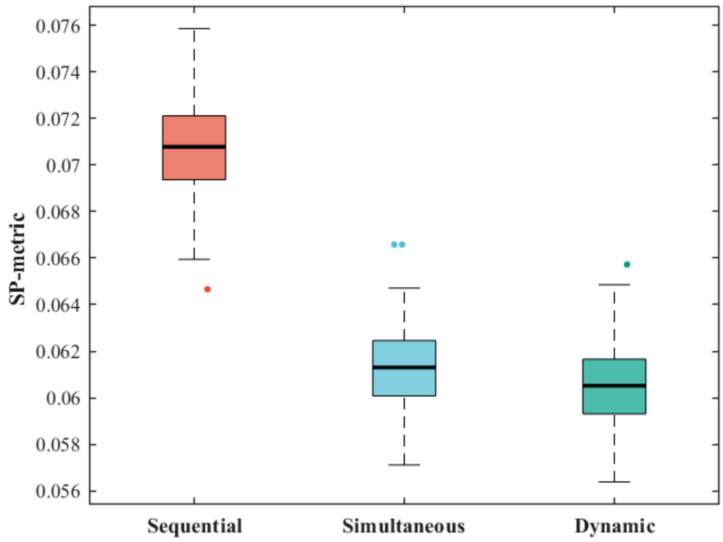

FIGURE 7.13: Box plot analysis of each planning mechanism for the 118-bus system

correctness of the proposed planning mechanism, which passed successfully. The computational time is relatively fast when considering the multiple phases for every iteration.

Using 50 independent simulation runs, Figure 7.13 illustrates the quality of solution distribution for each planning mechanism. It is seen that there is a strong similarity among all boxes, meaning that they have closely uniform distribution that a small variance and an efficient mechanism.

7.4.7 Further Discussions

In this section, we discuss more on the numerical results from the simulation of the planning model. Attention is paid to the impact of the planning mechanism and the optimization scheme on different system scales, aiming at efficiency and optimality. Sampling the simulation results for each case, it is seen that the introduction of EVCS facilities deters the grid operation performance, even with a control strategy. Although still improved by the CoSAGDE optimizer, it is important to know the significance of introducing such facilities to a distribution network. The introduction of capacitors reduces the negative effect, as seen in Case 2 for all study systems. This effect is even more distinct in Section 7.4.5, where another case is introduced - allocating only PV-DG, BESS, and EVCS facilities. However, it is essential to note that capacitors are expensive and may not be practically viable. Bearing this in mind, another case; Case 5, was introduced to inject reactive power from EV chargers into the grid network. As a result, relatively minimized real and reactive power losses can be seen in Figures 7.8 and 7.9, hence improving grid performance.

Another observation is the performance of the optimizers on different study systems. The 15-bus and 69-bus systems clearly improve grid performance after implementing all cases, while the 118-bus has a less significant improvement. This effect shows the influence of a scaled problem on the algorithm performance and the manifesting of the No Free Lunch Theorem even for the same problem of different scales. Furthermore, Figures 7.10 and 7.11 shows a convergence curve that depicts the behaviour of the proposed CoSGADE-I, particularly for the 118-bus system, where the optimizer converges differently for different cases. It is seen that introducing EVCS facilities influences the time complexity of the model, which results in the slow convergence of the CoSGADE-I. The slowness results from a frequent exploration and exploitation of the search space, which proves fruitful as it has a better power loss for its allocation variables.

Finally, the impact of evolutionary algorithms for discrete optimization is obvious in the location variables. Remembering that the adopted benchmark hybrid algorithms - WOAGA and PSOGA are implemented using the same approach as the CoSGADE, where each algorithm solves different variable types, it is seen that the optimal location variables produced by all adopted algorithms are very similar. The EVCS locations are the same for the 15-bus, 65-bus system, and varying a little for the 118-bus system. The same is observed for the location of other unit types, with only the PSO algorithm producing dissimilar solutions.

7.5 Summary

In this chapter, we investigated the impact of planning mechanisms on optimal allocation variables in smart grid planning frameworks. To this effect, we formulated a single and multiobjective planning problem, considering power loss, voltage stability, and voltage deviation. After that, an adaptive-dynamic planning mechanism, which is an underlay for the optimization process, is proposed to generate optimal solutions. The planning mechanism, formed using a recombination technique, showed an expanded solution space, validated using two-, three-, and four-unit type allocation schemes for both single and multiobjective optimization frameworks on 15-bus, 69-bus, and 118-bus distribution networks. The numerical simulations demonstrate a good variance in the distribution of optimal allocation variables but come with relatively higher time complexity when compared to conventional planning mechanisms. To address this challenge, two implementations of the proposed CoSGADE is developed, which reduce the time complexity (adopting computational time) and also improve grid performance.

The next chapter contains the conclusion of this thesis, and also discusses the recommendations for future work.

Chapter 8

Conclusions and Future Works

8.1 Conclusions

Traditional power system networks are faced with many timeous challenges. These challenges include unsustainable power generation, high carbon emission index, and costly power transmission. Hence, distributed energy resources and Flexible Alternating Current Transmission System units are integrated into distribution networks to tackle these challenges. Unfortunately, this task is difficult, given that renewable energy sources have a highly variable power output. It is, therefore, necessary to carefully allocate these distributed units into distribution networks. Hence, the need for a smart grid planning framework.

This research focused on improving hybrid optimization algorithms for smart grid planning. Unlike previous works, which only concentrate on better planning solutions and ignore the optimizer's efficiency, we hybridize metaheuristic algorithms using the decomposition level technique to designate each algorithm to a conforming problem. When benchmarked with other algorithms, the simulation results in Chapters 4 and 7 show a lower computational time and better convergence characteristics while yielding improved objective values such as power loss minimization, voltage stability, and voltage deviation reduction.

Electric vehicles are also a potential threat to the utility grid, even with their capability to mitigate carbon emissions and improve grid stability. Hence, previous studies have worked on the optimal placement of EV charging stations (EVCS) in distribution networks. However, these studies only consider the range anxiety of EVs or making EVCS a basic load without considering the random behaviour of EV drivers. This research models in Chapters 6 and 7, the stochasticity of EV charging in an EV charging station allocation scheme, generating a normal distribution of EV charging for an EV charging control strategy. Given the spatially varying nature of the planning framework, where locations of EV charging stations keep changing at every iteration, we introduced a reinforcement learning (RL) technique to solve optimum EVCS locations. This contribution makes it possible to consider an EV charging station allocation model using a more practical approach.

Generally, planning projects involve satisfying multiple benefits or objectives, mostly economical. In smart grid planning projects, we look for the improved grid performance of the upgraded distribution network, its economic viability, and its impact on global warming. Therefore, smart grid planning frameworks require a suitable multiobjective optimization (MOO) framework. There are, however, some challenges such as the difficulty in representing many objectives and the problem of elusive, uncontrollable bias when optimizing closely related objectives with other distinct ones.

Existing studies have overcome these challenges by adopting only a similar (collective) objective, for example, technical or economic objectives. Some studies adopted a maximum of three objectives from different collective objectives. However, while these studies achieve a suitable planning framework, they reduce the robustness of the planning framework. In some cases, they introduce bias to the planning solutions. We presented, in Chapter 4 a category-based MOO framework. The framework uses a multi-stage approach that optimizes similar objectives in a collective order. As a result, the MOO framework could optimize many objectives while maintaining minimal bias among dissimilar objectives. The framework can be adapted for other applications involving the optimization of multiple objectives.

Another form of MOO was developed for multiple decision-makers in an EV charging coordination model. The problem is the bias between two decision-makers — the technical personnel (i.e. a distribution network operator) and business-inclined personnel, an EV aggregator. The proposed approach uses a cooperative game to model the final utility value that represents the interest of both decision-makers. The results in Chapter 5 provide new insights on developing EV charging coordination models and can be replicated for multiple decision-makers.

Most planning frameworks involve a planning mechanism, which is an underlay for optimization schemes to produce planning solutions. However, existing planning mechanisms have only considered simultaneous allocation of all units or a multi-stage (or sequential) approach for allocation. These mechanisms cannot independently evaluate unit locations in relation to another. Hence, optimization algorithms can only choose from a limited number of planning solutions. Chapters 6 and 7 presented a dynamic planning mechanism that uses a recombination technique to sort different units' locations at every iteration. This technique is invaluable for producing an extensive solutions space. Furthermore, knowing that the model's complexity is increased, we adopted a convergence barometer that monitors the utility value at the sub-iteration level. This barometer enables the termination of the iteration process when the utility value shows an insignificant change, reducing the complexity.

8.2 Recommendations for Future Work

With the investigation of planning mechanisms and developing a dynamic planning mechanism, smart grid planning frameworks can produce improved planning solutions regardless of the optimization algorithm with substantial computational complexity. Further studies can investigate the dynamic mechanism and develop a less complex planning mechanism. In addition, future studies can carry out other works on the newly developed category-based multiobjective framework. Presently, the framework is limited to weight assignment in the first stage before non-dominating solutions are generated for the final stage. While uncontrollable bias is mitigated, it will be interesting to see if non-dominating solutions can be generated for all stages. This feat will further reduce the bias. Furthermore, the weights can be varied to evaluate the bias levels among objective functions. Another interesting idea for future works will be enhancing the reinforcement learning-based EV charging control strategy for EV charging station allocation. A charging price scheme can be included in the allocation model, thereby increasing its practicality.

Bibliography

[1] European Commission. "Regulation (EU) no 347/2013 of the European Parliament and of the Council of 17 April 2013 on guidelines for Trans-European Energy Infrastructure." Accessed on 15th June 2022, Apr 2019. URL http://data.europa.eu/eli/reg/2013/347/oj.

[2] H. A. Abdel-Ghany, A. M. Azmy, N. I. Elkalashy, and E. M. Rashad. "Optimizing DG penetration in distribution networks concerning protection schemes and technical impact." *Electric Power Systems Research*, vol. 128, pp. 113–122, 2015.

[3] H. Saboori, R. Hemmati, and M. A. Jirdehi. "Reliability improvement in radial electrical distribution network by optimal planning of energy storage systems." *Energy*, vol. 93, pp. 2299–2312, 2015.

[4] S. C. Johnson, D. J. Papageorgiou, M. R. Harper, J. D. Rhodes, K. Hanson, and M. E. Webber. "The economic and reliability impacts of grid-scale storage in a high penetration renewable energy system." *Advances in Applied Energy*, vol. 3, p. 100052, 2021.

[5] J. Marqusee, W. Becker, and S. Ericson. "Resilience and Economics of Microgrids with PV, Battery Storage, and Networked Diesel Generators." *Advances in Applied Energy*, p. 100049, 2021.

[6] S. Shao, M. Pipattanasomporn, and S. Rahman. "Grid integration of electric vehicles and demand response with customer choice." *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 543–550, 2012.

[7] X.-s. Yang. *Nature-Inspired Metaheuristic Algorithms*. Frome, UK: Luniver Press, 2010.

[8] H. Li, Q. Zhang, and J. Deng. "Biased multiobjective optimization and decomposition algorithm." *IEEE transactions on cybernetics*, vol. 47, no. 1, pp. 52–66, 2016.

[9] Y. Dujardin and I. Chadès. "Solving multi-objective optimization problems in conservation with the reference point method." *PloS one*, vol. 13, no. 1, p. e0190748, 2018.

[10] B. Jeddi, V. Vahidinasab, P. Ramezanpour, J. Aghaei, M. Shafie-khah, and J. P. Catalão. "Robust optimization framework for dynamic distributed energy resources planning in distribution networks." *International Journal of Electrical Power and Energy Systems*, vol. 110, pp. 419–433, 2019. URL https://doi.org/10.1016/j.ijepes.2019.03.026.

[11] S. Zeynali, N. Rostami, and M. R. Feyzi. "Multi-objective optimal short-term planning of renewable distributed generations and capacitor banks in power system considering different uncertainties

including plug-in electric vehicles." *International Journal of Electrical Power and Energy Systems*, vol. 119, no. January, p. 105885, 2020. URL https://doi.org/10.1016/j.ijepes.2020.105885.

[12] H. Lotfi, R. Ghazi, and M. bagher Naghibi-Sistani. "Multi-objective dynamic distribution feeder reconfiguration along with capacitor allocation using a new hybrid evolutionary algorithm." *Energy Systems*, vol. 11, pp. 779–809, 2019.

[13] M. H. Moradi and M. Abedini. "A novel method for optimal DG units capacity and location in Microgrids." *International Journal of Electrical Power and Energy Systems*, vol. 75, pp. 236–244, 2016. URL http://dx.doi.org/10.1016/j.ijepes.2015.09.013.

[14] N. K. Meena, S. Parashar, A. Swarnkar, N. Gupta, and K. R. Niazi. "Improved Elephant Herding Optimization for Multiobjective der Accommodation in Distribution Systems." *IEEE Transactions on Industrial Informatics*, vol. 14, no. 3, pp. 1029–1039, 2018.

[15] P. Singh, S. K. Bishnoi, and N. K. Meena. "Moth Search Optimization for Optimal DERs Integration in Conjunction to OLTC Tap Operations in Distribution Systems." *IEEE Systems Journal*, vol. 14, no. 1, pp. 880–888, 2020.

[16] NIST. "NIST Special Publication 1108R2 NIST Framework and Roadmap for Smart Grid Interoperability Standards , NIST Special Publication 1108R2 NIST Framework and Roadmap for Smart Grid Interoperability Standards." *Nist Special Publication*, pp. 1–90, 2012.

[17] J. Li, R. Xiong, Q. Yang, F. Liang, M. Zhang, and W. Yuan. "Design/test of a hybrid energy storage system for primary frequency control using a dynamic droop method in an isolated microgrid power system." *Applied Energy*, vol. 201, pp. 257–269, 2017. URL http://dx.doi.org/10.1016/j.apenergy.2016.10.066.

[18] P. S. Indu and M. V. Jayan. "Frequency regulation of an isolated hybrid power system with Superconducting Magnetic Energy Storage." *Proceedings of 2015 IEEE International Conference on Power, Instrumentation, Control and Computing, PICC 2015*, vol. 1, pp. 5–10, 2016.

[19] I. Patrao, E. Figueres, G. Garcerá, and R. González-Medina. "Microgrid architectures for low voltage distributed generation." *Renewable and Sustainable Energy Reviews*, vol. 43, pp. 415–424, 2015. URL http://dx.doi.org/10.1016/j.rser.2014.11.054.

[20] O. Palizban and K. Kauhaniemi. "Energy storage systems in modern grids—Matrix of technologies and applications." *Journal of Energy Storage*, vol. 6, pp. 248–259, 2016. URL http://dx.doi.org/10.1016/j.est.2016.02.001.

[21] K. Khalid Mehmood, S. U. Khan, S.-J. Lee, Z. M. Haider, M. K. Rafique, and C.-H. Kim. "Optimal sizing and allocation of battery energy storage systems with wind and solar power DGs in a distribution network for voltage regulation considering the lifespan of batteries." *IET Renewable Power Generation*, vol. 11, no. 10, pp. 1305–1315, 2017.

[22] M. Ramírez, R. Castellanos, G. Calderón, and O. Malik. "Placement and sizing of battery energy storage for primary frequency control in an isolated section of the Mexican power system." *Electric Power Systems Research*, vol. 160, pp. 142–150, 2018. URL https://doi.org/10.1016/j.epsr.2018.02.013.

[23] C. D. Rodríguez-Gallegos, D. Yang, O. Gandhi, M. Bieri, T. Reindl, and S. K. Panda. "A multi-objective and robust optimization approach for sizing and placement of PV and batteries in off-grid systems fully operated by diesel generators: An Indonesian case study." *Energy*, vol. 160, pp. 410–429, 2018.

[24] W. Dong, Y. Li, and J. Xiang. "Optimal sizing of a stand-alone hybrid power system based on battery/hydrogen with an improved ant colony optimization." *Energies*, vol. 9, no. 10, p. 785, 2016. URL https://doi.org/10.3390/en9100785.

[25] C. K. Das, O. Bass, G. Kothapalli, T. S. Mahmoud, and D. Habibi. "Optimal placement of distributed energy storage systems in distribution networks using artificial bee colony algorithm." *Applied Energy*, vol. 232, pp. 212–228, 2018. URL https://doi.org/10.1016/j.apenergy.2018.07.100.

[26] V. Jani and H. Abdi. "Optimal allocation of energy storage systems considering wind power uncertainty." *Journal of Energy Storage*, vol. 20, pp. 244–253, 2018. URL https://doi.org/10.1016/j.est.2018.09.017.

[27] P. Dehghanian, S. H. Hosseini, M. Moeini-Aghtaie, and A. Arabali. "Optimal siting of DG units in power systems from a probabilistic multi-objective optimization perspective." *International Journal of Electrical Power and Energy Systems*, vol. 51, pp. 14–26, 2013. URL http://dx.doi.org/10.1016/j.ijepes.2013.02.014.

[28] M. H. Moradi and M. Abedini. "A novel method for optimal DG units capacity and location in Microgrids." *International Journal of Electrical Power and Energy Systems*, vol. 75, pp. 236–244, 2016. URL http://dx.doi.org/10.1016/j.ijepes.2015.09.013.

[29] C. G. Boktor, A.-R. Youssef, A. H. Ali, and S. Kamel. "Optimal distribution power flow including shunt capacitor allocation based on voltage deviation and power loss minimization." In *2017 Nineteenth International Middle East Power Systems Conference (MEPCON)*, pp. 909–914. IEEE, 2017.

[30] M. Dixit, P. Kundu, and H. R. Jariwala. "Optimal placement of PV array in distribution system for power loss minimization considering feeder reconfiguration." *EEEIC 2016 - International Conference on Environment and Electrical Engineering*, pp. 1–6, 2016.

[31] K. Adetunji, O. Akinlabi, and M. Joseph. "Developing a Microgrid for Tafelkop using HOMER." In *2018 International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD)*, pp. 1–6. IEEE, 2018.

[32] V. Motjoadi, K. E. Adetunji, and M. K. Joseph. "Planning of a sustainable microgrid system using HOMER software." In *2020 Conference on Information Communications Technology and Society (ICTAS)*, pp. 1–5. IEEE, 2020.

[33] Y. Mohamed Shuaib, M. Surya Kalavathi, and C. Christober Asir Rajan. "Optimal capacitor placement in radial distribution system using Gravitational Search Algorithm." *International Journal of Electrical Power and Energy Systems*, vol. 64, pp. 384–397, 2015. URL http://dx.doi.org/10.1016/j.ijepes.2014.07.041.

[34] A. Y. Abdelaziz, E. S. Ali, and S. M. Abd Elazim. "Optimal sizing and locations of capacitors in radial distribution systems via flower pollination optimization algorithm and power loss index." *International Journal of Engineering Science and Technology*, vol. 19, no. 1, pp. 610–618, 2016. URL http://dx.doi.org/10.1016/j.jestch.2015.09.002.

[35] M. Montazeri and A. Askarzadeh. "Capacitor placement in radial distribution networks based on identification of high potential busses." *International Transactions on Electrical Energy Systems*, vol. 29, no. 3, pp. 1–15, 2019.

[36] E. S. Ali, S. M. Abd Elazim, and A. Y. Abdelaziz. "Improved Harmony Algorithm for optimal locations and sizing of capacitors in radial distribution systems." *International Journal of Electrical Power and Energy Systems*, vol. 79, pp. 275–284, 2016. URL http://dx.doi.org/10.1016/j.ijepes.2015.11.085.

[37] D. B. Prakash and C. Lakshminarayana. "Optimal siting of capacitors in radial distribution network using Whale Optimization Algorithm." *Alexandria Engineering Journal*, vol. 56, no. 4, pp. 499–509, 2017. URL https://doi.org/10.1016/j.aej.2016.10.002.

[38] G. Mendoza, V. Vacas, and N. Ferreira. "Optimal capacitor allocation and sizing in distribution networks using particle swarm optimization algorithm." In *2018 Workshop on Communication Networks and Power Systems (WCNPS)*, pp. 1–5. IEEE, 2018.

[39] J. Modarresi, E. Gholipour, and A. Khodabakhshian. "A comprehensive review of the voltage stability indices." *Renewable and Sustainable Energy Reviews*, vol. 63, pp. 1–12, 2016. URL http://dx.doi.org/10.1016/j.rser.2016.05.010.

[40] B. Pinnangudi, M. Kuykendal, and S. Bhadra. "Smart grid energy storage." In *The Power Grid*, pp. 93–135. Elsevier, 2017.

[41] C. K. Das, O. Bass, G. Kothapalli, T. S. Mahmoud, and D. Habibi. "Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality." *Renewable and Sustainable Energy Reviews*, vol. 91, pp. 1205–1230, 2018. URL https://doi.org/10.1016/j.rser.2018.03.068.

[42] A. Ahmadi, A. Tavakoli, P. Jamborsalamati, N. Rezaei, M. R. Miveh, F. H. Gandoman, A. Heidari, and A. E. Nezhad. "Power quality improvement in smart grids using electric vehicles: A review." *IET Electrical Systems in Transportation*, vol. 9, no. 2, pp. 53–64, 2019.

[43] K. Ginigeme and Z. Wang. "Distributed Optimal Vehicle-To-Grid Approaches with Consideration of Battery Degradation Cost under Real-Time Pricing." *IEEE Access*, vol. 8, pp. 5225–5235, 2020.

[44] K. Adetunji, I. Hofsajer, and L. Cheng. "A Coordinated Charging Model for Electric Vehicles in a Smart Grid using Whale Optimization Algorithm." In *2020 IEEE 23rd International Conference on Information Fusion (FUSION)*, pp. 1–7. IEEE, July 2020. URL 10.23919/FUSION45008.2020.9190284.

[45] Y. Zheng, S. Niu, Y. Shang, Z. Shao, and L. Jian. "Integrating plug-in electric vehicles into power grids: A comprehensive review on power interaction mode, scheduling methodology and mathematical foundation." *Renewable and Sustainable Energy Reviews*, vol. 112, no. June, pp. 424–439, 2019. URL https://doi.org/10.1016/j.rser.2019.05.059.

[46] M. Z. Zeb, K. Imran, A. Khattak, A. K. Janjua, A. Pal, M. Nadeem, J. Zhang, and S. Khan. "Optimal Placement of Electric Vehicle Charging Stations in the Active Distribution Network." *IEEE Access*, vol. 8, pp. 68124–68134, 2020.

[47] H. Parastvand, V. Moghaddam, O. Bass, M. A. Masoum, A. Chapman, and S. Lachowicz. "A graph automorphic approach for placement and sizing of charging stations in EV network considering traffic." *IEEE Transactions on Smart Grid*, vol. 11, no. 5, pp. 4190–4200, 2020.

[48] B. Zeng, H. Dong, F. Xu, and M. Zeng. "Bilevel Programming Approach for Optimal Planning Design of EV Charging Station." *IEEE Transactions on Industry Applications*, vol. 56, no. 3, pp. 2314–2323, 2020.

[49] Y. Zhang, Q. Zhang, A. Farnoosh, S. Chen, and Y. Li. "GIS-Based Multi-Objective Particle Swarm Optimization of charging stations for electric vehicles." *Energy*, vol. 169, pp. 844–853, 2019.

[50] A. Mohamed Imran, M. Kowsalya, and D. P. Kothari. "A novel integration technique for optimal network reconfiguration and distributed generation placement in power distribution networks." *International Journal of Electrical Power and Energy Systems*, vol. 63, pp. 461–472, 2014. URL http://dx.doi.org/10.1016/j.ijepes.2014.06.011.

[51] R. Sirjani and A. Rezaee Jordehi. "Optimal placement and sizing of distribution static compensator (D-STATCOM) in electric distribution networks: A review." *Renewable and Sustainable Energy Reviews*, vol. 77, pp. 688–694, 2017. URL http://dx.doi.org/10.1016/j.rser.2017.04.035.

[52] E. Grover-Silva, R. Girard, and G. Kariniotakis. "Optimal sizing and placement of distribution grid connected battery systems through an SOCP optimal power flow algorithm." *Applied Energy*, vol. 219, pp. 385–393, 2018. URL https://doi.org/10.1016/j.apenergy.2017.09.008.

[53] C. Ju, P. Wang, L. Goel, and Y. Xu. "A two-layer energy management system for microgrids with hybrid energy storage considering degradation costs." *IEEE Transactions on Smart Grid*, vol. 9, no. 6, pp. 6047–6057, 2018.

[54] N. K. Meena, S. Parashar, A. Swarnkar, N. Gupta, and K. R. Niazi. "Improved elephant herding optimization for multiobjective DER accommodation in distribution systems." *IEEE Transactions on Industrial Informatics*, vol. 14, no. 3, pp. 1029–1039, 2017.

[55] R. S. Sutton and A. G. Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

[56] M. Pipattanasomporn, H. Feroze, and S. Rahman. "Multi-agent systems in a distributed smart grid: Design and implementation." In *2009 IEEE/PES Power Systems Conference and Exposition*, pp. 1–8. IEEE, 2009.

[57] M. H. Shwehdi, S. R. Mohamed, and D. Devaraj. "Optimal capacitor placement on West–East inter-tie in Saudi Arabia using genetic algorithm." *Computers and Electrical Engineering*, vol. 68, pp. 156–169, 2018. URL https://doi.org/10.1016/j.compeleceng.2018.04.002.

[58] J. Singh and R. Tiwari. "Real power loss minimisation of smart grid with electric vehicles using distribution feeder reconfiguration." *IET Generation, Transmission and Distribution*, vol. 13, no. 18, pp. 4249–4261, 2019.

[59] S. Das and P. N. Suganthan. "Differential evolution: A survey of the state-of-the-art." *IEEE transactions on evolutionary computation*, vol. 15, no. 1, pp. 4–31, 2010.

[60] P. D. Huy, V. K. Ramachandaramurthy, J. Y. Yong, K. M. Tan, and J. B. Ekanayake. "Optimal placement, sizing and power factor of distributed generation: A comprehensive study spanning from the planning stage to the operation stage." *Energy*, vol. 195, p. 117011, 2020. URL https://doi.org/10.1016/j.energy.2020.117011.

[61] M. Moazzami, G. B. Gharehpetian, H. Shahinzadeh, and S. H. Hosseinian. "Optimal locating and sizing of DG and D-STATCOM using Modified Shuffled Frog Leaping Algorithm." In *Proceedings of the 2nd Conference on Swarm Intelligence and Evolutionary Computation, CSIEC 2017*, pp. 54–59. IEEE, 2017.

[62] A. Azizivahed, A. Arefi, S. Ghavidel, M. Shafie-Khah, L. Li, J. Zhang, and J. P. Catalao. "Energy management strategy in dynamic distribution network reconfiguration considering renewable energy resources and storage." *IEEE Transactions on Sustainable Energy*, vol. 11, no. 2, pp. 662–673, 2020.

[63] H. Karimi and R. Dashti. "Comprehensive framework for capacitor placement in distribution networks from the perspective of distribution system management in a restructured environment." *International Journal of Electrical Power and Energy Systems*, vol. 82, pp. 11–18, 2016. URL http://dx.doi.org/10.1016/j.ijepes.2016.02.025.

[64] H. HassanzadehFard and A. Jalilian. "Optimal sizing and siting of renewable energy resources in distribution systems considering time varying electrical/heating/cooling loads using PSO algorithm." *International Journal of Green Energy*, vol. 15, no. 2, pp. 113–128, 2018. URL https://doi.org/10.1080/15435075.2018.1423981.

[65] V. B. Pamshetti and S. Singh. "Coordinated allocation of BESS and SOP in high PV penetrated distribution network incorporating DR and CVR schemes." *IEEE Systems Journal*, 2020.

[66] C. K. Das, O. Bass, T. S. Mahmoud, G. Kothapalli, M. A. Masoum, and N. Mousavi. "An optimal allocation and sizing strategy of distributed energy storage systems to improve performance of distribution networks." *Journal of Energy Storage*, vol. 26, p. 100847, 2019. URL https://doi.org/10.1016/j.est.2019.100847.

[67] M. Mavrovouniotis, G. Ellinas, and M. Polycarpou. "Electric Vehicle Charging Scheduling Using Ant Colony System." *2019 IEEE Congress on Evolutionary Computation, CEC 2019 - Proceedings*, pp. 2581–2588, 2019.

[68] G. Loganathan, Z. W. Geem, and J. H. Kim. "A New Heuristic Optimization Algorithm: Harmony Search." *Simulation*, vol. 76, no. 2, pp. 60–68, 2001. URL http://sim.sagepub.com/cgi/doi/10.1177/003754970107600201.

[69] A. Askarzadeh. "Solving electrical power system problems by harmony search: a review." *Artificial Intelligence Review*, vol. 47, no. 2, pp. 217–251, 2017.

[70] C. Liu, S. S. Abdulkareem, A. Rezvani, S. Samad, N. Aljojo, L. K. Foong, and K. Nishihara. "Stochastic scheduling of a renewable-based microgrid in the presence of electric vehicles using modified harmony search algorithm with control policies." *Sustainable Cities and Society*, vol. 59, p. 102183, 2020. URL https://doi.org/10.1016/j.scs.2020.102183.

[71] R. Sirjani. "Optimal capacitor placement in wind farms by considering harmonics using discrete lightning search algorithm." *Sustainability*, vol. 9, no. 9, p. 1669, 2017.

[72] A. Rezaee Jordehi and J. Jasni. "Parameter selection in particle swarm optimisation: a survey." *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 25, no. 4, pp. 527–542, 2013.

[73] S. Kumar, K. K. Mandal, and N. Chakraborty. "Optimal DG placement by multi-objective opposition based chaotic differential evolution for techno-economic analysis." *Applied Soft Computing Journal*, vol. 78, pp. 70–83, 2019. URL https://doi.org/10.1016/j.asoc.2019.02.013.

[74] S. Saha and V. Mukherjee. "Optimal placement and sizing of DGs in RDS using chaos embedded SOS algorithm." *IET Generation, Transmission & Distribution*, vol. 10, no. 14, pp. 3671–3680, 2016.

[75] G. Celli, F. Pilo, G. Pisano, and G. G. Soma. "Distribution energy storage investment prioritization with a real coded multi-objective Genetic Algorithm." *Electric Power Systems Research*, vol. 163, pp. 154–163, 2018. URL https://doi.org/10.1016/j.epsr.2018.06.008.

[76] J. Vuletić and M. Todorovski. "Optimal capacitor placement in distorted distribution networks with different load models using Penalty Free Genetic Algorithm." *International Journal of Electrical Power and Energy Systems*, vol. 78, pp. 174–182, 2016.

[77] T. Huiling, W. Jiekang, W. Fan, C. Lingmin, L. Zhijun, and Y. Haoran. "An optimization framework for collaborative control of power loss and voltage in distribution systems with DGs and EVs using stochastic fuzzy chance constrained programming." *IEEE Access*, vol. 8, pp. 49013–49027, 2020.

[78] T. George, A.-R. Youssef, M. Ebeed, and S. Kamel. "Ant lion optimization technique for optimal capacitor placement based on total cost and power loss minimization." In *2018 International Conference on Innovative Trends in Computer Engineering (ITCE)*, pp. 350–356. IEEE, 2018.

[79] E. E. Elattar and S. K. ElSayed. "Modified JAYA algorithm for optimal power flow incorporating renewable energy sources considering the cost, emission, power loss and voltage profile improvement." *Energy*, vol. 178, pp. 598–609, 2019.

[80] M. Kumawat, N. Gupta, N. Jain, and R. C. Bansal. "Optimally allocation of distributed generators in three-phase unbalanced distribution network." *Energy Procedia*, vol. 142, pp. 749–754, 2017.

[81] L. A. Wong, V. K. Ramachandaramurthy, S. L. Walker, P. Taylor, and M. J. Sanjari. "Optimal placement and sizing of battery energy storage system for losses reduction using whale optimization algorithm." *Journal of Energy Storage*, vol. 26, no. July, p. 100892, 2019. URL https://doi.org/10.1016/j.est.2019.100892.

[82] S. Deb, K. Tammi, X.-Z. Gao, K. Kalita, and P. Mahanta. "A Hybrid Multi-Objective Chicken Swarm Optimization and Teaching Learning Based Algorithm for Charging Station Placement Problem." *IEEE Access*, vol. 8, pp. 92573–92590, 2020. URL https://ieeexplore.ieee.org/document/9091834/.

[83] T. Zhang, X. Xu, Z. Li, A. Abu-Siada, and Y. Guo. "Optimum Location and Parameter Setting of STATCOM Based on Improved Differential Evolution Harmony Search Algorithm." *IEEE Access*, vol. 8, pp. 87810–87819, 2020. URL https://ieeexplore.ieee.org/document/9088950/.

[84] B. Poornazaryan, P. Karimyan, G. B. Gharehpetian, and M. Abedi. "Optimal allocation and sizing of DG units considering voltage stability, losses and load variations." *International Journal of Electrical Power and Energy Systems*, vol. 79, pp. 42–52, 2016. URL http://dx.doi.org/10.1016/j.ijepes.2015.12.034.

[85] A. A. El-Ela, R. A. El-Sehiemy, and A. S. Abbas. "Optimal Placement and Sizing of Distributed Generation and Capacitor Banks in Distribution Systems Using Water Cycle Algorithm." *IEEE Systems Journal*, vol. 12, no. 4, pp. 3629–3636, 2018.

[86] B. Mukhopadhyay and D. Das. "Multi-objective dynamic and static reconfiguration with optimized allocation of PV-DG and battery energy storage system." *Renewable and Sustainable Energy Reviews*, vol. 124, p. 109777, 2020. URL https://doi.org/10.1016/j.rser.2020.109777.

[87] S. R. Gampa, K. Jasthi, P. Goli, D. Das, and R. C. Bansal. "Grasshopper optimization algorithm based two stage fuzzy multiobjective approach for optimum sizing and placement of distributed generations, shunt capacitors and electric vehicle charging stations." *Journal of Energy Storage*, vol. 27, pp. 101–117, 2020. URL https://doi.org/10.1016/j.est.2019.101117.

[88] A. M. Shaheen and R. A. El-Sehiemy. "Optimal Co-ordinated Allocation of Distributed Generation Units/ Capacitor Banks/ Voltage Regulators by EGWA." *IEEE Systems Journal*, vol. Early Access, no. 1, pp. 1–8, 2020. URL https://ieeexplore.ieee.org/document/9086471/.

[89] P. Gangwar, S. N. Singh, and S. Chakrabarti. "Multi-objective planning model for multiphase distribution system under uncertainty considering reconfiguration." *IET Renewable Power Generation*, vol. 13, no. 12, pp. 2070–2083, 2019.

[90] N. M. Pindoriya, S. N. Singh, and K. Y. Lee. "A comprehensive survey on multi-objective evolutionary optimization in power system applications." In *IEEE PES General Meeting*, pp. 1–8. IEEE, jul 2010. URL http://ieeexplore.ieee.org/document/5589511/.

[91] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. "A fast and elitist multiobjective genetic algorithm: NSGA-II." *IEEE transactions on evolutionary computation*, vol. 6, no. 2, pp. 182–197, 2002.

[92] P. P. Biswas, R. Mallipeddi, P. N. Suganthan, and G. A. Amaratunga. "A multiobjective approach for optimal placement and sizing of distributed generators and capacitors in distribution network." *Applied Soft Computing Journal*, vol. 60, pp. 268–280, 2017. URL https://doi.org/10.1016/j.asoc.2017.07.004.

[93] K. Deb. "Multi-objective optimization." In *Search methodologies*, pp. 403–449. Springer, 2014.

[94] J. Branke, J. Branke, K. Deb, K. Miettinen, and R. Slowiński. *Multiobjective optimization: Interactive and evolutionary approaches*, vol. 5252. Springer Science & Business Media, 2008.

[95] G. Battapothula, C. Yammani, and S. Maheswarapu. "Multi-objective simultaneous optimal planning of electrical vehicle fast charging stations and DGs in distribution system." *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 4, pp. 923–934, 2019. URL https://doi.org/10.1007/s40565-018-0493-2.

[96] M. B. Jannat and A. S. Savić. "Optimal capacitor placement in distribution networks regarding uncertainty in active power load and distributed generation units production." *IET Generation, Transmission & Distribution*, vol. 10, no. 12, pp. 3060–3067, 2016.

[97] C. Buchheim and J. Kurtz. "Min-max-min robustness: A new approach to combinatorial optimization under uncertainty based on multiple solutions." *Electronic Notes in Discrete Mathematics*, vol. 52, pp. 45–52, 2016. URL http://dx.doi.org/10.1016/j.endm.2016.03.007.

[98] H. Salmei and M. A. Yaghoobi. "Improving the min–max method for multiobjective programming." *Operations Research Letters*, vol. 48, no. 4, pp. 480–486, 2020. URL https://doi.org/10.1016/j.orl.2020.05.013.

[99] A. Selim, S. Kamel, A. S. Alghamdi, and F. Jurado. "Optimal Placement of DGs in Distribution System Using an Improved Harris Hawks Optimizer Based on Single- And Multi-Objective Approaches." *IEEE Access*, vol. 8, pp. 52815–52829, 2020.

[100] S. Sharma, K. R. Niazi, K. Verma, and T. Rawat. "Coordination of different DGs, BESS and demand response for multi-objective optimization of distribution network with special reference to Indian power sector." *International Journal of Electrical Power and Energy Systems*, vol. 121, p. 106074, 2020. URL https://doi.org/10.1016/j.ijepes.2020.106074.

[101] S. Nagaballi and V. S. Kale. "Pareto optimality and game theory approach for optimal deployment of DG in radial distribution system to improve techno-economic benefits." *Applied Soft Computing Journal*, vol. 92, p. 106234, 2020. URL https://doi.org/10.1016/j.asoc.2020.106234.

[102] H. Zhang, S. J. Moura, Z. Hu, and Y. Song. "PEV Fast-Charging Station Siting and Sizing on Coupled Transportation and Power Networks." *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 2595–2605, 2018.

[103] M. E. Hamidi and R. M. Chabanloo. "Optimal Allocation of Distributed Generation with Optimal Sizing of Fault Current Limiter to Reduce the Impact on Distribution Networks Using NSGA-II." *IEEE Systems Journal*, vol. 13, no. 2, pp. 1714–1724, 2019.

[104] S. Roy Ghatak, S. Sannigrahi, and P. Acharjee. "Multi-Objective Approach for Strategic Incorporation of Solar Energy Source, Battery Storage System, and DSTATCOM in a Smart Grid Environment." *IEEE Systems Journal*, vol. 2, pp. 1–12, 2018.

[105] M. T. Mouwafi, R. A. El-Sehiemy, and A. A. Abou El-Ela. "A two-stage method for optimal placement of distributed generation units and capacitors in distribution systems." *Applied Energy*, p. 118188, 2021.

[106] S. R. Biswal, G. Shankar, R. M. Elavarasan, and L. Mihet-Popa. "Optimal Allocation/Sizing of DGs/Capacitors in Reconfigured Radial Distribution System Using Quasi-Reflected Slime Mould Algorithm." *IEEE Access*, vol. 9, pp. 125658–125677, 2021.

[107] P. Singh, S. K. Bishnoi, and N. K. Meena. "Moth Search Optimization for Optimal DERs Integration in Conjunction to OLTC Tap Operations in Distribution Systems." *IEEE Systems Journal*, vol. 14, no. 1, pp. 880–888, 2020.

[108] V. Janamala and D. S. Reddy. "Coyote optimization algorithm for optimal allocation of interline–Photovoltaic battery storage system in islanded electrical distribution network considering EV load penetration." *Journal of Energy Storage*, vol. 41, p. 102981, 2021.

[109] A. A. Abou El-Ela, R. A. El-Seheimy, A. M. Shaheen, W. A. Wahbi, and M. T. Mouwafi. "PV and battery energy storage integration in distribution networks using equilibrium algorithm." *Journal of Energy Storage*, vol. 42, p. 103041, 2021.

[110] L. D. Pereira, I. Yahyaoui, R. Fiorotti, L. S. de Menezes, J. F. Fardin, H. R. Rocha, and F. Tadeo. "Optimal allocation of distributed generation and capacitor banks using probabilistic generation models with correlations." *Applied Energy*, vol. 307, p. 118097, 2022.

[111] S. Pirouzi, M. Zaghian, J. Aghaei, H. Chabok, M. Abbasi, M. Norouzi, M. Shafie-khah, and J. P. Catalão. "Hybrid planning of distributed generation and distribution automation to improve reliability and operation indices." *International Journal of Electrical Power & Energy Systems*, vol. 135, p. 107540, 2022.

[112] R. A. Thokar, N. Gupta, K. Niazi, A. Swarnkar, and N. K. Meena. "Multiobjective nested optimization framework for simultaneous integration of multiple photovoltaic and battery energy storage systems in distribution networks." *Journal of Energy Storage*, vol. 35, p. 102263, 2021.

[113] K. E. Adetunji, I. W. Hofsajer, A. M. Abu-Mahfouz, and L. Cheng. "Category-Based Multiobjective Approach for Optimal Integration of Distributed Generation and Energy Storage Systems in Distribution Networks." *IEEE Access*, vol. 9, pp. 28237–28250, 2021.

[114] S. A. Bozorgavari, J. Aghaei, S. Pirouzi, V. Vahidinasab, H. Farahmand, and M. Korpås. "Two-stage hybrid stochastic/robust optimal coordination of distributed battery storage planning and flexible energy management in smart distribution network." *Journal of Energy Storage*, vol. 26, p. 100970, 2019.

[115] O. Erdinc, A. Tascikaraoglu, N. G. Paterakis, I. Dursun, M. C. Sinim, and J. P. Catalao. "Comprehensive Optimization Model for Sizing and Siting of DG Units, EV Charging Stations, and Energy Storage Systems." *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3871–3882, 2018.

[116] M. Barukčić, T. Varga, V. Jerković Štil, and T. Benšić. "Co-simulation framework for optimal allocation and power management of dgs in power distribution networks based on computational intelligence techniques." *Electronics*, vol. 10, no. 14, p. 1648, 2021.

[117] H. Abdel-Mawgoud, S. Kamel, M. Khasanov, and T. Khurshaid. "A strategy for PV and BESS allocation considering uncertainty based on a modified Henry gas solubility optimizer." *Electric Power Systems Research*, vol. 191, p. 106886, 2021.

[118] T. Tušar and B. Filipič. "Differential Evolution versus Genetic Algorithms in Multiobjective Optimization." In *Evolutionary Multi-Criterion Optimization*, vol. 4403, pp. 257–271. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007. URL http://link.springer.com/10.1007/978-3-540-70928-2{_}22.

[119] A. Ehsan and Q. Yang. "Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques." *Applied Energy*, vol. 210, pp. 44–59, 2018. URL https://doi.org/10.1016/j.apenergy.2017.10.106.

[120] T. Ackermann, G. Andersson, and L. Söder. "Distributed generation: A definition." *Electric Power Systems Research*, vol. 57, no. 3, pp. 195–204, 2001.

[121] K. Balamurugan, D. Srinivasan, and T. Reindl. "Impact of distributed generation on power distribution systems." *Energy Procedia*, vol. 25, pp. 93–100, 2012. URL http://dx.doi.org/10.1016/j.egypro.2012.07.013.

[122] L. I. Dulău and M. Abrudean. "Economic Issues of Distributed Generation in Power Networks." In *Acta Electrotehnica*, May, pp. 18–21. 2015.

[123] E. Nabil. "A Modified Flower Pollination Algorithm for Global Optimization." *Expert Systems with Applications*, vol. 57, pp. 192–203, 2016.

[124] Y. Chen. "Problem Definitions and Evaluation Criteria for the CEC 2005 Special Session on Real-Parameter Optimization Problem Definitions and Evaluation Criteria for the CEC 2005 Special Session on Real-Parameter Optimization." *Natural Computing*, 2005. URL http://www.ntu.edu.sg/home/EPNSugan/index{_}files/CEC2013/CEC2013.htm.

[125] M. Karimi, M. R. Jannati Oskuee, M. J. Amroony Boushehry, and S. Najafi Ravadanegh. "Optimal planning of distributed generation with application of multi-objective algorithm including economic, environmental and technical issues with considering uncertainties." *International Journal of Ambient Energy*, vol. 38, no. 8, pp. 849–857, 2017. URL https://doi.org/10.1080/01430750.2016.1222955.

[126] K. E. Adetunji, I. W. Hofsajer, A. M. Abu-Mahfouz, and L. Cheng. "A Review of Metaheuristic Techniques for Optimal Integration of Electrical Units in Distribution Networks." *IEEE Access*, vol. 9, pp. 5046–5068, 2021.

[127] K. Li, K. Deb, Q. Zhang, and S. Kwong. "An evolutionary many-objective optimization algorithm based on dominance and decomposition." *IEEE Transactions on Evolutionary Computation*, vol. 19, no. 5, pp. 694–716, 2014.

[128] B. Li, J. Li, K. Tang, and X. Yao. "Many-objective evolutionary algorithms: A survey." *ACM Computing Surveys (CSUR)*, vol. 48, no. 1, pp. 1–35, 2015.

[129] C. K. Das, O. Bass, T. S. Mahmoud, G. Kothapalli, N. Mousavi, D. Habibi, and M. A. Masoum. "Optimal allocation of distributed energy storage systems to improve performance and power quality of distribution networks." *Applied Energy*, vol. 252, p. 113468, 2019. URL https://doi.org/10.1016/j.apenergy.2019.113468.

[130] J. Xiao, L. Bai, Z. Zhang, and H. Liang. "Determination of the optimal installation site and capacity of battery energy storage system in distribution network integrated with distributed generation." *IET Generation, Transmission & Distribution*, vol. 10, no. 3, pp. 601–607, 2015.

[131] H. Xiao, W. Pei, Z. Dong, and L. Kong. "Bi-level planning for integrated energy systems incorporating demand response and energy storage under uncertain environments using novel metamodel." *CSEE Journal of Power and Energy Systems*, vol. 4, no. 2, pp. 155–167, 2018.

[132] S. Sharma and S. Ghosh. "FIS and hybrid ABC-PSO based optimal capacitor placement and sizing for radial distribution networks." *Journal of Ambient Intelligence and Humanized Computing*, vol. 11, no. 2, pp. 901–916, 2020.

[133] N. L. Johnson, S. Kotz, and N. Balakrishnan. *Continuous univariate distributions, volume 2*, vol. 289. Hoboken, NJ: John wiley & sons, 1995.

[134] A. Zakaria, F. B. Ismail, M. S. Lipu, and M. A. Hannan. "Uncertainty models for stochastic optimization in renewable energy applications." *Renewable Energy*, vol. 145, pp. 1543–1571, 2020. URL https://doi.org/10.1016/j.renene.2019.07.081.

[135] T. Niknam, M. Zare, and J. Aghaei. "Scenario-based multiobjective volt/var control in distribution networks including renewable energy sources." *IEEE Transactions on Power Delivery*, vol. 27, no. 4, pp. 2004–2019, 2012.

[136] R. Al-Foraih, K. J. Sreekanth, and A. Al-Mulla. "A techno-economic analysis of the integration of energy storage technologies in electric power systems." *Journal of Renewable and Sustainable Energy*, vol. 10, no. 5, 2018.

[137] E. E. Elattar. "Modified harmony search algorithm for combined economic emission dispatch of microgrid incorporating renewable sources." *Energy*, vol. 159, pp. 496–507, sep 2018.

[138] H. Wu, X. Liu, and M. Ding. "Dynamic economic dispatch of a microgrid: Mathematical models and solution algorithm." *International Journal of Electrical Power and Energy Systems*, vol. 63, pp. 336–346, 2014.

[139] T. Shekari, S. Golshannavaz, and F. Aminifar. "Techno-Economic Collaboration of PEV Fleets in Energy Management of Microgrids." *IEEE Transactions on Power Systems*, vol. 32, no. 5, pp. 3833–3841, 2017.

[140] S. Kansal, V. Kumar, and B. Tyagi. "Optimal placement of different type of DG sources in distribution networks." *International Journal of Electrical Power and Energy Systems*, vol. 53, no. 1, pp. 752–760, 2013. URL http://dx.doi.org/10.1016/j.ijepes.2013.05.040.

[141] C. K. Das, O. Bass, G. Kothapalli, T. S. Mahmoud, and D. Habibi. "Optimal placement of distributed energy storage systems in distribution networks using artificial bee colony algorithm." *Applied Energy*, vol. 232, pp. 212–228, 2018. URL https://doi.org/10.1016/j.apenergy.2018.07.100.

[142] K. Kaur, N. Kumar, and M. Singh. "Coordinated Power Control of Electric Vehicles for Grid Frequency Support: MILP-Based Hierarchical Control Design." *IEEE Transactions on Smart Grid*, 2019.

[143] S. Mirjalili and A. Lewis. "The Whale Optimization Algorithm." *Advances in Engineering Software*, vol. 95, pp. 51–67, 2016. URL http://www.alimirjalili.com/WOA.html.

[144] K. Rani and V. Kumar. "Solving travelling salesman problem using genetic algorithm based on heuristic crossover and mutation operator." *International Journal of Research in Engineering & Technology*, vol. 2, no. 2, pp. 27–34, 2014.

[145] S. Das and P. N. Suganthan. "Differential evolution: A survey of the state-of-the-art." *IEEE Transactions on Evolutionary Computation*, vol. 15, no. 1, pp. 4–31, 2011.

[146] K. Deep and M. Thakur. "A new mutation operator for real coded genetic algorithms." *Applied mathematics and Computation*, vol. 193, no. 1, pp. 211–230, 2007.

[147] IEA. "Global EV Outlook 2018: Towards cross-modal electrification." Tech. rep., IEA, Paris, 2018.

[148] H. Nguyen, C. Zhang, and M. A. Mahmud. *Smart charging and discharging of electric vehicles to support grid with high penetration of renewable energy*, vol. 19. IFAC, 2014. URL http://dx.doi.org/10.3182/20140824-6-ZA-1003.02109.

[149] U. Datta, A. Kalam, J. Shi, and J. Li. "Electric vehicle charging station for providing primary frequency control in microgrid." In *Proceedings of the 14th IEEE Conference on Industrial Electronics and Applications, ICIEA 2019*, pp. 2440–2444. Institute of Electrical and Electronics Engineers Inc., jun 2019.

[150] H. H. Alhelou and M. E. Golshan. "Hierarchical plug-in EV control based on primary frequency response in interconnected smart grid." In *2016 24th Iranian Conference on Electrical Engineering, ICEE 2016*, pp. 561–566. 2016.

[151] H. Xing, M. Fu, Z. Lin, and Y. Mou. "Decentralized optimal scheduling for charging and discharging of plug-in electric vehicles in smart grids." *IEEE Transactions on Power Systems*, vol. 31, no. 5, pp. 4118–4127, 2016. URL http://www.ieee.org/publications{_}standards/publications/rights/index.html.

[152] M. Zhu, X. Y. Liu, L. Kong, R. Shen, W. Shu, and M. Y. Wu. "The charging-scheduling problem for electric vehicle networks." *IEEE Wireless Communications and Networking Conference, WCNC*, pp. 3178–3183, 2014.

[153] J. Tong, T. Zhao, X. Yang, and J. Zhang. "Intelligent charging strategy for PHEVs in a parking station based on Multi-objective optimization in smart grid." *IEEE Transportation Electrification Conference and Expo, ITEC Asia-Pacific 2014 - Conference Proceedings*, pp. 1–6, 2014.

[154] J. Singh and R. Tiwari. "Multi-Objective Optimal Scheduling of Electric Vehicles in Distribution System." *2018 20th National Power Systems Conference, NPSC 2018*, 2018.

[155] W. Jiang and Y. Zhen. "A Real-Time EV Charging Scheduling for Parking Lots with PV System and Energy Store System." *IEEE Access*, vol. 7, pp. 86184–86193, 2019.

[156] R. Mehta, P. Verma, D. Srinivasan, and J. Yang. "Double-layered intelligent energy management for optimal integration of plug-in electric vehicles into distribution systems." *Applied Energy*, vol. 233-234, no. April 2018, pp. 146–155, 2019. URL https://doi.org/10.1016/j.apenergy.2018.10.008.

[157] J. G. Alvarez, M. Á. González, C. R. Vela, and R. Varela. "Electric Vehicle Charging Scheduling by an Enhanced Artificial Bee Colony Algorithm." *Energies*, vol. 11, no. 10, pp. 1–19, 2018.

[158] A. S. Al-Ogaili, T. J. Tengku Hashim, N. A. Rahmat, A. K. Ramasamy, M. B. Marsadek, M. Faisal, and M. A. Hannan. "Review on scheduling, clustering, and forecasting strategies for controlling electric vehicle charging: Challenges and recommendations." *IEEE Access*, vol. 7, pp. 128353–128371, 2019.

[159] J. Zhong, L. He, C. Li, Y. Cao, J. Wang, B. Fang, L. Zeng, and G. Xiao. "Coordinated control for large-scale EV charging facilities and energy storage devices participating in frequency regulation." *Applied Energy*, vol. 123, pp. 253–262, jun 2014.

[160] R. T. Marler and J. S. Arora. "Survey of multi-objective optimization methods for engineering." *Structural and Multidisciplinary Optimization*, vol. 26, no. 6, pp. 369–395, 2004.

[161] M. H. Amini, B. Nabi, and M. R. Haghifam. "Load management using multi-agent systems in smart distribution network." *IEEE Power and Energy Society General Meeting*, pp. 1–5, 2013.

[162] M. E. Baran and F. F. Wu. "Optimal capacitor placement on radial distribution systems." *IEEE Transactions on Power Delivery*, 1989.

[163] G. Evans, R. Vailati, K. Brekke, W. Friedl, H. Schotman, M. Steiner, M. Bollen, T. Kapetanovic, and F. Villa. "European energy regulators' views on regulation smart distribution networks." In *International Conference on Electricity Distribution: 06/06/2011-09/06/2011*, pp. 1–4. 2011.

[164] R. Jing, X. Wang, Y. Zhao, Y. Zhou, J. Wu, and J. Lin. "Planning urban energy systems adapting to extreme weather." *Advances in Applied Energy*, vol. 3, p. 100053, 2021.

[165] O. Van Vliet, A. S. Brouwer, T. Kuramochi, M. van Den Broek, and A. Faaij. "Energy use, cost and CO2 emissions of electric cars." *Journal of power sources*, vol. 196, no. 4, pp. 2298–2310, 2011.

[166] W. Ma, W. Wang, Z. Chen, X. Wu, R. Hu, F. Tang, and W. Zhang. "Voltage regulation methods for active distribution networks considering the reactive power optimization of substations." *Applied Energy*, vol. 284, p. 116347, 2021.

[167] P. W. Griffin, G. P. Hammond, and R. C. McKenna. "Industrial Energy Use and Decarbonisation in the Glass Sector: A UK Perspective." *Advances in Applied Energy*, p. 100037, 2021.

[168] Renault. "Renault ZOE Specifications." https://www.renault.ie/vehicles/new-vehicles/zoe/battery-andcharging.html, 2019. Accessed: 2020-10-30.

[169] Tesla. "Tesla Super Charger Specifications." https://www.tesla.com/supercharger, 2019. Accessed: 2020-10-30.

[170] A. Ali, D. Raisz, and K. Mahmoud. "Optimal oversizing of utility-owned renewable DG inverter for voltage rise prevention in MV distribution systems." *International Journal of Electrical Power & Energy Systems*, vol. 105, pp. 500–513, 2019.

[171] A. Ali, K. Mahmoud, D. Raisz, and M. Lehtonen. "Probabilistic approach for hosting high PV penetration in distribution systems via optimal oversized inverter with watt-var functions." *IEEE Systems Journal*, vol. 15, no. 1, pp. 684–693, 2020.

[172] X. Zhang, Z. Wang, and Z. Lu. "Multi-objective load dispatch for microgrid with electric vehicles using modified gravitational search and particle swarm optimization algorithm." *Applied Energy*, vol. 306, p. 118018, 2022.

[173] A. Singh and A. Khamparia. "A hybrid whale optimization-differential evolution and genetic algorithm based approach to solve unit commitment scheduling problem: WODEGA." *Sustainable computing: informatics and systems*, vol. 28, p. 100442, 2020.

[174] W. He, M. King, X. Luo, M. Dooner, D. Li, and J. Wang. "Technologies and Economics of Electric Energy Storages in Power Systems: Review and Perspective." *Advances in Applied Energy*, p. 100060, 2021.

[175] P. Singh, N. K. Meena, J. Yang, E. Vega-Fuentes, and S. K. Bishnoi. "Multi-criteria decision making monarch butterfly optimization for optimal distributed energy resources mix in distribution networks." *Applied Energy*, vol. 278, p. 115723, 2020.

[176] S. Zhong, J. Qiu, L. Sun, Y. Liu, C. Zhang, and G. Wang. "Coordinated planning of distributed WT, shared BESS and individual VESS using a two-stage approach." *International Journal of Electrical Power and Energy Systems*, vol. 114, no. October 2018, p. 105380, 2020. URL `https://doi.org/10.1016/j.ijepes.2019.105380`.

[177] K. E. Adetunji, I. Hofsajer, A. M. Abu-Mahfouz, and L. Cheng. "Miscellaneous Energy Profile Management Scheme for Optimal Integration of Electric Vehicles in a Distribution Network Considering Renewable Energy Sources." In *2021 Southern African Universities Power Engineering Conference/Robotics and Mechatronics/Pattern Recognition Association of South Africa (SAUPEC/RobMech/PRASA)*, pp. 1–6. 2021.

[178] S. Wang, S. Bi, and Y. A. Zhang. "Reinforcement learning for real-time pricing and scheduling control in EV charging stations." *IEEE Transactions on Industrial Informatics*, vol. 17, no. 2, pp. 849–859, 2019.

[179] T. Qian, C. Shao, X. Wang, and M. Shahidehpour. "Deep reinforcement learning for EV charging navigation by coordinating smart grid and intelligent transportation system." *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1714–1723, 2019.

[180] Z. Yuan, W. Wang, H. Wang, and A. Yildizbasi. "A new methodology for optimal location and sizing of battery energy storage system in distribution networks for loss reduction." *Journal of Energy Storage*, vol. 29, p. 101368, 2020.

[181] M. T. Mouwafi, R. A. El-Sehiemy, and A. A. Abou El-Ela. "A two-stage method for optimal placement of distributed generation units and capacitors in distribution systems." *Applied Energy*, vol. 307, p. 118188, 2022.

[182] P. D. P. Reddy, V. C. V. Reddy, and T. G. Manohar. "Whale optimization algorithm for optimal sizing of renewable resources for loss reduction in distribution systems." *Renewables: Wind, Water, and Solar*, vol. 4, no. 1, pp. 1–13, 2017.

[183] A. Uniyal and S. Sarangi. "Optimal network reconfiguration and DG allocation using adaptive modified whale optimization algorithm considering probabilistic load flow." *Electric Power Systems Research*, vol. 192, p. 106909, 2021.

[184] S. K. Injeti and N. P. Kumar. "A novel approach to identify optimal access point and capacity of multiple DGs in a small, medium and large scale radial distribution systems." *International Journal of Electrical Power & Energy Systems*, vol. 45, no. 1, pp. 142–151, 2013.

[185] M. M. Salama and A. Y. Chikhani. "A simplified network approach to the var control problem for radial distribution systems." *IEEE Transactions on Power Delivery*, vol. 8, no. 3, pp. 1529–1535, 1993.

[186] Y. Yang, H. Li, A. Aichhorn, J. Zheng, and M. Greenleaf. "Sizing strategy of distributed battery storage system with high penetration of photovoltaic for voltage regulation and peak load shaving." *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 982–991, 2014.

[187] A. S. Awad, T. H. El-Fouly, and M. M. Salama. "Optimal ESS allocation for load management application." *IEEE Transactions on Power Systems*, vol. 30, no. 1, pp. 327–336, 2015.

[188] F. C. Schweppe and J. Wildes. "Power System Static-State Estimation, Part I: Exact Model." *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-89, no. 1, pp. 120–125, 1970.

[189] P. Paliwal, N. P. Patidar, and R. K. Nema. "Planning of grid integrated distributed generators: A review of technology, objectives and techniques." *Renewable and Sustainable Energy Reviews*, vol. 40, pp. 557–570, 2014. URL http://dx.doi.org/10.1016/j.rser.2014.07.200.

[190] M. Uddin, M. F. Romlie, M. F. Abdullah, S. Abd Halim, A. H. Abu Bakar, and T. Chia Kwang. "A review on peak load shaving strategies." *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 3323–3332, 2018. URL https://doi.org/10.1016/j.rser.2017.10.056.

[191] P. B. Miltersen, S. Subramanian, J. S. Vitter, and R. Tamassia. "Complexity models for incremental computation." *Theoretical Computer Science*, vol. 130, no. 1, pp. 203–236, 1994.

[192] W. K. Dawson, K. Fujiwara, and G. Kawai. "Prediction of RNA pseudoknots using heuristic modeling with mapping and sequential folding." *PloS one*, vol. 2, no. 9, p. e905, 2007.

[193] S. M. Islam, S. Das, S. Ghosh, S. Roy, and P. N. Suganthan. "An adaptive differential evolution algorithm with novel mutation and crossover strategies for global numerical optimization." *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 42, no. 2, pp. 482–500, 2012.