TÜRKİYE CUMHURİYETİ
ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL
ELECTRICAL AND ELECTRONIC ENGINEERING DEPARTMENT

LOCATING CHARGING STATIONS FOR ELECTRIC BUSES

CELAL CAN

Ph.D.

ADANA 2025

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ADANA, 2025

DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences if a situation is found contrary to my statement regarding my work.

17/07/2025

Celal CAN

ABSTRACT

LOCATING CHARGING STATIONS FOR ELECTRIC BUSES

Celal CAN
Ph.D., Department of Electrical and Electronic Engineering

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Co-Supervisor: Assoc. Prof. Dr. Yasin KAYA
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Electric buses are a crucial component of public transportation systems, as they have the potential to reduce greenhouse gas emissions, as well as air and noise pollution. This thesis presents a novel optimization-based spatial planning framework for the deployment of fast-charging stations, designed explicitly for e-bus networks. The primary objective of the proposed model is to determine the most suitable location for charging stations by minimizing the total system cost, which encompasses installation costs, operation and maintenance costs, transportation costs between e-bus routes and charging stations, and infrastructure costs associated with energy distribution lines. To solve the complex optimization problem, this study proposes a binary version of the Walrus Optimization Algorithm (BWAOA), a recently developed nature-inspired metaheuristic technique. The performance of BWAOA is benchmarked against three metaheuristic algorithms, the Arithmetic Optimization Algorithm, the Grey Wolf Optimization, and the Whale Optimization Algorithm, to verify its efficiency and robustness. The proposed model is applied to two real-world case studies based on datasets from Adana, Turkey, which include both public transportation network data and electric power infrastructure data. Experimental results reveal that the BWAOA-based model achieves superior performance in terms of cost minimization, solution stability, and convergence behavior. Additionally, the spatial distribution of selected charging station locations demonstrates improved accessibility for the e-bus network.

Keywords: charging station, e-bus, facility location, metaheuristic algorithms

ÖZET

ELEKTRİKLİ OTOBÜSLER İÇİN ŞARJ İSTASYONLARI KONUMU BELİRLENMESİ

Celal CAN
Doktora, Elektrik-Elektronik Mühendisliği Anabilim Dalı
Danışman: Doç. Dr. Fatih KILIÇ
II. Danışman: Doç. Dr. Yasin KAYA
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Elektrikli otobüsler, sera gazı emisyonlarının yanı sıra hava ve gürültü kirliliğini azaltma potansiyeline sahip oldukları için toplu taşıma sistemlerinin önemli bir bileşenidir. Bu tez, özellikle elektrikli otobüs ağları için tasarlanmış hızlı şarj istasyonlarının dağıtımı için yeni bir optimizasyon tabanlı mekansal planlama çerçevesi sunmaktadır. Önerilen modelin temel amacı, kurulum maliyetleri, işletme ve bakım maliyetleri, e-otobüs güzergahları ile şarj istasyonları arasındaki ulaşım maliyetleri ve enerji dağıtım hatlarıyla ilişkili altyapı maliyetlerini kapsayan toplam sistem maliyetini en aza indirerek şarj istasyonları için en uygun yeri belirlemektir. Karmaşık optimizasyon problemini çözmek için bu çalışma, yakın zamanda geliştirilen doğadan ilham alan bir metasezgisel teknik olan Walrus Optimizasyon Algoritması'nın (BWAOA) ikili bir versiyonunu önermektedir. BWAOA'nın performansı, verimliliğini ve sağlamlığını doğrulamak için Aritmetik Optimizasyon Algoritması, Gri Kurt Optimizasyonu ve Balina Optimizasyon Algoritması olmak üzere üç metasezgisel algoritmaya göre kıyaslanmaktadır. Önerilen model, hem toplu taşıma ağı verilerini hem de elektrik enerjisi altyapısı verilerini içeren Adana, Türkiye'den veri kümelerine dayalı iki gerçek dünya vaka çalışmasına uygulanır. Deneysel sonuçlar, BWAOA tabanlı modelin maliyet minimizasyonu, çözüm kararlılığı ve yakınsama davranışı açısından üstün performans elde ettiğini ortaya koymaktadır. Ek olarak, seçilen şarj istasyonu konumlarının mekansal dağılımı, e-otobüs ağı için iyileştirilmiş erişilebilirliği göstermektedir.

Anahtar Kelimeler: şarj istasyonu, e-otobüs, tesis lokasyonu, metasezgisel algoritmalar

Dedication

to My Deceased Mother

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LIST OF ABBREVIATIONS

EV	: Electric Vehicle
EB	: Electric Bus
CS	: Charging Station
FCS	: Fast Charging Station
FLP	: Facility Location Problem
BAOA	: Binary Arithmetic Optimization Algorithm
BGWO	: Binary Grey Wolf Optimizer
BWaOA	: Binary Walrus Optimization Algorithm
BWOA	: Binary Whale Optimization Algorithm
SOC	: State of Charge
SOC_{min}	: Minimum SOC value of the e-bus battery
SOC_{max}	: Maximum SOC value of the e-bus battery

LIST OF SYMBOLS

λ	: The damping factor
P	: Charging power of the charging facilities
C_{bat}	: Battery capacity of electric bus
u	: Energy consumption of electric buses per kilometer
α	: Fluctuation coefficient of charging demand
k_s	: Operation of simultaneous charging facility rate
k_{eff}	: Charging efficiency of the charging station
TR_j	: the operation time for route j
TS_j	: the spacing interval for route j
$L_{i,j}$	: Length of route j operated by the i^{th} terminus
η_b	: Assumed scaling factor
g_t	: Electricity price for charging
N	: Number of distribution grid nodes
μ	: Redundancy in the charging capacity of the fast-charging station
r_0	: Discount rate
γ	: Length of route j operated by the i^{th} terminus
p_1	: Unit price of the charging facility
p_2	: Unit price of the transformer
ω_c	: Construction expense of charging station c
α_{cn}	: Equipment and installation expense of power line per kilometer

1. INTRODUCTION

Rapid urbanization, the growing urgency to combat climate change, the need to reduce greenhouse gas emissions, and increasingly alarming environmental issues have encouraged governments and local municipalities worldwide to pursue cleaner, greener, and more sustainable transportation systems. Among the many sustainable mobility solutions, public transportation, which significantly contributes to reducing global gas emissions and energy consumption, has become a primary focus of decarbonization efforts (Wang et al., 2024). The adoption of electric buses (EBs), particularly in bus fleets, presents promising solutions for various improvements, including reducing dependence on fossil fuels, lowering greenhouse gas emissions, and enhancing energy efficiency in densely populated cities (Orji, 2024). However, the transition from traditional diesel-powered buses to EBs poses several challenges that require careful planning, strategic investment, and infrastructure redesign (Y. Zhou et al., 2023).

One of the most significant obstacles to the widespread adoption of EBs is the development of a practical and durable charging infrastructure, as well as the associated high costs. Unlike the fueling processes of conventional vehicles, the longer charging times of electric cars require processes such as careful energy load balancing and intelligent integration with existing power distribution systems (Sarda et al., 2024). A poorly designed charging station network can lead to route inefficiencies, range anxiety, energy losses, grid instability, and, consequently, service interruptions. Therefore, determining the most suitable locations for electrical bus (EB) charging stations (CSs) has become a significant research problem in the field of smart urban mobility and sustainable energy systems (Deniz & Aydin, 2024).

In traditional transportation planning, the facility location problem (FLP) has been widely used to optimize the placement of key infrastructure elements, such as depots, service stations, and terminals (Saldanha-da-Gama, 2022). However, traditional models often simplify the problem by focusing solely on travel distance, neglecting critical factors such as energy demand and grid accessibility. In the case of EBs, these simplifications are inadequate because each charging point must be supported by a reliable and sufficiently powerful electricity network. Otherwise, significant technical and economic inefficiencies may arise (Shariatzadeh et al., 2025).

Integrating the electrical distribution system into the planning of CSs adds extra costs and complexity to the issue (Unterluggauer et al., 2022). Electrical grids in urban areas are typically designed and calculated based on static demand models for cities. Therefore, the grids must be structured to accommodate the instantaneous high power needs of fast charging stations (FCSs) (Acharige et al., 2025). For a single bus, each charge requires power levels exceeding several hundred kilowatts, particularly in depot charging or opportunity charging configurations. Hence, it is crucial to assess the feasibility of each potential charging station in terms of its connection to a nearby substation, the available spare capacity at that substation, and the possible impacts on grid stability and load balancing (Rogge et al., 2015). Given the complexity of electricity grid constraints and the large-scale scope of the planning problem, the use of advanced meta-heuristic methods becomes essential for designing a feasible and effective charging infrastructure.

Metaheuristic algorithms offer a powerful alternative to exact methods, particularly for addressing large-scale, nonlinear, and combinatorial optimization problems, as discussed in this study. Unlike classical linear programming techniques, metaheuristic algorithms can navigate highly complex solution spaces and often produce near-optimal solutions in a reasonable computational time (Baghel et al., 2012; Yang, 2013). In this thesis, the Binary version of the Walrus Optimization Algorithm (BWaOA), the Arithmetic Optimization Algorithm (BAOA), Grey Wolf Optimizer (BGWO), and Whale Optimization Algorithm (BWOA) have been adapted and employed to solve the proposed location model.

Each algorithm has distinct characteristics related to exploration and exploitation phases, convergence behavior, and sensitivity to parameters. Adapting these algorithms to a constrained binary search space required the development of specialized coding strategies and constraint-handling mechanisms. To achieve this, a repair algorithm was developed and customized for each algorithm. Additionally, a detailed comparative analysis was performed between two datasets, DS1 and DS2, which represent different urban configurations and demand scenarios.

The datasets include substation locations, route information, bus details, and terminal locations, providing a robust testbed for evaluating algorithm performance.

1.1. Motivation

Today, with increasing environmental concerns and the need for energy efficiency, ensuring sustainability in urban transportation makes the role of electric buses in public transit increasingly crucial. However, the success of the sustainability depends not only on vehicle technologies but also on the proper and efficient planning of the infrastructure. The suitable location of fast charging stations is crucial for both transportation continuity and the stability of the electricity grid. In this context, this dissertation has been motivated by the motivation to investigate how a cost-effective, environmentally friendly, and grid-compatible charging infrastructure can be planned for electric buses. This optimization-focused approach, supported by real datasets, aims to contribute to the academic literature and serve as a guide for local governments and urban planners.

1.2. Purpose and scope of the dissertation

This dissertation aims to address the issue by proposing a comprehensive methodology to identify the most suitable locations for EB charging stations while considering both transportation network characteristics and the power distribution system. The proposed method features a specially designed fitness function that evaluates the suitability of potential charging station locations based on multiple criteria. The fitness function is formulated as a multi-objective expression and is optimized using advanced metaheuristic algorithms tailored to the binary and constrained aspects of the problem. It aims to minimize total operational costs, maintenance costs, installation costs, transportation costs to the charging station, and energy distribution line costs. Furthermore, the methodology allows urban planners to simulate various future scenarios and make data-driven investment decisions regarding the quantity, location, and prioritization of stations.

Several key assumptions and constraints define the scope of the study. It assumes fixed bus routes, route lengths, the number of buses, predefined potential charging stations (typically located at the start and end terminal of routes), and specific energy demand profiles for each bus. It also presumes that the grid topology is included in the planning model and remains static. Although the model does not directly consider real-time charging dynamics or renewable energy integration, it offers a foundational framework that can be expanded to incorporate such complexities in future studies. The datasets developed for the thesis were utilized to benchmark alternative methods or test hybrid optimization approaches.

1.3. Contribution

Innovations of this work include developing a new fitness function that unifies transportation network and energy distribution system parameters within an optimization framework. Unlike previous studies that focus on passenger demand or grid load separately, this research proposes a comprehensive evaluation metric that considers multiple dimensions simultaneously. The fitness function is designed to be modular, allowing for the inclusion of additional criteria such as land availability, charging rate, and environmental impact in future studies.

Another significant contribution is the systematic benchmarking of different metaheuristic algorithms under controlled experimental conditions. The performance of each algorithm is evaluated based on standard metrics, including the best fitness value, average solution, standard deviation, convergence speed, and execution time. The results from the experiments are valuable not only for infrastructure planners but also for advancing the broader field of computational intelligence and optimization. The results provide evidence of the suitability of different nature-inspired algorithms for addressing high-dimensional, real-world location problems with complex constraints. Thus, the model can be applied in other areas, such as logistics, telecommunications, and energy system planning, where similar optimization issues are also present.

Additionally, the study guides the design of infrastructure investment strategies that align with both transportation needs and energy system constraints. Municipalities can improve the return on public spending by identifying optimal locations that minimize investment costs while maximizing coverage and reliability. The model also supports long-term strategic planning by allowing for scenario-based simulations and sensitivity analysis.

1.4. Dissertation Outlines

The dissertation is organized as follows. Chapter 2 presents a comprehensive review of the relevant literature on electric bus infrastructure, grid-aware planning, and metaheuristic optimization techniques. Chapter 3 defines the problem in detail, introduces the assumptions, and formulates the mathematical model, including the proposed fitness function, repair function, and associated constraints. The chapter also describes the metaheuristic algorithms used in this study and explains how they were adapted for binary and constrained optimization. At the end of the chapter, it outlines the structure and characteristics of the datasets developed for experimental analysis. Chapter 4 presents the experimental results, including algorithm performance comparisons, convergence analyses, and fitness evaluations. The findings from each dataset are analyzed to identify strengths among the algorithms. The chapter also discusses the scientific contributions and practical implications of the study, especially in the context of smart city planning and sustainable energy systems. Finally, Chapter 5 concludes the dissertation with a summary of key findings, limitations, and recommendations for future research.

2. LITERATURE REVIEW

The global transition to electric vehicles has led to an increasing interest in research on infrastructure planning of charging systems. Among all types of EVs, e-buses have been receiving increasing attention due to their positive impact on reducing carbon emissions in public transportation. This literature review presents studies on charging technology, the use of metaheuristic algorithms in sustainable transportation systems, charging infrastructure planning, electric power system integration, and facility layout problems related to the dissertation.

Electric buses are increasingly recognized for their environmental, economic, and operational advantages in urban transportation systems. From an ecological perspective, electric buses produce zero gas emissions, which contributes significantly to improving air quality in densely populated cities. Economically, although the initial investment is higher compared to diesel buses, lower energy and maintenance costs make electric buses more cost-effective in the long term (Ramingwong et al., 2025). Additionally, electric buses offer smoother acceleration, quieter operation, and improved energy efficiency, thereby enhancing passenger comfort and reducing urban noise pollution.

The global shift from fossil-fueled vehicles to electric alternatives has gained remarkable momentum over the last decade. In 2023, approximately 50,000 electric buses were sold worldwide, bringing the total number of electric buses in stock to 635,000. While electric bus sales are ahead of other heavy vehicle segments, this increase is particularly concentrated in urban buses. In some countries, such as Belgium, Norway, Switzerland, and China, the share of electric bus sales exceeds 50%. In contrast, in the European Union, the share of battery electric vehicle (BEV) sales in urban buses has reached 43% (Global EV Outlook, 2024). This widespread shift reflects the need for sustainable and low-emission transportation options.

One of the most critical obstacles to the widespread adoption of electric buses is the lack of adequately planned charging infrastructure. Improperly located charging stations cause service interruptions, extended vehicle downtime, and inefficient fleet utilization (Liang et al., 2022). The absence of a well-structured charging infrastructure leads to operational inefficiencies that increase costs and complicate fleet management. Additionally, charging delays can reduce vehicle availability and disrupt service reliability, leading to increased fleet size requirements and higher operating expenses.

Charging technologies and strategies are critical components of electric vehicle systems. Charging technologies are broadly categorized into slow, fast, and ultra-fast charging. Alternating current charging is commonly used for slow or overnight charging, typically offering power levels of 7–22 kW, making it suitable for depot-based, low-demand environments. In contrast, direct current fast charging technologies deliver higher power levels, ranging from 50 kW to 350 kW or more, and are better suited for rapid recharging during operational hours. Ultra-fast charging systems, which can exceed 500 kW, are emerging but often require substantial electrical infrastructure and specialized thermal management systems. Wireless inductive charging and battery swapping technologies present alternative paradigms, offering minimal driver involvement or near-zero downtime, though they involve high capital costs and complex standardization challenges (Khaligh & Dusmez, 2012; Lim et al., 2022; Xue et al., 2025).

In a study that emphasizes the importance of developing charging infrastructure to support the transition from conventional vehicles to EVs, traditional and advanced battery charging methods, power topologies, and EV charging stations are comparatively examined in terms of location, duration, connection types, and performance. Furthermore, advanced charging technologies, including fast, intelligent, and wireless charging, as well as battery swapping, are discussed in detail, along with the role of renewable energy integration and energy management algorithms (Hemavathi & Shinisha, 2022).

Charging strategies, such as opportunity charging, depot charging, and end-of-line charging, play a critical role in determining how and where charging infrastructure should be deployed. Opportunity charging enables electric buses to recharge during brief layovers at terminals or key stops, thereby reducing battery size requirements but necessitating high-power charging stations along the route (Hu et al., 2022). Depot charging, typically performed overnight, is easier to manage logistically but requires longer idle times and larger battery capacities to meet daily operational needs (Hendriks & Sturmberg, 2024). End-of-line charging is a hybrid charging strategy that involves charging buses both before they depart from the depot at the beginning of their journey and the terminal or end-of-line stops when they reach the end of their route (Can et al., 2025). The approach offers the flexibility to optimize battery sizes and use charging infrastructure efficiently, while meeting the operational range requirements of buses throughout the day. The mentioned strategies directly impact scheduling flexibility, grid load distribution, and overall system cost efficiency.

A study on opportunity charging proposes a solution to the operational efficiency issue of battery electric buses resulting from fast opportunity charging. A variable trip scheduling strategy is developed for EB networks with multiple garages, and shifting the trip start times is proposed as a solution. A case study in Dalian, China, demonstrates that this strategy can mitigate the efficiency loss caused by charging and reduce operating costs by optimizing fleet size with minimal time delays (Tang et al., 2024). In a study on depot charging, a simultaneous optimization model is introduced that aims to balance the charging infrastructure of electric buses and the garages that serve them with the load on the electricity grid. The model combines energy consumption prediction based on route data with garage charging optimization, reducing the load on the grid (Hendriks & Sturmberg, 2024). Lin et al. focus on citywide planning for large-scale electric bus charging stations and introduce a model that considers the operation and charging behaviors of electric buses. The model identifies depots, first stops, and last stops as potential charging locations. It integrates the transportation network and power grid, accounting for the interactive constraints of both systems. An application study using a real transportation network in Shenzhen demonstrates the model's effectiveness and practical advantages (Lin et al., 2019).

Charging station location problems have been extensively studied in the literature through various mathematical formulations, many of which originate from classical facility location theory (Çelik & Ok, 2024). Models such as the set covering problem (de Vos et al., 2024; Kunith et al., 2014), p-median problem (Serra & Marianov, 1998), and capacitated facility location problem (Ala et al., 2024) have been adapted to reflect the unique operational characteristics of EV infrastructure. In the context of electric bus networks, these models are modified to consider dynamic route structures, fleet-level constraints, and spatial-temporal demand distributions. For instance, Vansola et al. addressed CS layout, which is one of the most critical factors affecting the adoption rate of EVs. The optimal design of fast charging stations for mixed traffic flow (two, three, four-wheelers, and commercial vehicles) in Delhi, India, is planned using a cluster coverage problem-based method that maximizes the coverage area (Vansola et al., 2022).

In the models, objective functions and constraints are formulated to strike a balance between cost efficiency and service performance. Standard objective functions include minimizing total investment and operational costs, maximizing route coverage or accessibility, and improving overall system reliability. Constraints are typically based on real-world physical and operational limitations such as battery capacity, maximum allowable charging time, transformer load capacity, and land availability (McCabe & Ban, 2023).

To validate and benchmark such models, many studies have used real-world datasets from cities such as Beijing (Liu et al., 2023), Shenzhen (Jiang et al., 2021), London (Y. Zhang et al., 2024), New York(Tessler & Traut, 2022), Helsinki (Deb & Gao, 2022) and Adana (Can et al., 2025). These datasets typically include geospatial bus route data, terminal locations, depot capacity, and electricity network layouts. The increasing availability of open datasets on transportation and energy has significantly expanded the practical applications of these methods in urban planning.

Metaheuristic algorithms constitute a critical component of the methodology presented in this dissertation, particularly due to the complexity and combinatorial nature of the charging station location problem. Classical optimization methods, such as linear programming, often become computationally intractable when applied to large-scale, non-linear, and multi-constrained formulations involving numerous candidate locations, demand nodes, and electrical limits. Metaheuristics offer a practical alternative, providing near-optimal solutions within a reasonable timeframe without requiring convexity or gradient information. Their ability to escape local minima and explore complex solution landscapes makes them particularly suitable for real-world infrastructure planning problems where exact solutions are not feasible (Yang, 2010).

While some studies have addressed the problem of electric vehicle charging station location detection using metaheuristic methods (Antarasee et al., 2022; Madhavan et al., 2025), others have sought a solution through a linear programming model (Dimitriadou et al., 2025; Veisi et al., 2025). Since FLP is an NP-hard problem (Kung & Liao, 2018), metaheuristic methods were employed in this dissertation, and a comparative study of recently used methods was conducted. In the context of the literature, where various techniques are discussed, the solutions developed in terms of both location optimization and energy efficiency demonstrate the flexibility and problem-solving capabilities of metaheuristic approaches.

Olsen & Kliewer present a new solution technique based on Variable Neighborhood Search that enables simultaneous optimization of charging station site selection and vehicle scheduling Olsen & Kliewer (2022). In another study, the authors introduced a hybrid metaheuristic algorithm created by combining Harris Hawk Optimization and Grey Wolf Optimization algorithms to reduce power losses by determining the optimal locations for EV and photovoltaic systems on the grid (Madhavan et al., 2025). Alhussan et al. conducted a study aimed at increasing the use of electric vehicles to mitigate environmental impacts. They emphasized that fast and ultra-fast charging station infrastructure should be established in urban areas to overcome obstacles such as limited range and long charging times of electric vehicles. In order to prevent the high energy demand of these stations from affecting service quality, they modeled the maximum hourly capacity of each station according to its location using the binary Graylag Goose Optimization algorithm (Alhussan et al., 2024).

These studies reveal that various meta-heuristic approaches have been developed to solve multidimensional problems, such as selecting charging station locations and managing energy for the effective planning of electric vehicle infrastructure. Comparative analyses often reveal that algorithmic performance varies with problem scale and constraint density, underlining the importance of algorithm selection and parameter tuning for reliable infrastructure planning.

One of the novel contributions of this dissertation is the integration of the electrical distribution network into the planning of electric bus charging stations. This topic has garnered increasing attention in recent literature. The deployment of high-power charging infrastructure can impose substantial stress on local distribution grids, particularly in terms of load balancing, voltage drop, power quality, and system stability. Rapid charging events can create sharp demand peaks that exceed local transformer capacities or lead to voltage fluctuations across the network. These impacts are especially critical in urban areas where grid flexibility is limited, making it imperative to co-optimize charging infrastructure with power system parameters (Acharige et al., 2025).

Substations are essential for placing EV charging infrastructure because they serve as key distribution points in the power grid. The proximity of potential charging sites to existing substations directly affects installation costs, voltage stability, and technical feasibility. Some research has analyzed how the placement of charging stations affects the electricity grid (Deb et al., 2017). Zeb et al. investigated the impact of electrification of the transportation sector on smart cities by examining the optimal placement of different types of electric vehicle charging stations. Since the random placement of chargers with high power demands is not suitable for system security, they developed an optimization model using particle swarm optimization to efficiently manage the load, reduce installation costs, energy losses, and transformer loading. According to the results, significant reductions in costs, losses, and transformer loading were achieved through the appropriate combination and placement of chargers (Zeb et al., 2020).

Recent research has increasingly focused on incorporating grid upgrade costs and transformer capacity constraints into optimization models for charging station planning. These models often use penalty terms or constraint sets to represent power flow limits, transformer loadability, and substation expansion thresholds (Chandra et al., 2025; Yin et al., 2024). Some approaches apply bi-level optimization, where the upper-level problem determines station locations while the lower-level power flow model ensures network feasibility (Ghanaei et al., 2025; Y. Xu et al., 2021; G. Zhou et al., 2023). Others employ robust or stochastic programming to address uncertainty in future demand and load profiles (Alabi et al., 2022; Nazari-Heris et al., 2021).

The literature on planning electric bus charging infrastructure focuses on developing integrated, technologically and operationally comprehensive solutions that are compatible with environmental sustainability goals. Existing studies analyze the effects of these systems on energy consumption, network load, and fleet management by examining basic components, including charging technologies, charging strategies (such as depot, opportunity, and end-of-line charging), and the placement of charging stations. At the same time, with the widespread adoption of electric buses in urban public transportation, the importance of models that optimize the interaction between these systems and the electricity transmission and distribution grid has increased. In this context, models that go beyond classical deterministic methods and provide solutions to multi-criteria, large-scale, and uncertain problems using meta-heuristic algorithms are drawing attention. In addition to the physical design of the charging infrastructure, the electrical safety, service quality, and cost-effectiveness of the system are also at the center of multi-layer optimization efforts.

This dissertation addresses these critical gaps by explicitly integrating the electrical distribution network, particularly transformer substations, into a novel optimization framework supported by a custom-designed fitness function. By combining this fitness function with advanced metaheuristic algorithms, including Arithmetic Optimization Algorithm, Grey Wolf Optimizer, Whale Optimization Algorithm, and Walrus Optimization Algorithm, the proposed approach enhances solution realism and scalability compared to traditional methods. Furthermore, the developed methodology enables the simultaneous evaluation of operational, economic, and electrical parameters, providing a multidimensional and practically implementable planning tool.

3. MATERIAL AND METHOD

This chapter presents the methodological framework developed to identify the optimal locations for electric bus charging stations in an urban transportation network. The study integrates transportation infrastructure and electrical grid constraints into a unified optimization model. The optimization process is formulated as a constrained binary decision problem. To solve this complex and multi-criteria problem, several metaheuristic algorithms have been employed and adapted. The proposed framework was tested on two datasets, DS1 and DS2, representing various urban scenarios. The datasets vary in terms of bus route density, transformer distribution, and candidate charging station locations. The chapter also outlines the mathematical structure of the fitness function and constraints. This framework provides a flexible and scalable approach suitable for real-world smart mobility planning. The following sections provide a detailed description of problem modeling, algorithm design, and dataset characteristics.

3.1. Problem definition

Mathematical notations and explanations of the problem are provided in this section. In the presented mathematical method, the mathematical models of the charging station location problem (CSLP) from (Can et al., 2025; Wu et al., 2021) are adopted and adjusted to minimize total cost and enhance the execution of other meta-heuristic algorithms. Table 3.1 presents the mathematical notation of variables and parameters utilized in this dissertation.

Table 3.1. Nomenclature

Abbreviation	**Description**
CSLP	Charging station location problem
e-bus	Electric Bus
SOC	State of Charge
WaOA	Walrus optimization algorithm

AOA	Arithmetic optimization algorithm
WOA	Whale optimization algorithm
GWO	Grey wolf optimizer
Parameters	
λ	The damping factor
P	Charging power of the charging facilities, kWh
C_{bat}	Battery capacity of electric bus, kWh
u	Energy consumption of electric bus per kilometer,kWh/km
α	Fluctuation coefficient of charging demand
k_s	Operation of simultaneous charging facility rate
k_{eff}	Charging efficiency of the charging station, %
TR_j	the operation time for route j, minute
TS_j	the spacing interval for route j, minute
SOC_{max}	Maximum SOC value of the e-bus battery
SOC_{min}	Minimum SOC value of the e-bus battery
$L_{i,j}$	Length of route j operated by the i^{th} terminus, km
η_b	Assumed scaling factor, %
g_t	Electricity price for charging, $/kWh
N	Number of distribution grid nodes
μ	Redundancy in charging capacity of the charging station
r_0	Discount rate, %
γ	Operating lifespan of the charging station, years
p_1	Unit price of the charging station, $
ω_c	Construction expense of charging station *c*, $
α_{cn}	Equipment and installation expense of power grid line per kilometer, $/km
p_2	Unit price of the transformer, $
Variables	
F	Objective function

$var1_{i,j,b,t}$	The operating state of e-buses
$var2_{i,j,b,t}$	The charging state of e-buses
$SOC1_{i,j,b,t}$	SOC value of e-buses at departure
$SOC2_{i,j,b,t}$	SOC value of e-bus on arrival
$E_{i,j}$	Energy consumption of route j used by the i^{th} terminus, kWh
$E_{i,c}$	Energy consumption from bus terminus i to charging station c, kWh
$TD_{i,j,b,t}$	Dwelling time of e-buses at terminus, minute
$TC_{i,j,b,t}$	Charging time of e-buses at charging station, minute
$T_{i,c}$	Driving time from bus terminus i to charging station c, minutes
$e_{i,j,b,t}$	Electric energy obtained of e-bus during charging, kWh
NS_c	Number of charging spots to be built for the fast-charging station c
NT_c	Number of transformers in the charging station c
$n_{c,i}$	Number of charging times of terminus i of charging station c
$Y_{c,n}$	State variable representing the connection between charging station c and node n in the distribution grid
$L_{c,n}$	Length of the power line, km
NB_j	Number of e-buses on route j
NI_c	Number of charging demand points
NJ_i	Number of bus routes used by charging demand point I
NT_b	Number of arrivals of e-bus b
NC	Number of charging stations
C_{1c}	Equipment and installation expense for charging station, $
C_{2c}	Construction expense of power distribution line, $.
C_{3c}	Operation and maintenance expense for charging station, $.
C_{4c}	Travel expense for e-bus to charging station, $.
w_1	Coefficient of equipment and installation expense

w_2	Coefficient of building expense of power distribution line
w_3	Coefficient of operation and maintenance expense of charging station
w_4	Coefficient of travel expense of e-bus to charging station
Sets and Indices	
i	Terminus node, $i \in \{1..I\}$
j	Route number, $j \in \{1..J\}$
b	E-bus index, where $b = 1, 2, \ldots, NB_j$
t	Tour number on the route for an e-bus, $t \in \{1..T\}$
c	The index of charging station, where $c = 1, 2, \ldots, NC$
$\overrightarrow{X_i}$	The set of e-bus terminus

This study aims to determine the optimal location of e-bus charging stations using metaheuristic methods, considering both transportation and power networks. The connections of the selected charging stations to the assigned power points are shown in Fig. 3.1.

3.2. Public bus transportation system

The public transportation system refers to the transportation system used for urban or intercity journeys, consisting of vehicles such as buses, minibuses, trains, trams, and metros, which enable the simultaneous transportation of large numbers of people. Using public transportation systems helps reduce factors such as traffic congestion, environmental pollution, and noise pollution caused by individual vehicles, while also lowering transportation costs. Buses are a vital part of public transportation, widely used in many cities. Therefore, this study discusses the public bus transportation system.

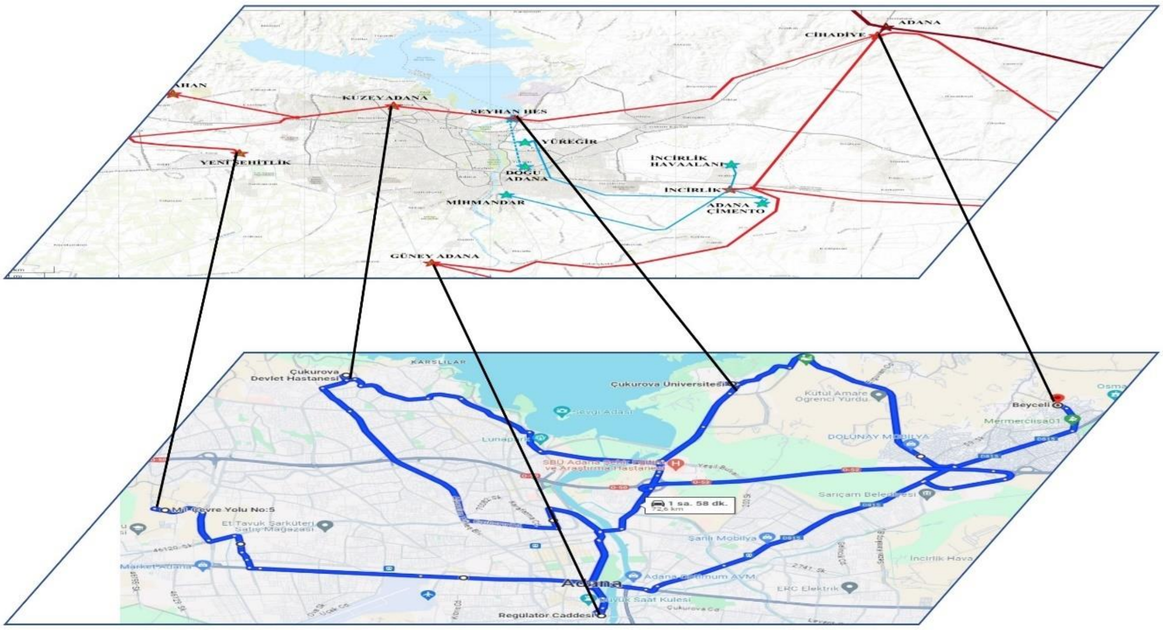

Figure 3.1. The coupled network scheme for CSLP

A Public Bus Transportation System (PBTS) can be visualized as a complex network comprising several routes, a transportation network, numerous bus terminals, common bus stops, and a bus scheduling system. Fig. 3.2 illustrates a sample transportation model that includes charging stations. The colored dashed-dotted lines represent the roads used by all types of vehicles within the city. Routes are a series of routes and are shown with colored dashed lines. E-buses use their route to serve their passengers based on a scheduled timetable. Also, e-buses can use the same route according to the timetable. E-buses, for example, using the blue-colored line serve from x_1 to x_4 or in the opposite direction. Colored dots show e-bus stops on their route. Numbered and colored squares (x_1,x_2,x_3, etc.) present the initial or final terminus for e-buses.

E-buses can be charged either at the terminal where they are located or at the nearest terminal during the waiting period for the next departure after their previous tour on the route. It is very costly to have a charging station at every bus terminal. Therefore, the most suitable location should be selected when determining the placement of the charging station.

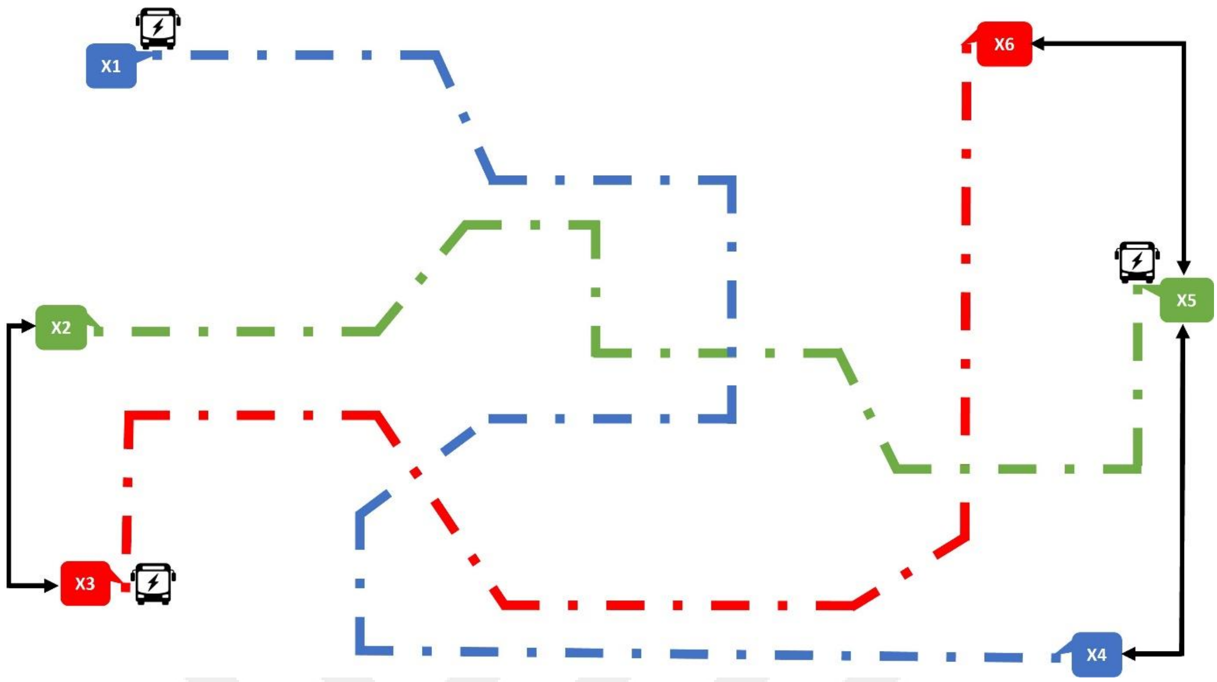

Figure 3.2. E-bus transportation system scheme with charging stations

Terminuses that show buses are selected to build charging stations that are candidate stations (x_1, x_3, and x_5). E-buses should select the nearest terminus with a charging station, if available. Electric buses travel to charging stations along the black-lined road with arrows indicating the route to the selected stations. For example, e-buses using the green-colored route on x_2 terminus use x_3 to charge their batteries when they are low. Similarly, the red and blue colored routes on x_6 and x_4, respectively, use x_5 terminus for charging their battery groups.

3.3. Power network system

Electrical grid systems are complex systems that produce, transmit, and distribute electrical energy. The system aims to transmit electrical energy to the consumer safely and efficiently. A power grid system can be considered a graph composed of nodes and edges. It is an extensive and complicated network containing substations and lines. The generators, bus bars, and loads can be recognized as nodes, and the connected transmission lines can be depicted as edges (Dwivedi et al., 2010; Lin et al., 2019). Graphs are divided into two main types: undirected graphs and directed graphs. An undirected graph shows the relationship between nodes without specifying direction. A directed graph expresses the direction of the relationship between nodes. Each edge has a start node and an end node. The distribution network is typically represented as a directed graph and illustrated as a tree. Nodes are points where the bus (the term "bus" refers to a different expression than the one used in transportation) is represented. The root of the tree, shown as node 1 in Fig. 3.3, is a substation bus that connects to the transmission network. Edges, on the other hand, connect nodes to each other. Fig. 3.3 shows the basic schemes for a power network.

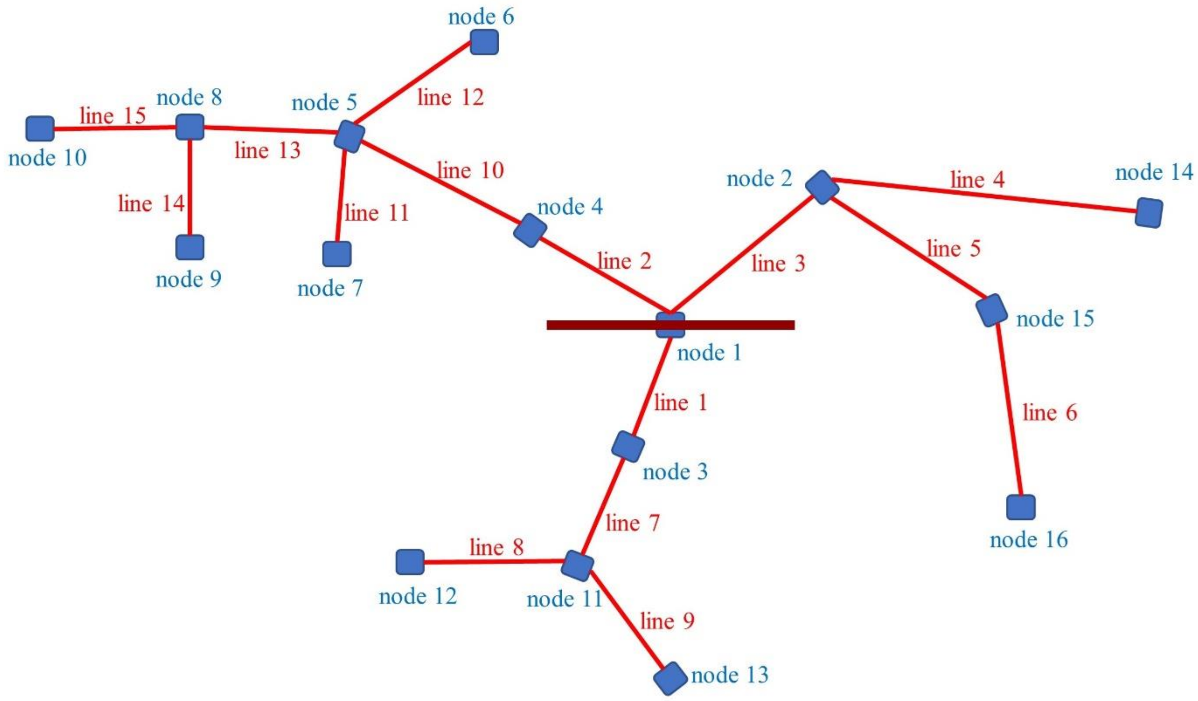

Figure 3.3. A simple power network scheme

The figure shows the high voltage line used throughout the country, indicated by the thick brown line. The red line represents the medium voltage level distribution network. Substations are shown with blue boxes. The distribution network is usually radial and can be demonstrated as a tree. node 1, the tree's root, is a substation bus that connects to the transmission network.

The network model used in this study is shown in Fig. 3.4, which applies to the Adana province area. The Turkish transmission network provides 380 kV, 154 kV, and 66 kV for rated voltage levels (Kocatepe et al., 2013). The line indicated by the thick brown line is the 380 kV level. The "ADANA" substation, a high-voltage substation, is a typical 380/154 kV open-air power station located in the rural area of Adana City, Türkiye. The red line shows the 154 kV level.

While the 154 kV lines partially pass through residential areas, all 66 kV lines, as indicated by the blue line, are located entirely within residential areas.

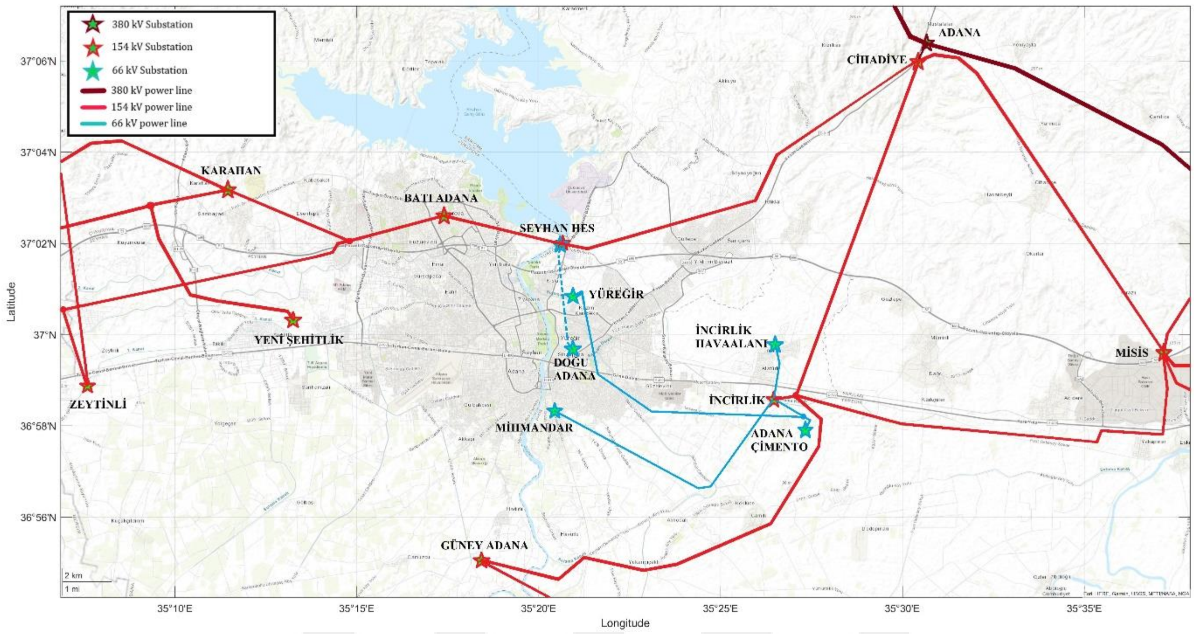

Figure 3.4. Power network system scheme in Adana

3.4. The planning model

The scenario in which the Adana Metropolitan Municipality plans to replace all existing diesel buses with electric buses is discussed. While adhering to the current bus operating plan, the most suitable locations for charging stations and the substations to which these stations should connect have been determined to minimize the total cost. The aim is to reduce the expenses of all charging stations, including equipment and facility expenses, power line expenses, operational and maintenance expenses, and the travel expenses of e-buses to charging stations for charging, by utilizing meta-heuristic algorithms for this problem. The following decision variables, parameters, and notations are used in this study.

$$x_i = \begin{cases} 1 \; if \; the \; terminus \; is \; selected \; for \; charging \; station \\ 0 \; otherwise \end{cases} \tag{3.1}$$

where x_i indicates whether terminus i is selected and x_i are either 1 or 0.

$$var1_{i,j,b,t} = \begin{cases} 1\ e-bus\ is\ ready\ for\ departure \\ 0\ otherwise \end{cases} \tag{3.2}$$

$$var2_{i,j,b,t} = \begin{cases} 1\ e-bus\ needs\ to\ be\ charged \\ 0\ otherwise \end{cases} \tag{3.3}$$

$var1_{i,j,b,t}$ is the operating state variable in Eq. 3.2, and it controls whether the e-bus is at the departure or the final stop. Similarly, $var2_{i,j,b,t}$ is the charging state variable in Eq. 3.3, and it controls whether the e-bus needs to be charged. The basic process illustrating the daily operation of e-buses is presented below, along with detailed explanations of the equations involved.

1) Firstly, the first bus starts its journey according to the scheduled time. At this moment $SOC1_{i,j,b,t} = 1$ and $var1_{i,j,b,t} = 1$.
2) The e-bus arrives at the final terminus after the running time of route *j*, at this moment $var1_{i,j,b,t} = 0$, the arrival time and $SOC2_{i,j,b,t}$ is recorded in Eq. 3.4.

$$SOC2_{i,j,b,t} = SOC1_{i,j,b,t} - \left(\frac{E_{i,j}}{C_{bat}}\right) \tag{3.4}$$

where $E_{i,j}$ is the energy consumption and can be calculated following the equation (Eq. 3.5).

$$E_{i,j} = u \cdot L_{i,j} \cdot \lambda_d \tag{3.5}$$

where u means energy consumption per kilometer, *kWh/km*, and $L_{i,j}$ denotes length of route *j* operated by the i^{th} terminus, *km*. λ_d indicates an affecting factor on the routes such as rugged degree, slope, etc., which are called an extensive factor and generally accepted between 1.1 and 1.3 (B. Zhou et al., 2016).

3) If the e-bus needs to be charged, set $var2_{i,j,b,t} = 1$; otherwise, set it to 0 and wait for the next departure time. Eq. 3.6 calculates whether buses need charging.

$$SOC2_{i,j,b,t} - \left(\frac{E_{i,j} + E_{i,c}}{C_{bat}}\right) \leq SOC_{min} \tag{3.6}$$

where $E_{i,c}$ indicates energy consumption from terminus *i* to charging station *c*, *kWh*.

4) If the e-bus needs to be charged, the charging time can be calculated by Eq. 3.7. By the way, to ensure that the *SOC* of the e-bus meets the next departure requirement and does not exceed the waiting interval, the charging time must satisfy the constraint in Eq. 3.8.

$$TC_{i,j,b,t} = \begin{cases} \dfrac{60 \cdot \left(SOC_{max} - SOC2_{i,j,b,t}\right) \cdot C_{bat} + E_{i,c}}{P} & if\ var2_{i,j,b,t} = 1 \\ 0\ otherwise \end{cases} \tag{3.7}$$

$$\begin{cases} TC_{i,j,b,t} \geq \dfrac{60 \cdot \left(SOC_{max} - SOC2_{i,j,b,t}\right) \cdot C_{bat} + E_{i,j} + E_{i,c}}{P} & if\ var2_{i,j,b,t} = 1 \\ TC_{i,j,b,t} \geq TD_{i,j,b,t} - 2 \cdot T_{i,c} \end{cases} \tag{3.8}$$

Eq. 3.9 can calculate the energy obtained from charging.

$$e_{i,j,b,t} = \frac{TC_{i,j,b,t} \cdot P}{C_{bat} \cdot 60} \tag{3.9}$$

5) It is time for departure after a period of dwelling time of e-bus, at this moment $SOC1_{i,j,b,t}$ is calculated by Eq. 3.10 again.

$$SOC1_{i,j,b,t} = \begin{cases} SOC2_{i,j,b,t} + e_{i,j,b,t} - \dfrac{2 \cdot E_{i,c}}{C_{bat}} & if\ var2_{i,j,b,t} = 1 \\ SOC2_{i,j,b,t} \end{cases} \tag{3.10}$$

6) Steps 2–5 should be repeated till all e-buses, bus routes, and terminuses have been traveled to determine each bus terminus's entire charging requirement and optimal charging time while in operation.

The number of points of charge needed for charging in the day can be calculated using the following Eq. 3.11.

$$NS_c = ceil\left(\frac{\sum_{i=1}^{NI_c}\sum_{j=1}^{NJ_i}\sum_{b=1}^{NB_j}\sum_{t=1}^{NT_b} e_{i,j,b,t} \cdot (1+\mu)}{TC_c \cdot P \cdot k_s \cdot k_{eff}} \cdot \alpha\right) \tag{3.11}$$

where NS_c is the number of charging spots needed for charging of a fast-charging station c. NI_c means the number of charging demand points of fast-charging station c. NJ_i indicates the number of bus routes used by charging demand point i. NT_b presents the number of arrivals of e-bus b. μ shows the charging capacity redundancy of the fast-charging station. TC_c introduces the adequate charging time of fast-charging station c, in minutes. k_s presents the operation's simultaneous rate of charging facilities. k_{eff} is the charging efficiency of the charging facility, and α shows the fluctuation coefficient of charging demand.

The objective function of charging station planning for e-buses presented by Eq. 3.12 is to minimize the overall cost of the charging station. Since multiple costs are attempted to be optimized in the objective function, each cost is weighted to determine which cost is more significant. Because one or more of the sub-objective values may be dominant over the others. In this study, to determine the optimal weights for each cost, a total of 200 random solutions were generated. Subsequently, the associated costs are computed based on the average expenses, utilizing the min-max normalization technique—a widely adopted method for data normalization.

$$Min\ F = \sum_{c=1}^{NC} (w1 \cdot C_{1c} + w2 \cdot C_{2c} + w3 \cdot C_{3c} + w4 \cdot C_{4c}) \tag{3.12}$$

where

F - the objective function.

NC - charging station number.

C_{1c} - equipment and installation expense of charging station *c*, $.

C_{2c} - building expense of the power distribution line, $.

C_{3c} - operation and maintenance expense of charging station *c*, $.

C_{4c} - travel expense of e-bus to charging station *c*, $.

$w1$ - coefficient of equipment and installation expense

$w2$ - coefficient of building expense of power distribution line

$w3$ - coefficient of operation and maintenance expense of charging station *c*

$w4$ - coefficient of travel expense of e-bus to charging station *c*

subject to

$$d_{i,c} \leq L\ \forall_i, \forall_c \tag{3.13}$$

$$\sum_{n=1}^{N} Y_{c,n} = 1\ \forall_c, \forall_n \tag{3.14}$$

where

$d_{i,c}$ - distance between the demand point *i* and the charging station *c*, km.

L - the radius of action from one charging station to another one for datasets, km.

$Y_{c,n}$ - state variable defining the connection between the charging stations and nodes in the power grid. If the charging station is connected to a power network node, then $Y_{c,n} = 1$. Otherwise, it is 0.

Eq. 3.13 shows that to satisfy the charging dependability, the e-bus energy consumption amount from the current station (i) to the charging station.

3.4.1. Equipment and installation expense of charging station

The equipment and installation expense of the charging station can be calculated in Eq. 3.15.

$$C_{1c} = (NS_c.p_1 + NT_c.p_2 + \omega_c)\frac{r_0.(1+r_0)^\gamma}{(1+r_0)^\gamma - 1} \tag{3.15}$$

where

r_0 - discount rate, %.

γ - operating lifespan of the charging station, year.

NS_c - number of charging facilities at charging station c.

p_1 - unit price of the charging facility, $.

NT_c - number of transformers in the charging station c.

p_2 - unit price of the transformer, $.

ω_c - construction expense of charging station c, $.

3.4.2. Construction expense of power distribution line

Eq. 3.16 shows the construction expense of the power network line.

$$C_{2c} = \alpha_{cn} Y_{c,n} L_{c,n} \frac{r_0.(1+r_0)^\gamma}{(1+r_0)^\gamma - 1} \tag{3.16}$$

where

α_{cn} - equipment and installation expense for power distribution line per kilometer, $/km.

$L_{c,n}$ - length of the power line connecting charging station *c* to node *n* of the distribution grid, km.

3.4.3. Charging station's annual operation and maintenance expenses

Eq. 3.17 shows the construction expense of the power network line.

$$C_{3c} = (C_{1c} + C_{2c})\eta_b \tag{3.17}$$

where

η_b- assuming scaling factor, %.

3.4.4. Round-trip expenses to the charging station

Eq. 3.18 calculates the travel expense to the charging station.

$$C_{4c} = 365 \sum_{c=1}^{NC} \sum_{i=1}^{NJ_c} 2 g_t E_{i,c} n_{c,i} \tag{3.18}$$

where

g_t - electricity price for charging, $/kWh.

$n_{c,i}$ - number of charging times.

3.5. Proposed metaheuristic methods

This section provides a comprehensive explanation of the binary implementation of the Walrus Optimization Algorithm (BWaOA) for solving the CSLP. Additionally, brief information is provided for other performance algorithms, including Binary Whale Optimization Algorithm (BWOA), Binary Arithmetic Optimization Algorithm (BAOA), and Binary Grey Wolf Optimizer (BGWO). Fig. 3.5 shows the scheme of the proposed model.

3.5.1. Binary solution representation for CSLP

Many real-world problems, such as feature selection (Wang et al., 2007), dimensionality reduction (Wang et al., 2007), and data mining (Srinivasa et al., 2007), in engineering are modeled using a discrete binary search space. The main metaheuristic techniques are first tested using well-known problems such as CEC-Function (García-Martínez et al., 2017), a set of benchmark instances for the 0-1 multidimensional knapsack problem (Azad et al., 2014). These methods and solution models must be implemented to find a good solution in different search spaces and constraints. In this study, a problem-specific binary form is implemented for CSLP. S-Shape transfer function is used for binary search space (Emary et al., 2016a).

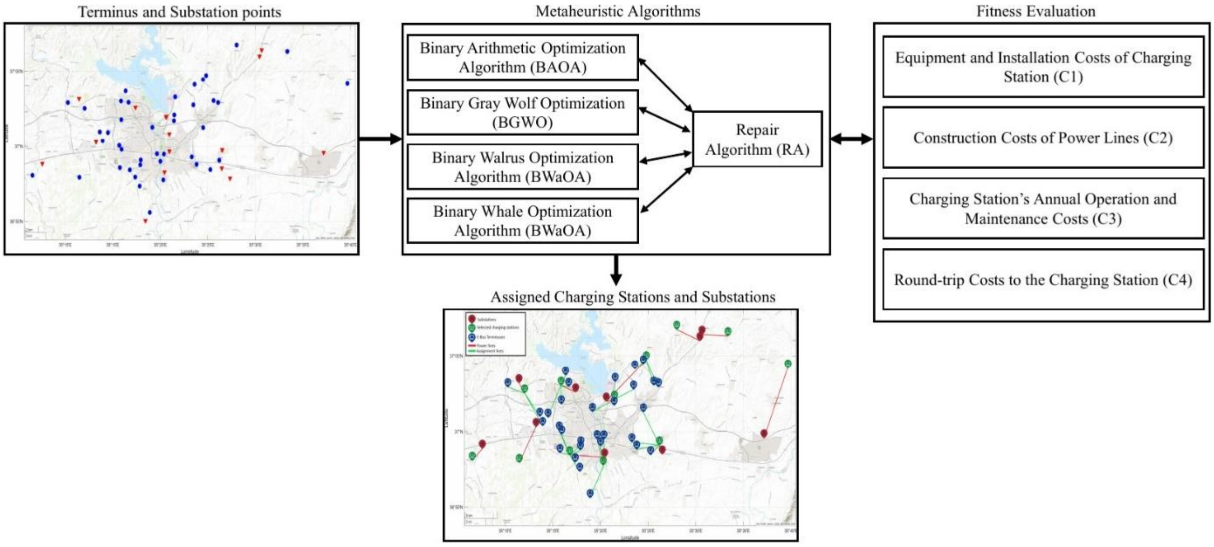

Figure 3.5. The proposed approach's scheme for CSLP

Table 3.2. A solution model for CSLP.

	1	**2**	**3**	**4**	**5**	**.**	**.**	**.**	***I***
Solution 1	1	0	0	1	1	.	.	.	1
Solution 2	0	0	1	1	0	.	.	.	0
Solution 3	1	1	1	0	0	.	.	.	1
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
Solution N	1	1	0	0	1	.	.	.	0

Table 3.2 shows the solution model for the binary format. Each solution has *I* binary bits, and *I* indicates the terminal number. Therefore, for *D* dimensional search space, *D* means *I*. Eq. 3.1 computes the position of the x_i. Whether a terminus is chosen for the charging station, the related position is 1 or 0.

A solution space is the set of all possible solutions that constitute the solution to a specific problem or optimization. In the solution space, all solutions contain feasible and unfeasible solutions. In this study, if one of the solutions is unfeasible, it is repaired by a repair algorithm.

Namely, if the service diameter (L) exceeds 5 kilometers, the solution must be repaired. The Algorithm 1 presents the repair algorithm (Can et al., 2025). The repair algorithm controls a solution that provides Eq. 3.13, which is used in real-world datasets.

Algorithm 1. The repair algorithm

```
Input: solution Sol
Output: new solution nSol
  TerminusList = NotCoveredTerminus(Sol)
  while TerminusList = Φ do
    selTerminus ← RandomSelectTerminus(TerminusList)
    nSol(selTerminus) ← 1
    TerminusList = NotCoveredTerminus(Sol)
  end while
```

3.5.2. Walrus optimization algorithm

The Walrus is the ocean's largest mammal apart from whales. Walruses build their territory on sandy areas when the mating season begins (Ray et al., 2016). The most vigorous males have the highest positions in the walrus population. Walruses depend on sound localization, like dolphins and bats, to forage and transmit food information by communicating with other walruses. While creating the WaOA algorithm, Han et al. drew inspiration from the behaviors of walruses, including migration, reproduction, roosting, and foraging. Fig. 3.6 shows the positions of the walrus herd within the population, and Fig. 3.7 shows the roosting, breeding, migration, and foraging behaviors of walruses (Han et al., 2024).

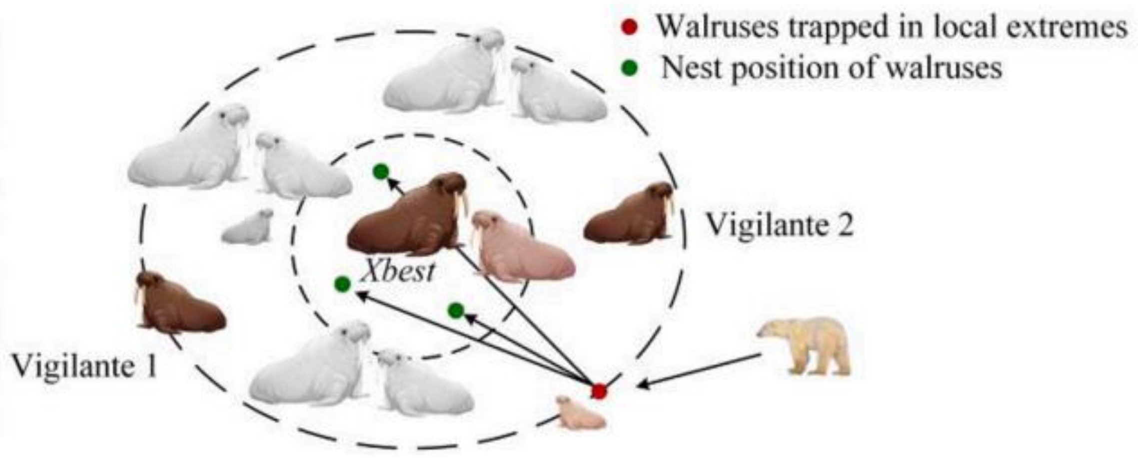

Figure 3.6. Walrus population

Figure 3.7. Walrus behaviors

3.5.2.1. Mathematical model

In the mathematical model of the Walrus optimization algorithm, as in other optimization algorithms, the search space is the area where the algorithm seeks the optimal solution. Generally, a multidimensional space comprises the problem's decision variables, which in this case are the candidate charging stations. The location of a walrus is a solution that describes a potential solution that can be a vector in the search space. The algorithm attempts to find the optimal solution within the search space.

Firstly, a population of walruses is randomly initialized. The population consists of *N* particles. Every particle contains a solution that has a *d*-dimensional vector.

$$X_i = \left\{x_i^1, x_i^2, \dots, x_i^j, \dots, x_i^d\right\} \tag{3.19}$$

where d is the decision variable number, i is the particle's index in the swarm, and j is the decision variable's index. Each unit is either 1 or 0 in a solution. The positions of Walruses are continuously updated with every iteration. The population of Walruses can be determined as a matrix using Eq. 3.20.

$$X_i = \begin{bmatrix} X_{1,1} & X_{1,j} & \dots & X_{1,d} \\ \vdots & \vdots & \ddots & \vdots \\ X_{i,1} & X_{i,j} & \dots & X_{i,d} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n,1} & X_{n,j} & \dots & X_{n,d} \end{bmatrix} \tag{3.20}$$

where *X* is the population of the Walruses, $X_{i,j}$ is the value of the j^{th} decision variable presented by the i^{th} Walrus, *n* is the Walrus numbers, and *d* is the decision variable numbers. The fitness values of search agents are stored using Eq. 3.21.

$$F_i = \begin{bmatrix} F_{1,1} & F_{1,j} & \dots & F_{1,d} \\ \vdots & \vdots & \ddots & \vdots \\ F_{i,1} & F_{i,j} & \dots & F_{i,d} \\ \vdots & \vdots & \ddots & \vdots \\ F_{n,1} & F_{n,j} & \dots & F_{n,d} \end{bmatrix} \tag{3.21}$$

Walruses are separated into youths and adults, which make up 10% and 90% of the population, respectively. The male-to-female proportion is 1:1 among adult walruses (Han et al., 2024).

3.5.2.2. Danger and safety signals

The walruses are highly attentive during both feeding and resting. When walruses sense a dangerous situation in their group, they keep 1 or 2 guard walruses who immediately send a danger signal. The danger signal and safety signal used in the algorithm can be expressed as Eq. 3.22 and Eq. 3.23.

$$signal_d = A \times R \tag{3.22}$$

$$A = 2 \times (1 - iter/Max_{iter}) \tag{3.23}$$

$$R = 2 \times r_1 - 1 \tag{3.24}$$

$$signal_s = r_2 \tag{3.25}$$

where A and R are risk parameters, r_1 and r_2 are random numbers in the interval (0,1), and Max_{iter} presents the maximum iteration.

3.5.2.3. Exploration Phase (Migration)

Walrus packs will relocate to safer locations for the population's survival when danger parameters become too high. Eq. 3.28 can be used to update the Walrus position.

$$migration_{step} = (X_m^t - X_n^t) \cdot \beta \cdot r_3^2 \tag{3.26}$$

$$\beta = 1 - \frac{1}{1 + \exp\left(\frac{iter - Max_{iter}/2}{Max_{iter}} \times 10\right)} \tag{3.27}$$

$$X_{i,j}^{t+1} = X_{i,j}^t + migration_{step} \tag{3.28}$$

where $X_{i,j}^{t+1}$ and $X_{i,j}^t$ are the new position and the existing position of the i^{th} walrus on the j^{th} dimension, respectively. $migration_{step}$ is the step size of walrus action, two guard walruses are randomly selected from the inhabitants, and the positions of the two guard walruses equal to X_m^t and X_n^t, β is the migration step control parameter which ranges with iteration, and r_3 is a random number (0, 1).

3.5.2.4. Exploitation Phase (Reproduction)

If risk parameters are low, walruses show breeding behavior during the reproductive phase. During this period, they roost on the shore and search for food underwater.

Walruses are consistently vulnerable to attacks by polar bears and killer whales. The tactic of escaping and fighting these predators causes the walruses to move their position in the neighborhood of their current location (Trojovský & Dehghani, 2023). The walrus population consists of male, female, and child walruses. Population diversity is crucial for the success and superiority of walruses within their population. The displacement behavior of each species within the population is different.

Adopting the Halton sequence distribution, a widely used technique for generating randomly distributed sequences for male walrus position updates, can enable a more expansive distribution of the population within the search space (Han et al., 2024). The basic principle is to divide the search area into several regions and select a random point in each region to ensure randomness and uniformity.

The leader walrus and male walruses affect the female walruses. Female walruses increasingly become attracted to the leader walrus rather than their mates. The new position of the female walrus can be calculated by Eq. 3.29.

$$Female_{i,j}^{t+1} = Female_{i,j}^{t} + \alpha \cdot (Male_{i,j}^{t} - Female_{i,j}^{t}) + (1+\alpha) \cdot (X_{best}^{t} - Female_{i,j}^{t}) \tag{3.29}$$

where, $Female_{i,j}^{t+1}$ is the new position, $Male_{i,j}^{t}$ is the positions of the i^{th} male, $Female_{i,j}^{t}$ is the positions of the i^{th} female on the j^{th} dimension, respectively.

Child walruses are the most vulnerable members of the pack. They are exposed to attacks by predators such as killer whales and polar bears. That's why their positions also need to be updated. It can be updated to Eq. 3.30.

$$Child_{i,j}^{t+1} = (O - Child_{i,j}^{t}) \cdot P \tag{3.30}$$

$$O = X_{best}^{t} + Child_{i,j}^{t} \cdot LF \tag{3.31}$$

where, $Child_{i,j}^{t+1}$ is the new position of the i^{th} child on the j^{th} dimension, $+Child_{i,j}^{t}$ is the positions of the i^{th} child on the j^{th} dimension. *P* is a random number (0,1) and presents the perturbation coefficient of a child walrus. *O* represents a safe position. *LF* depicts Levy's distribution.

Predators prey on walruses while walruses feed underwater. Therefore, they escape from their current position due to dangerous signals from other walruses. The walrus position can be updated Eq. 3.32.

$$X_{i,j}^{t+1} = X_{i,j}^{t} \cdot R - \left|X_{best}^{t} - X_{i,j}^{t}\right| \cdot r_4^2 \tag{3.32}$$

where $\left|X_{best}^{t} - X_{i,j}^{t}\right|$ indicates the distance between the best walrus and the current walrus, r_4 is a random number (0,1).

Walruses collaborate with other walruses in the pack to search for food and move safely. Thus, they share their location with others to find more food.

$$X_{i,j}^{t+1} = \frac{X_1 + X_2}{2} \tag{3.33}$$

$$\begin{cases} X_1 = X_{best}^{t} - \alpha_1 \times b_1 \times \left|X_{best}^{t} - X_{i,j}^{t}\right| \\ X_2 = X_{second}^{t} - \alpha_2 \times b_2 \times \left|X_{second}^{t} - X_{i,j}^{t}\right| \end{cases} \tag{3.34}$$

$$\alpha = \beta \times r_5 - \beta \tag{3.35}$$

$$b = \tan(\theta) \tag{3.36}$$

where X_1 and X_2 are two weights influencing the gathering action of the walrus, X_{second}^{t} is the position of the 2^{th} walrus in the existing iteration.$\left|X_{second}^{t} - X_{i,j}^{t}\right|$ indicates the distance between the 2^{th} walrus and the current walrus, α and b are the gathering parameters. r_5 is a random number (0,1) and θ is values that ranking (0,π).

3.5.2.5. The pseudo-code of the algorithm

In the Walrus Optimization Algorithm, the danger signal value determines whether the algorithm will use the exploration or exploitation phase. If the absolute value of the signal is more significant than or equal to one, the algorithm will use the exploration phase. Otherwise, the algorithm will use the exploitation phase. In the exploitation phase, the safety signal is used for a specific behavior that walruses exhibit. If the value of the signal is more significant than or equal to 0.5, the walruses will breed. However, the walruses will forage if the signal's value is lower than 0.5. The Walruses exhibit either gathering or fleeing behavior depending on the danger signal during the foraging phase. The pseudo-code of BaWOA is described in detail in Algorithm 2.

Algorithm 2. The pseudo-code of binary WaOA for locating a charging station

```
Input: Population size N, Maximum iteration T
Output: the best solution
Randomly initialize solutions in the population of the Walrus and define the
related parameters
 for Each X_i in the population of walruses do
   Evaluate X_i using F by Eq. 3.12
 end for
 while iter < Iter_max do
   Repair X_i walrus considering the constraints
   Calculate the fitness value
   Update the best and second position of the walruses
   if |signald| ≥ 1 then
     Update the new position of walruses using Eq. 3.28
   else
     if signals ≥ 0.5 then
       for Each male walrus do
         Update the new position of male walruses depending on the Halton sequence
       end for
       for Each female walrus do
         Update the new position of female walruses using Eq. 3.29
       end for
       for Each child walrus do
         Update the new position of child walruses using Eq. 3.30
       end for
     else
       if signald ≥ 0.5 then
         Update the new position of walruses using Eq. 3.32
       else
         Update the new position of walruses using Eq. 3.33
       end if
     end if
   end if
   Update the new position of each walrus using S-shape transfer function
   Compute the fitness value and update the existing best solution
   iter = iter + 1
end while
```

3.5.3. Grey wolf optimizer

TThe Grey Wolf Optimizer (GWO), one of the most popular swarm intelligence approaches, imitates the hunting and searching for prey behaviours and movements of grey wolves (Mirjalili et al., 2014). GWO is a population-based search technique and divides the population into two parts: three swarm leaders (alpha, beta, and delta) and omega wolves. The alpha wolf is the pack's leader and dominates other population members. While the beta wolf acts as the second in a swarm, the delta wolf is the third leader. Omega wolves obey and follow the leader's commands. The three solutions with the swarm best fitness values are α, β, and δ. The other solutions are called ω. To solve difficulties with continuous values, GWO was initially presented in 2014 (Mirjalili et al., 2014). Binary GWO (BGWO) is introduced using S-shape and V-shape transfer functions by Emary et al. (Emary et al., 2016b). We modified BGWO to solve FLCSP. The original BGWO is detailed in (Emary et al., 2016b). In this section, BGWO is explained. The pseudo-code of BGWO is presented in Algorithm 3.

Algorithm 3. The pseudo-code of modified BGWO for locating a charging station

Input: Population size N, Maximum iteration T
Output: the best solution
Randomly initialize solutions in the population of grey wolves
  for Each X_i in the population of walruses **do**
    Evaluate X_i using F by Eq. 3.12
  end for
  while iter < Iter_{max} **do**
    for Each X_i ϵ the population of grey wolves **do**
      Update the position of the current search agent
      Compute $X_1, X_{2,}\, X_3$ using Eq. 3.43 – Eq. 3.45
      Generate X_i^{new} by applying Eq. 3.44
      Repair X_i wolf considering the constraints
    end for
    Evaluate the fitness of all grey wolves
    Update the position of alpha, beta, and delta
    Update a, A and C parameters
    iter = iter + 1
end while

The behaviours of grey wolves are mathematically modelled using three methods: surrounding, hunting, and attacking for prey. The following equations (Eq. 3.37 – Eq. 3.40) are used to simulate encircling prey in hunting prey process.

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{3.37}$$

where t indicates the number of iterations, $\vec{A}$ and $\vec{C}$ are coefficient values and calculated using Eq. 3.39, respectively. $\vec{X}_p$ is the prey's position while the wolf vector's position is shown as $\vec{X}$.

$\vec{D}$ is calculated using Eq. 3.38.

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)\right| \tag{3.38}$$

$$\vec{A} = 2 \cdot a \cdot \vec{r}_1 - a \ , \ \vec{C} = 2 \cdot \vec{r}_2 \tag{3.39}$$

where $\vec{r}_1$ and $\vec{r}_2$ are random vectors ranging between 0 and 1. $\vec{a}$ elements are generated using Eq. 3.40 and decrease linearly from 2 to 0 across iterations.

$$\vec{a} = 2 - t \cdot \frac{2}{maxIt} \tag{3.40}$$

where $maxIt$ shows the maximum number of iterations. Four wolves are in a wolf pack's leadership hierarchy: α, β, δ, and ω. α, β, and δ represent the positions of the three best search agents, and the positions of each wolf represent a solution for the problem. In every iteration, the new positions of the wolves are updated using Eq. 3.41.

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{3.41}$$

where Eqs. 3.42, the positions of all wolves are updated by the positions α, β, δ. $\vec{A}_1$, $\vec{A}_2$, and $\vec{A}_3$ are calculated using Eq. 3.39. Eq. 3.43 calculate $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$, respectively.

$$\vec{X}_1 = \left|\vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha\right| , \vec{X}_2 = \left|\vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta\right|, \ \vec{X}_3 = \left|\vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta\right| \tag{3.42}$$

$$\vec{D}_\alpha = \left|\overrightarrow{C_1} \cdot \vec{X}_\alpha - \vec{X}\right| , \ \vec{D}_\beta = \left|\overrightarrow{C_2} \cdot \vec{X}_\beta - \vec{X}\right| , \vec{D}_\delta = \left|\overrightarrow{C_3} \cdot \vec{X}_\delta - \vec{X}\right| \tag{3.43}$$

where Eq. 3.39 is adapted to calculate $\overrightarrow{C_1}$, $\overrightarrow{C_2}$, and $\overrightarrow{C_3}$.

To binarize the solution space used in the original version of the algorithm, the S-shaped transfer function was implemented, as in Eq. 3.44. The equation shows the S-shaped transfer function for binary solution space.

$$X^d(t+1) = \begin{cases} 1 \; if \; S(\frac{X_1^d + X_2^d + X_3^d}{3} \geq r_7) \\ 0 \qquad otherwise \end{cases} \quad (3.44)$$

where r_7 is a random vector ranging between 0 and 1, d is the size of search space, and S represents the Sigmoid function.

$$S(x) = \frac{1}{1 + e^{(-10(x-0.5))}} \quad (3.45)$$

3.5.4. Arithmetic optimization algorithm

The Arithmetic Optimization Algorithm (AOA) is a novel metaheuristic algorithm inspired by fundamental arithmetic operations, such as subtraction, addition, multiplication, and division. These operations are the basis for AOA's search mechanism within the search space. The global search framework of AOA is primarily driven by multiplication and division, while the local search framework relies on addition and subtraction operations (Abualigah et al., 2021). M. Xu et al. introduced a binary variant of the algorithm, Binary Arithmetic Optimization Algorithm (BAOA). The authors enhanced this version by integrating a Levy flight strategy to help escape local optima. The BAOA has been modified and implemented in this study.

3.5.5. Whale optimization algorithm

Another well-known meta-heuristic algorithm is the Whale Optimization Algorithm (WOA), which is inspired by the bubble-net hunting technique used by humpback whales to solve complex optimization problems. WOA was proposed by Mirjalili & Lewis. A binary version of WOA, known as BWOA, was introduced by Hussien et al.. This version modifies the prey search phase while keeping the shrinking and encircling phases unchanged. This paper aims to adapt BWOA to solve the CSLP problem, leveraging its straightforward and effective search mechanisms for finding optimal solutions.

3.6. Datasets

Two real-world datasets, referred to as DS1 and DS2, were developed to evaluate the performance of the proposed algorithms. Both datasets represent the urban transportation network of Adana, a metropolitan city in Türkiye. The data, including information on bus lines, routes, and terminal locations, were obtained from the official transportation web portal of the

Adana Metropolitan Municipality in 2022 (Adana Metropolitan Municipality Transportation Department, 2022). The first dataset, DS1, comprises 30 routes and 142 buses operating within the city center. The second dataset, DS2, is an extended version of DS1 and includes 46 routes and 187 buses serving areas adjacent to the city center.

3.6.1. Dataset 1

The first dataset, referred to as DS1, was compiled using public bus network data made available on the official website of the Adana Metropolitan Municipality's Transportation Department (Adana Metropolitan Municipality Transportation Department, 2022). The dataset covers public transportation lines that provide intensive service in the city center, focusing on areas with high passenger potential in the central districts of Adana. This dataset comprises 30 bus lines and 142 buses, with detailed information available for each, including line number, total line length, and bus departure times. Additionally, the number of buses assigned to each line has been determined and included in the data. The departure intervals of the buses are crucial for determining the frequency of trips, while route duration information indicates the one-way travel time for each line.

The dataset also includes the number of laps the buses make throughout the day, which are vital parameters for estimating energy consumption in charging station planning. The information collected establishes a solid foundation for modeling the city's dynamic public transportation system. This dataset was created based on data from 2022. The departure and arrival terminals of the routes were evaluated as potential locations for charging stations, with a total of 60 terminal points defined in the dataset, 21 of which correspond to different locations. With this structure, the dataset effectively reflects the heavy bus traffic in the city center. Detailed information about the bus lines is given in the Table 3.3.

Table 3.3. Bus line information of the DS1.

Route ID	Departure Terminal ID	Arrival Terminal ID	Number Of Buses	Route Length (km)	Running Time (min)	Time Headway (min)	First Bus	Last Bus
105	9	18	7	6	3,85	3,85	10	10
106	1	1	19	2	3,1	3,1	8	15

110	2	4	3	8	27,7	27,7	67	30
111	3	7	3	4	13,7	13,7	33	60
112	4	9	2	5	31,5	31,5	76	60
114	5	2	4	16	22,6	22,6	55	12
115	5	19	5	2	20,1	20,1	49	75
116	6	1	2	5	27,4	27,4	66	60
118	7	9	3	4	34,5	34,5	83	60
121	2	1	3	5	36,3	36,3	88	48
122	8	9	4	3	25,3	25,3	61	60
123	8	9	4	3	25,7	25,7	62	60
124	9	2	3	8	30	30	72	30
125	10	20	4	6	19,8	19,8	48	30
126	11	8	3	4	24,7	24,7	60	60
127	12	9	4	2	21,6	21,6	52	90
132	9	13	4	3	20,5	20,5	50	60
133	13	9	5	2	21,3	21,3	52	80
135	10	9	3	4	20,6	20,6	50	60
142	7	2	4	8	24,6	24,6	60	30
144	2	1	3	6	34,4	34,4	83	40
151	1	2	4	2	28,4	28,4	69	90
154	9	21	4	6	22,4	22,4	54	30
155	14	1	4	6	23,9	23,9	58	40
156	2	9	6	2	18,6	18,6	45	70
157	2	7	5	2	23,9	23,9	58	80
159	15	19	4	3	21,1	21,1	51	60
160	16	1	5	3	31,2	31,2	75	70
161	2	9	2	5	30,1	30,1	73	60
174	17	8	5	2	18,6	18,6	45	90

Table 3.4 presents data defining the departure and arrival points of specific bus lines within the Adana urban transportation network. Each row of the table represents a bus line, showing the names and identification numbers of the departure and arrival terminals for that line.

Table 3.4. Terminal information of the DS1.

Route ID	Departure ID	Departure Name	Destination ID	Destination Name
105	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)	18	YURTLAR ÖNÜ 1A
106	1	ATÜ 1A	1	ATÜ 1A
110	2	M1 AVM 1A	4	YILDIRIM BEYAZIT CD. 4B
111	3	DSİ TOKİ 1A	7	ESKİ VİLAYET
112	4	YILDIRIM BEYAZIT CD. 4B	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
114	5	OPTİMUM AVM 1A	2	M1 AVM 1A
115	5	OPTİMUM AVM 1A	19	83061 SK. 1B
116	6	Ş.MÜCAHİT TOPAL CD. 1B	1	ATÜ 1A
118	7	ESKİ VİLAYET	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
121	2	M1 AVM 1A	1	ATÜ 1A
122	8	ŞHT. JND. ER GÖKHAN YILMAZ CD. 2A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
123	8	ŞHT. JND. ER GÖKHAN YILMAZ CD. 2A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
124	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)	2	M1 AVM 1A
125	10	BARIŞ BLV 1A	20	3598 SK. 1B
126	11	MODERN SANAYİ SİTESİ 1A	8	ŞHT. JND. ER GÖKHAN YILMAZ CD. 2A
127	12	İNCİRLİK 179 SK. 1A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)

132	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)	13	BAHÇELİEVLER CD. 13B
133	13	BAHÇELİEVLER CD. 13B	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
135	10	BARIŞ BLV 1A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
142	7	ESKİ VİLAYET	2	M1 AVM 1A
144	2	M1 AVM 1A	1	ATÜ 1A
151	1	ATÜ 1A	2	M1 AVM 1A
154	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)	21	YEŞİLOBA TOKİ 3B
155	14	H.ÖMER SABANCI BLV. 1A	1	ATÜ 1A
156	2	M1 AVM 1A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
157	2	M1 AVM 1A	7	ESKİ VİLAYET
159	15	OBALAR CD. 18A	19	83061 SK. 1B
160	16	76034 SK. 1A	1	ATÜ 1A
161	2	M1 AVM 1A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
174	17	MERKEZ OTOGAR 1A	8	ŞHT. JND. ER GÖKHAN YILMAZ CD. 2A

The candidate charging station points of the bus lines in the dataset were connected to suitable substations, taking into account the existing electrical infrastructure in the region. A total of 7 substations were identified in the first dataset, which focused on the city center. Table 3.5 presents data defining the substation ID and its names within the Adana distribution network. The identities are not official, they were created for this dissertation.

Table 3.5. Substation information of the DS1.

Substation ID	Substation Name
1	Seyhan 154kV TM

2	Seyhan 66kV TM
3	Doğu Adana TM
4	Yeni Şehitlik
5	Kuzey Adana TM
6	Yüreğir TM
7	Mihmandar TM

Each candidate charging station points were matched with the most suitable and closest substations. The locations of the substations and the candidate points for the charging station are clearly shown in Figure 3.8.

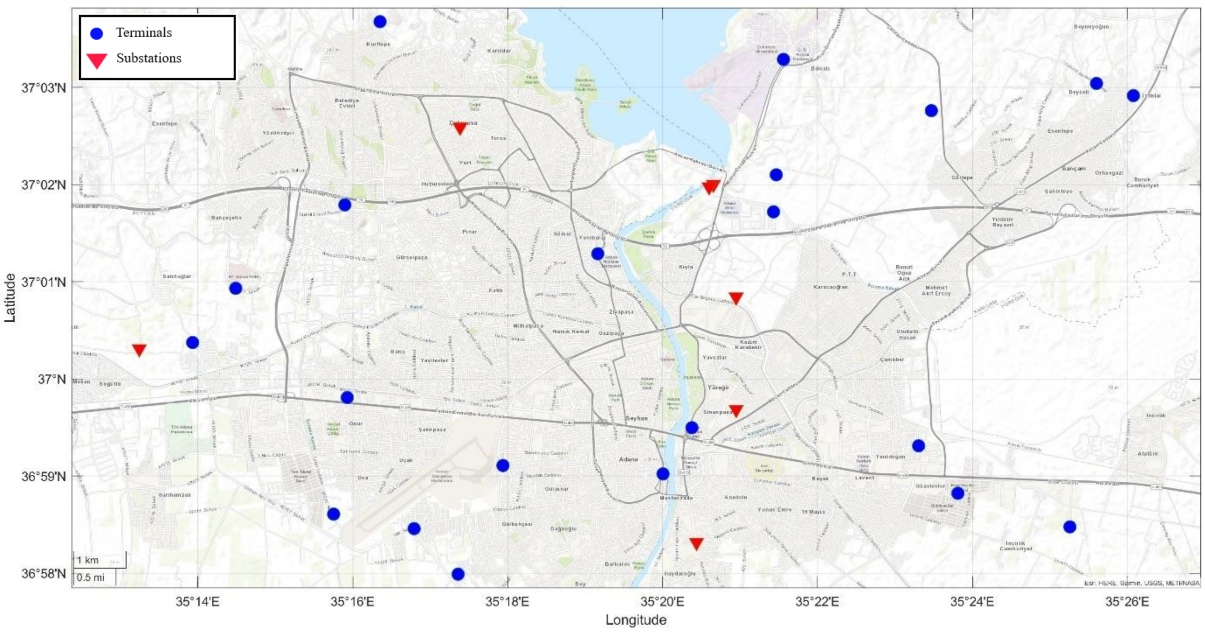

Figure 3.8. Locations of terminal and substations for DS1

3.6.2. Dataset 2

The second dataset, known as DS2, also contains information about bus lines serving lower-density residential areas surrounding Adana's city center. The dataset was created to address the challenges faced in public transport planning for regions outside the city center.

The bus lines included in this dataset cover longer distances and operate at infrequent intervals. Each route is uniquely identified by its line number, while the line length represents the total distance traveled by buses throughout the day. This dataset comprises 30 bus lines and 142 buses. 92 terminal points defined in the dataset, 42 of which correspond to different locations. The departure times indicate service patterns in areas with low transportation density. The number of buses operating on each line and the departure intervals highlight the low demand for transportation in these locations. Typically, the route durations are longer than those in the city center. The number of round trips made by the buses is crucial for planning the charging infrastructure.

The dataset enables the analysis of how energy requirements vary for rural bus lines. Potential locations for charging stations were assessed based on the starting and ending points of the bus routes, many of which are located outside the city or in semi-rural areas. DS2 emphasizes the need for customized strategies to integrate electric buses into the city's peripheral areas. In this regard, the dataset serves a complementary role in the large-scale planning of charging infrastructure. Detailed information about the bus lines is given in the Table 3.6.

Table 3.6. Bus line information of the DS2.

Route ID	Departure Terminal ID	Arrival Terminal ID	Number Of Buses	Route Length (km)	Running Time (min)	Time Headway (min)	First Bus	Last Bus
105	9	18	7	6	3,85	3,85	10	10
106	1	1	19	2	3,1	3,1	8	15
110	2	4	3	8	27,7	27,7	67	30
111	3	7	3	4	13,7	13,7	33	60
112	4	9	2	5	31,5	31,5	76	60
113	22	33	4	3	25,5	25,5	62	60
114	5	2	4	16	22,6	22,6	55	12
115	5	19	5	2	20,1	20,1	49	75
116	6	1	2	5	27,4	27,4	66	60
117	7	34	3	2	22,2	22,2	54	150

118	7	9	3	4	34,5	34,5	83	60
119	7	35	3	4	34,2	34,2	83	70
120	7	36	3	2	57,9	57,9	139	150
121	2	1	3	5	36,3	36,3	88	48
122	8	9	4	3	25,3	25,3	61	60
123	8	9	4	3	25,7	25,7	62	60
124	9	2	3	8	30	30	72	30
125	10	20	4	6	19,8	19,8	48	30
126	11	8	3	4	24,7	24,7	60	60
127	12	9	4	2	21,6	21,6	52	90
130	23	9	4	3	28,1	28,1	68	60
131	24	9	4	3	25,3	25,3	61	60
132	9	13	4	3	20,5	20,5	50	60
133	13	9	5	2	21,3	21,3	52	80
135	10	9	3	4	20,6	20,6	50	60
140	2	33	5	6	35	35	84	40
142	7	2	4	8	24,6	24,6	60	30
144	2	1	3	6	34,4	34,4	83	40
151	1	2	4	2	28,4	28,4	69	90
153	26	9	2	6	36,3	36,3	88	50
154	9	21	4	6	22,4	22,4	54	30
155	14	1	4	6	23,9	23,9	58	40
156	2	9	6	2	18,6	18,6	45	70
157	2	7	5	2	23,9	23,9	58	80
158	27	2	3	5	36,2	36,2	87	48
159	15	19	4	3	21,1	21,1	51	60
160	16	1	5	3	31,2	31,2	75	70
161	2	9	2	5	30,1	30,1	73	60
162	28	37	2	4	35	35	84	80

164	14	38	3	4	30,2	30,2	73	60
165	29	39	2	4	32,4	32,4	78	90
166	6	40	3	4	23,3	23,3	56	60
174	17	8	5	2	18,6	18,6	45	90
185	30	41	3	2	19,2	19,2	47	150
303	31	42	5	6	9,3	9,3	23	30
304	32	26	4	3	13,1	13,1	32	60

Table 3.7 provides information about the departure and arrival points of specific bus lines in the Adana urban transportation network. Each row in the table corresponds to a different bus line, detailing the names and identification numbers of both the departure and arrival terminals associated with that line.

Table 3.7. Terminal information of the DS2.

Route ID	Departure ID	Departure Name	Destination ID	Destination Name
105	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)	18	YURTLAR ÖNÜ 1A
106	1	ATÜ 1A	1	ATÜ 1A
110	2	M1 AVM 1A	4	YILDIRIM BEYAZIT CD. 4B
111	3	DSİ TOKİ 1A	7	ESKİ VİLAYET
112	4	YILDIRIM BEYAZIT CD. 4B	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
113	22	HASAN TUĞAL CD. 6A	33	1812 SK. 1A
114	5	OPTİMUM AVM 1A	2	M1 AVM 1A
115	5	OPTİMUM AVM 1A	19	83061 SK. 1B
116	6	Ş.MÜCAHİT TOPAL CD. 1B	1	ATÜ 1A
117	7	ESKİ VİLAYET	34	KIZILKAŞ MAH. 4A
118	7	ESKİ VİLAYET	11	MODERN SANAYİ SİTESİ 1A

119	7	ESKİ VİLAYET	35	YENİYAYLA MAH. 1A
120	7	ESKİ VİLAYET	36	ÜNLÜCE MAH. 1A
121	2	M1 AVM 1A	1	ATÜ 1A
122	8	ŞHT. JND. ER GÖKHAN YILMAZ CD. 2A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
123	8	ŞHT. JND. ER GÖKHAN YILMAZ CD. 2A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
124	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)	2	M1 AVM 1A
125	10	BARIŞ BLV 1A	20	3598 SK. 1B
126	11	MODERN SANAYİ SİTESİ 1A	8	ŞHT. JND. ER GÖKHAN YILMAZ CD. 2A
127	12	İNCİRLİK 179 SK. 1A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
130	23	ATATÜRK CD 6B	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
131	24	ŞIH CEMİL CD. 1A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
132	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)	13	BAHÇELİEVLER CD. 13B
133	13	BAHÇELİEVLER CD. 13B	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
135	25	AHMET GÜVEN KAYPAK BLV 1B	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
140	2	M1 AVM 1A	33	1812 SK. 1A
142	7	ESKİ VİLAYET	2	M1 AVM 1A
144	2	M1 AVM 1A	1	ATÜ 1A
151	1	ATÜ 1A	2	M1 AVM 1A
153	26	ŞAMBAYADI	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)

154	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)	21	YEŞİLOBA TOKİ 3B
155	14	H.ÖMER SABANCI BLV. 1A	1	ATÜ 1A
156	2	M1 AVM 1A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
157	2	M1 AVM 1A	7	ESKİ VİLAYET
158	27	2023 SK. 1A	2	M1 AVM 1A
159	15	OBALAR CD. 18A	19	83061 SK. 1B
160	16	76034 SK. 1A	1	ATÜ 1A
161	2	M1 AVM 1A	9	DR.M.ÖZSAN BULVARI 10. DURAK (BALCALI HASTANESİ)
162	28	VEFA CD. 9B	37	ÇINARLI MAH. 1A
164	14	H.ÖMER SABANCI BLV. 1A	38	GÖKÇELER MAH. 2A
165	29	M.AKİF ERSOY MAH. 14A	39	YOLGEÇEN MAH. 1A
166	6	Ş.MÜCAHİT TOPAL CD. 1B	40	SARIHUĞLAR MAH. 1A
174	17	MERKEZ OTOGAR 1A	8	ŞHT. JND. ER GÖKHAN YILMAZ CD. 2A
185	30	T.CEMAL BERİKER BLV. 2A	41	YENİ MAH. 2A
303	31	YEŞİL VADİ KONUTLARI 2A	42	T.ÖZAL BULVARI 18. DURAK (RUH SAĞLIĞI)
304	32	T.ÖZAL BLV. 15A	26	ŞAMBAYADI

The candidate charging station points of the bus lines in the dataset were connected to appropriate substations, considering the current electrical infrastructure in the region.A total of 16 substations were identified in the dataset, which focused on the city center and rural areas. Table 3.8 displays data that defines the substation ID and names within the Adana distribution network. Please note that the identities are not official; they have been created specifically for this dissertation.

Table 3.8. Substation information of the DS2.

Substation ID	Substation Name
1	Adana TM
2	Cihadiye TM
3	Karahan TM
4	Zeytinli TM
5	Seyhan 154kV TM
6	Seyhan 66kV TM
7	Doğu Adana TM
8	Yeni Şehitlik
9	Kuzey Adana TM
10	İncirlik TM
11	İncirlik Havaalanı TM
12	Adana Çimento TM
13	Yüreğir TM
14	Mihmandar TM
15	Güney Adana TM
16	Misis TM

Each candidate charging station point was matched with the most appropriate and nearest substation. The locations of the substations and the candidate points for the charging stations are shown in Figure 3.9.

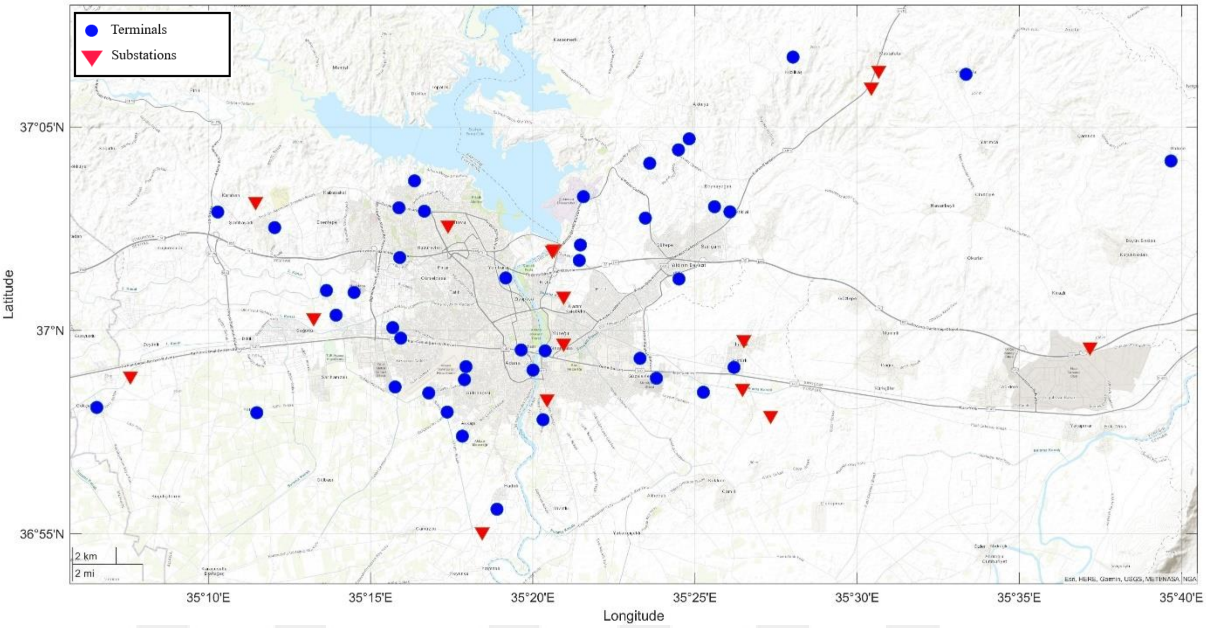

Figure 3.9. Locations of terminal and substations for DS2

4. RESULTS AND DISCUSSIONS

This section presents the experimental results obtained from the proposed model, employing the binary variants of AOA, GWO, WaOA, and WOA. The performance of these methods is evaluated on two datasets, DS1 and DS2. Each algorithm is executed independently for both datasets, performing 10 runs with 20 search agents across 100 iterations.

All experiments are conducted on a PC equipped with 8 GB of RAM, an Intel i5-3.0 GHz CPU, and Windows 11 Pro operating system. Detailed information about the algorithm parameters is presented in Table 4.1.

Table 4.1. Parameters for the algorithms

Parameters	Value
Common parameter values for all methods	
Number of search individuals	20
Number of iterations	100
the number of runs	10
Weights for DS1	
$w1$	0.349688425
$w2$	0.407261975
$w3$	0.418006037
$w4$	0.412866264
Weights for DS2	
$w1$	0.40263079
$w2$	0.442311171
$w3$	0.443308241
$w4$	0.321939565
Parameters for BAOA	
K	5

B	0.5
MOA_{max}	0.9
MOA_{min}	0.1
Parameters for BGWO	
A	Coefficient decreases linearly from 2 to 0
Parameters for BWaOA	
P (proportion of females)	0.4
Parameters for BWOA	
b	1

Some experimental parameters and real-world values used in this study are gathered from previous studies and presented in Table 4.2.

Table 4.2. Parameters for the experimental tests

Parameters	Values
Discount rate (r_0)	5 % (Vepsalainen et al., 2018)
Operating lifespan of the charging station (γ)	20 years (Lajunen, 2018)
The charging facility unit price	777000 $ (Barraza & Estrada, 2021)
The transformer unit price	40000 $ (Meishner & Uwe Sauer, 2020)
Charging station construction expense	63400 $ (Chen et al., 2018)
Assumed scaling factor	0.5 % (X. Zhang et al., 2021)
Electricity price for charging	0.9822 $/kWh (X. Zhang et al., 2021)

4.1. The Results of DS1

Table 4.3 presents the average, minimum, maximum, and standard deviation of fitness values. BWaOA showed the most remarkable result for DS1. It yielded the same result in all trials (minimum, maximum, and average), indicating that the algorithm is highly stable. Additionally, the fact that its standard deviation is zero means that the algorithm exhibits no variation. This may indicate that it is very stable. BWaOA also showed the lowest mean value, meaning that it achieved the best performance. BAOA, BWOA, and BGWO have higher mean and standard deviation values, indicating that they tried wider solution ranges but showed instability.

Table 4.3. The numerical results of fitness values of DS1.

Method	Avg.	Min.	Max.	StdDev.
BAOA	1,932,654.654	**1,464,624.234**	5,539,669.823	1,281,566.850
BGWO	1,989,999.697	**1,464,624.234**	6,718,378.859	1,661,383.088
BWaOA	**1,464,624.234**	**1,464,624.234**	**1,464,624.234**	**0**
BWOA	1,931,109.249	**1,464,624.234**	6,129,474.383	1,475,155.141

Figs. 4.1 show the average convergence rates on DS1. The figure indicates that the "BWaOA" algorithm demonstrates the best convergence performance for the DS1. It achieves a superior solution compared to the other algorithms by reaching the lowest final fitness value. In contrast, the other algorithms (BAOA, BGWO, and BWOA) perform similarly, stabilizing at a fitness value of approximately 2 x 10^6.

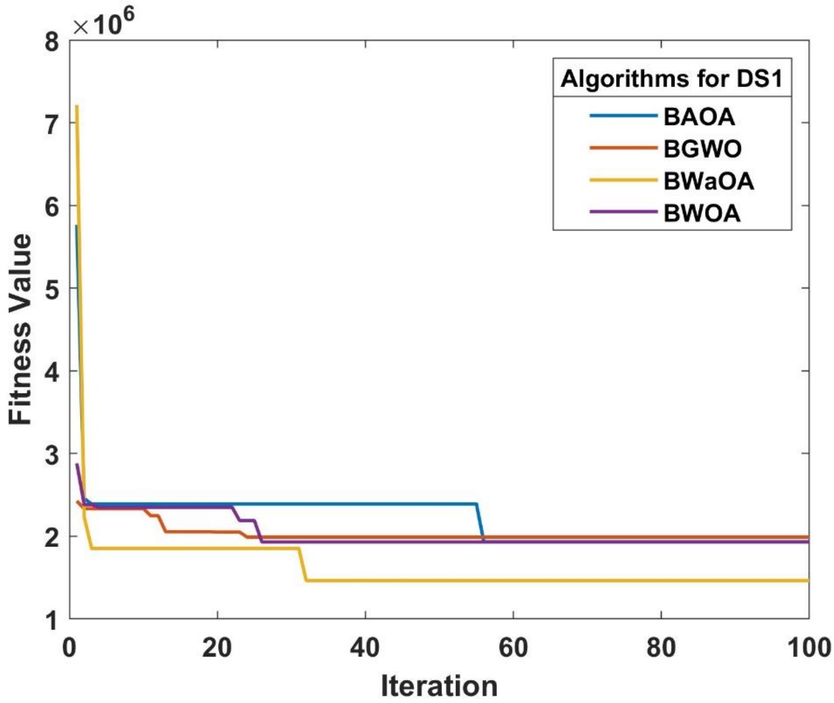

Figure 4.1 Convergence curves of DS1

Table 4.4 presents the average execution times of four different metaheuristic algorithms running on the DS1 dataset, along with the minimum, maximum, and standard deviation values of these times. Upon examination of the results, the BAOA algorithm has the highest average execution time (16.128 seconds) and also produces the longest maximum execution time (17.365 seconds). It shows that BAOA works more slowly compared to the other methods. BGWO exhibits the shortest average execution time, at 15.937 seconds, and also reveals the consistency of the results with the lowest standard deviation value (0.276). It indicates that the BGWO algorithm works both fast and stably. BWaOA is very close to BGWO in terms of average execution time and stands out as the second-fastest method, with 15.723 seconds. Its standard deviation is 0.439, and although not as much as BGWO, it provides relatively stable results. The BWOA algorithm is the fastest method, with a runtime of 15.553 seconds, but it has the highest standard deviation value of 0.734. It indicates that BWOA exhibits more variable performance over time.

Table 4.4. The numerical results of execution times of DS1.

Method	Avg.	Min.	Max.	StdDev.
BAOA	16,128	15,469	17,365	0.522
BGWO	15,937	15,413	16,232	**0.276**
BWaOA	15,723	14,813	16,213	0.439
BWOA	**15,553**	**14,115**	**16,178**	0.734

Fig. 4.2 shows the charging stations, other terminals connected to this station, and selected substations determined for the Adana urban transportation system. In the figures, green-colored icons indicate the selected charging stations, blue-colored icons denote other charging stations connected to the selected station, and red-colored icons indicate the locations of the selected substations. Figure illustrates the charging stations and substations identified by the BWaOA algorithm, which yields the most cost-effective result for DS1, particularly for city center terminals. A total of 5 charging stations and 4 substations were selected for DS1.

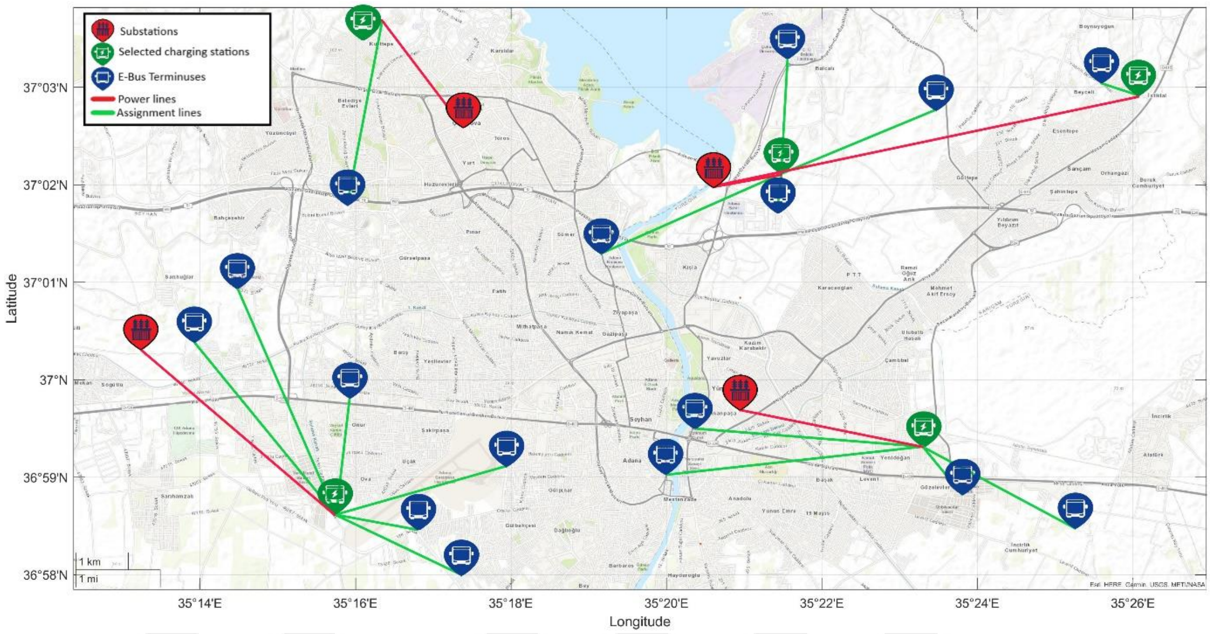

Figure 4.2. Selected charging stations and assigned substations of DS1 by BWaOA algorithm

Table 4.5 shows that the four examined algorithms achieve the same total cost for the DS1 dataset. It indicates that these algorithms either find the same optimal solution or are very close to it for the DS1 dataset. It suggests that the algorithms yield similar results regarding their convergence abilities, or that the complexity of the problem leads all of them to reach the same optimum.

Table 4.5. Costs of DS1.

Method	Total Cost	C1	C2	C3	C4
BAOA	3,742,610.464	1,268,000	1,226,759.208	1,247,379.604	471.651
BGWO	3,742,610.464	1,268,000	1,226,759.208	1,247,379.604	471.651
BWaOA	3,742,610.464	1,268,000	1,226,759.208	1,247,379.604	471.651
BWOA	3,742,610.464	1,268,000	1,226,759.208	1,247,379.604	471.651

4.2. The Results of DS2

Table 4.6 presents the numerical results of the fitness values of four different algorithms for the DS2 dataset. Regarding average performance, BWaOA ranks as the best, followed by BGWO. BAOA and BWOA perform worse on average. Both BWaOA and BWOA were able to achieve the best possible fitness value for the DS2 dataset, indicating that these two algorithms have the potential to find optimal or nearly optimal solutions. BAOA and BGWO also obtained very close minimum values, suggesting that the global optimum of the problem is likely around this value.

Table 4.6. The numerical results of fitness values of DS2.

Method	Avg.	Min.	Max.	StdDev.
BAOA	125,709,264.199	89,683,261.022	246,998,901.817	59,983,640.547
BGWO	89,777,743.628	89,683,261.022	90,627,396.567	298,537.618
BWaOA	**89,683,341.972**	**89,683,225.103**	**89,683,707.174**	**156.900**
BWOA	125,922,042.728	**89,683,225.103**	286,531,329.809	76,753,473.866

Figs. 4.3 illustrates the performance of the four algorithms for the DS2 dataset. The BWaOA algorithm demonstrates superior performance compared to the other algorithms, achieving the fastest convergence, the lowest fitness values, and the highest consistency. BGWO ranks second in performance, whereas BAOA and BWOA appear to be less effective and reliable algorithms for this issue. This analysis strongly indicates that BWaOA is the most appropriate optimization algorithm for the DS2 dataset.

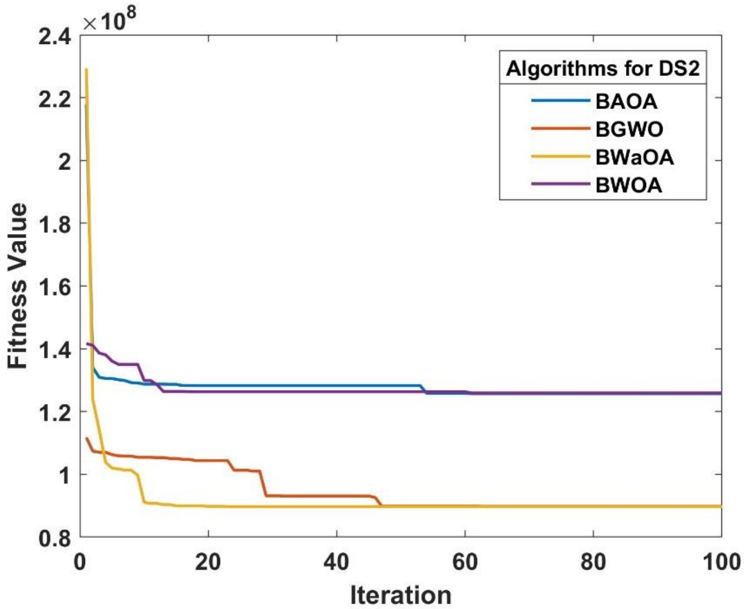

Figure 4.3 Convergence curves of DS2

Table 4.7 presents the execution times of the algorithm for the DS2 dataset. These times reflect the computational duration needed for the algorithms to reach a solution. Regarding average execution time, BAOA is the fastest algorithm. The other three algorithms closely follow, being slightly slower than BAOA. In terms of the quickest single execution time, BAOA leads, with BWaOA not far behind. This indicates that both algorithms can operate exceptionally fast in specific scenarios. BGWO provides the most consistent and swiftest execution time, even in worst-case situations. While BWOA might record the slowest single execution times, BGWO remains the most reliable algorithm overall. BWaOA ranks closely behind, whereas BAOA and BWOA exhibit less consistency.

Table 4.7. The numerical results of execution times of DS2.

Method	Avg.	Min.	Max.	StdDev.
BAOA	**28,012**	**27,264**	30,828	1.023
BGWO	28,781	28,382	**29,049**	**0.217**
BWaOA	28,822	27,280	29,608	0.620
BWOA	28,819	27,692	31,854	1.130

Fig. 4.4 illustrates the charging stations, other terminals connected to this station, and the selected substations determined for the Adana urban transportation system. In the figure, green icons represent the selected charging stations, blue icons denote other e bus terminuses connected to the selected station, and red icons indicate the locations of the selected substations. The figure illustrates the charging stations and transformer substations identified by the BWaOA algorithm, which yields the most cost-effective result for DS2, particularly for terminals in rural areas, as well as in the city center. A total of 12 charging stations and 10 substations were chosen for DS2.

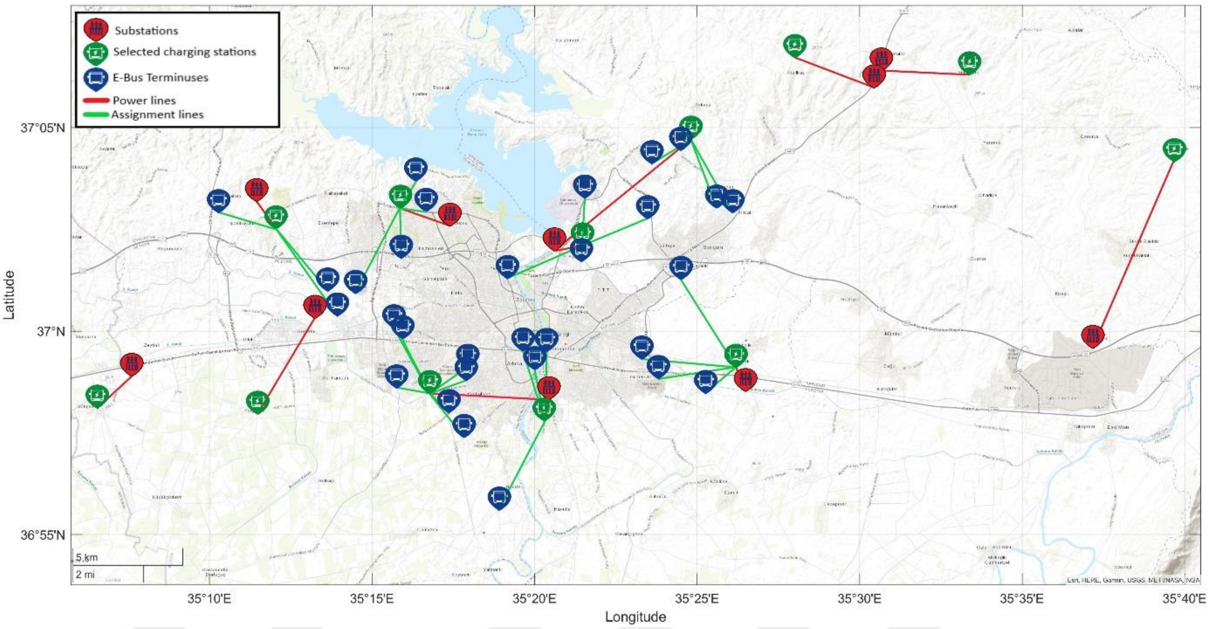

Figure 4.4. Selected charging stations and assigned substations of DS2 by BWaOA algorithm

Table 4.8 shows that the four examined algorithms achieve the same total cost for the DS2 dataset. The table indicates that the BWaOA and BWOA algorithms achieve lower total costs than BAOA and BGWO for the DS2 dataset. This cost difference is due to the algorithms' ability to optimize the C4 cost component. When evaluated in conjunction with the previous fitness value and execution time analyses, this table reinforces that BWaOA is the most consistent and effective algorithm for the DS2 problem in terms of both fitness and cost efficiency. BWOA, however, is inconsistent in terms of fitness, but in its best cases, it was able to approach BWaOA in terms of cost efficiency.

Table 4.8. Costs of DS2.

Method	Total Cost	C1	C2	C3	C4
BAOA	202,881,740.291	3,043,200	132,209,786.458	67,626,493.229	2,260.604
BGWO	202,881,740.291	3,043,200	132,209,786.458	67,626,493.229	2,260.604
BWaOA	**202,881,628.721**	3,043,200	132,209,786.458	67,626,493.229	**2,149.034**
BWOA	**202,881,628.721**	3,043,200	132,209,786.458	67,626,493.229	**2,149.034**

5. CONCLUSIONS

This dissertation aimed to develop a comprehensive and practical approach for identifying optimal locations for electric bus charging stations within an urban transportation system. By incorporating both transportation network requirements and electrical grid constraints, the research addressed a significant gap in the literature where previous studies often considered these two domains separately. A custom multi-criteria fitness function was formulated to evaluate candidate locations based on factors such as route coverage, detour minimization for charging, energy efficiency, and compatibility with nearby transformer substations. The problem was modeled as a binary constrained optimization task and solved using four nature-inspired metaheuristic algorithms: Binary Arithmetic Optimization Algorithm (BAOA), Binary Grey Wolf Optimizer (BGWO), Binary Whale Optimization Algorithm (BWOA), and Binary Walrus Optimization Algorithm (BWaOA). Extensive experiments were conducted on two distinct datasets (DS1 and DS2) that represent different urban configurations, enabling a robust performance comparison of the algorithms under varying complexity levels.

The simulation results demonstrated that the proposed framework successfully identifies charging station locations that ensure both operational efficiency and electrical feasibility. Among the tested algorithms, BWaOA exhibited superior performance in terms of convergence speed and average fitness value, especially in more complex datasets (DS1 and DS2). BGWO provided the most stable and robust results across all datasets, as indicated by its low standard deviation. BAOA and BWOA showed moderate performance, with strengths in specific configurations but with slightly higher computational times. The study confirmed that integrating transformer substation locations as hard constraints significantly enhances the realism and applicability of the model. The visualized station selection outcomes align with high-demand needs while ensuring that the electrical infrastructure can support the load. Additionally, the methodology offers flexibility for scenario-based planning, allowing urban planners to simulate future demand changes or infrastructure developments.

In summary, this dissertation contributes to the fields of intelligent transportation and energy-aware infrastructure planning by presenting a scalable, data-driven, and algorithmically robust approach to siting electric bus charging stations. The integration of grid parameters into the location optimization model fills a critical gap in both transportation and power systems literature. The proposed methodology can guide municipalities and decision-makers in making informed investment and planning decisions. Furthermore, the developed datasets and modeling framework provide a foundation for future research in dynamic scheduling, real-time demand prediction, and integration of renewable energy sources or vehicle-to-grid (V2G) systems. Furthermore, this thesis supports the broader goals of reducing urban emissions, enhancing energy resilience, and promoting sustainable, intelligent city systems.

Future studies may explore hybrid metaheuristic techniques, adaptive learning-based optimization, or multimodal transportation planning to enhance model performance and applicability further. One promising direction is the integration of dynamic demand modeling and real-time route variability. In practice, electric bus usage and charging demand can fluctuate significantly based on the time of day, weather conditions, or special events. Incorporating temporal variables and predictive analytics could allow for dynamic charging strategies and adaptive infrastructure deployment. Additionally, future models could consider mixed charging scenarios, including both fast-charging and overnight depot charging, with variable costs and energy profiles.

Another potential avenue is the inclusion of renewable energy sources and V2G capabilities in the optimization process. By co-optimizing charging stations with local solar PV or wind generation systems, municipalities can reduce reliance on the central grid and improve energy resilience. Moreover, V2G integration enables electric buses to function as mobile energy storage units, thereby contributing to grid stability during peak hours or in emergency situations. Incorporating these energy interactions into the fitness function and constraint structure would enrich the model and align it with next-generation smart grid paradigms.

REFERENCES

Abualigah, L., Diabat, A., Mirjalili, S., Abd Elaziz, M., & Gandomi, A. H. (2021). The Arithmetic Optimization Algorithm. *Computer Methods in Applied Mechanics and Engineering*, *376*, 113609. https://doi.org/10.1016/j.cma.2020.113609

Acharige, S. S. G., Haque, M. E., Arif, M. T., Hosseinzadeh, N., Hasan, K. N., Hossain, M. J., & Muttaqi, K. M. (2025). Grid integration of electric vehicles - Impact assessment and remedial measures. *Journal of Power Sources*, *650*, 236697. https://doi.org/10.1016/j.jpowsour.2025.236697

Adana Metropolitan Municipality Transportation Department. (2022). *Transportation*. https://ulasimbilgi.adana.bel.tr/Otobusler

Ala, A., Deveci, M., Bani, E. A., & Sadeghi, A. H. (2024). Dynamic capacitated facility location problem in mobile renewable energy charging stations under sustainability consideration. *Sustainable Computing: Informatics and Systems*, *41*, 100954. https://doi.org/10.1016/j.suscom.2023.100954

Alabi, T. M., Lu, L., & Yang, Z. (2022). Data-driven optimal scheduling of multi-energy system virtual power plant (MEVPP) incorporating carbon capture system (CCS), electric vehicle flexibility, and clean energy marketer (CEM) strategy. *Applied Energy*, *314*, 118997. https://doi.org/10.1016/j.apenergy.2022.118997

Alhussan, A. A., Khafaga, D. S., El-kenawy, E.-S. M., Eid, M. M., & Ibrahim, A. (2024). Urban Electric Vehicle Charging Station Placement Optimization with Graylag Goose Optimization Voting Classifier. *Computers, Materials & Continua*, *80*(1), 1163–1177. https://doi.org/10.32604/cmc.2024.049001

Antarasee, P., Premrudeepreechacharn, S., Siritaratiwat, A., & Khunkitti, S. (2022). Optimal Design of Electric Vehicle Fast-Charging Station's Structure Using Metaheuristic Algorithms. *Sustainability*, *15*(1), 771. https://doi.org/10.3390/su15010771

Azad, Md. A. K., Rocha, A. M. A. C., & Fernandes, E. M. G. P. (2014). Improved binary artificial fish swarm algorithm for the 0–1 multidimensional knapsack problems. *Swarm and Evolutionary Computation*, *14*, 66–75. https://doi.org/10.1016/j.swevo.2013.09.002

Baghel, M., Agrawal, S., & Silakari, S. (2012). Survey of Metaheuristic Algorithms for Combinatorial Optimization. *International Journal of Computer Applications*, *58*(19), 21–31. https://doi.org/10.5120/9391-3813

Barraza, O., & Estrada, M. (2021). Battery Electric Bus Network: Efficient Design and Cost Comparison of Different Powertrains. *Sustainability*, *13*(9), 4745. https://doi.org/10.3390/su13094745

Can, C., Kilic, F., & Kaya, Y. (2025). A Novel Approach for Location Planning of Fast-Charging Stations for E-Buses. *International Journal of Simulation Modelling*, *24*(2), 213–224. https://doi.org/10.2507/IJSIMM24-2-714

Çelik, S., & Ok, Ş. (2024). Electric vehicle charging stations: Model, algorithm, simulation, location, and capacity planning. *Heliyon*, *10*(7), e29153. https://doi.org/10.1016/j.heliyon.2024.e29153

Chandra, I., Singh, N. K., Samuel, P., Bajaj, M., Singh, A. R., & Zaitsev, I. (2025). Optimal scheduling of solar powered EV charging stations in a radial distribution system using opposition-based competitive swarm optimization. *Scientific Reports*, *15*(1), 4880. https://doi.org/10.1038/s41598-025-88758-y

Chen, Z., Yin, Y., & Song, Z. (2018). A cost-competitiveness analysis of charging infrastructure for electric bus operations. *Transportation Research Part C: Emerging Technologies*, *93*, 351–366. https://doi.org/10.1016/j.trc.2018.06.006

de Vos, M. H., van Lieshout, R. N., & Dollevoet, T. (2024). Electric Vehicle Scheduling in Public Transit with Capacitated Charging Stations. *Transportation Science*, *58*(2), 279–294. https://doi.org/10.1287/trsc.2022.0253

Deb, S., & Gao, X.-Z. (2022). Prediction of Charging Demand of Electric City Buses of Helsinki, Finland by Random Forest. *Energies*, *15*(10), 3679. https://doi.org/10.3390/en15103679

Deb, S., Kalita, K., & Mahanta, P. (2017). Review of impact of electric vehicle charging station on the power grid. *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy)*, 1–6. https://doi.org/10.1109/TAPENERGY.2017.8397215

Deniz, R., & Aydin, N. (2024). Sustainable and smart electric bus charging station deployment via hybrid spherical fuzzy BWM and MULTIMOORA framework. *Neural Computing and Applications*, *36*(25), 15685–15703. https://doi.org/10.1007/s00521-024-09788-7

Dimitriadou, A., Gkiotsalitis, K., Liu, T., & Cats, O. (2025). An exact optimization model for the electric bus charging station location problem under inter-station travel time and energy consumption uncertainties. *Transportation Research Part C: Emerging Technologies*, *178*, 105182. https://doi.org/10.1016/j.trc.2025.105182

Dwivedi, A., Yu, X., & Sokolowski, P. (2010). Analyzing power network vulnerability with maximum flow based centrality approach. *2010 8th IEEE International Conference on Industrial Informatics*, 336–341. https://doi.org/10.1109/INDIN.2010.5549398

Emary, E., Zawbaa, H. M., & Hassanien, A. E. (2016a). Binary grey wolf optimization approaches for feature selection. *Neurocomputing*, *172*, 371–381. https://doi.org/10.1016/j.neucom.2015.06.083

Emary, E., Zawbaa, H. M., & Hassanien, A. E. (2016b). Binary grey wolf optimization approaches for feature selection. *Neurocomputing*, *172*, 371–381. https://doi.org/https://doi.org/10.1016/j.neucom.2015.06.083

García-Martínez, C., Gutiérrez, P. D., Molina, D., Lozano, M., & Herrera, F. (2017). Since CEC 2005 competition on real-parameter optimisation: a decade of research, progress and comparative analysis's weakness. *Soft Computing*, *21*(19), 5573–5583. https://doi.org/10.1007/s00500-016-2471-9

Ghanaei, N., Samiei Moghaddam, M., Alibeaki, E., Salehi, N., & Davarzani, R. (2025). Bi-level stochastic optimization model of smart distribution grids considering the transmission network to reduce vulnerability. *Energy Systems*, *16*(2), 851–884. https://doi.org/10.1007/s12667-023-00628-6

Global EV Outlook. (2024). *International Energy Agency*. https://www.iea.org/reports/global-ev-outlook-2024/

Han, M., Du, Z., Yuen, K. F., Zhu, H., Li, Y., & Yuan, Q. (2024). Walrus optimizer: A novel nature-inspired metaheuristic algorithm. *Expert Systems with Applications*, *239*, 122413. https://doi.org/10.1016/j.eswa.2023.122413

Hemavathi, S., & Shinisha, A. (2022). A study on trends and developments in electric vehicle charging technologies. *Journal of Energy Storage*, *52*, 105013. https://doi.org/10.1016/j.est.2022.105013

Hendriks, J. N., & Sturmberg, Björn. C. P. (2024). An integrated model of electric bus energy consumption and optimised depot charging. *Npj Sustainable Mobility and Transport*, *1*(1), 10. https://doi.org/10.1038/s44333-024-00008-2

Hu, H., Du, B., Liu, W., & Perez, P. (2022). A joint optimisation model for charger locating and electric bus charging scheduling considering opportunity fast charging and uncertainties. *Transportation Research Part C: Emerging Technologies*, *141*, 103732. https://doi.org/10.1016/j.trc.2022.103732

Hussien, A. G., Hassanien, A. E., Houssein, E. H., Amin, M., & Azar, A. T. (2020). New binary whale optimization algorithm for discrete optimization problems. *Engineering Optimization*, *52*(6), 945–959. https://doi.org/10.1080/0305215X.2019.1624740

Jiang, M., Zhang, Y., & Zhang, Y. (2021). Multi-Depot Electric Bus Scheduling Considering Operational Constraint and Partial Charging: A Case Study in Shenzhen, China. *Sustainability*, *14*(1), 255. https://doi.org/10.3390/su14010255

Khaligh, A., & Dusmez, S. (2012). Comprehensive Topological Analysis of Conductive and Inductive Charging Solutions for Plug-In Electric Vehicles. *IEEE Transactions on Vehicular Technology*, *61*(8), 3475–3489. https://doi.org/10.1109/TVT.2012.2213104

Kocatepe, C., KEKEZOĞLU, B., BOZKURT, A., YUMURTACI, R., ARIKAN, O., BAYSAL, M., AKKAYA, Y., & İNAN, A. (2013). Survey of power quality in Turkish national transmission network. *TURKISH JOURNAL OF ELECTRICAL ENGINEERING & COMPUTER SCIENCES*, *21*, 1880–1892. https://doi.org/10.3906/elk-1201-21

Kung, L.-C., & Liao, W.-H. (2018). An approximation algorithm for a competitive facility location problem with network effects. *European Journal of Operational Research*, *267*(1), 176–186. https://doi.org/10.1016/j.ejor.2017.11.037

Kunith, A., Goehlich, D., & Mendelevitch, R. (2014). Planning and optimization of a fast-charging infrastructure for electric urban bus systems. *Proceedings of the 2nd International Conference on Traffic and Transport Engineering*, *27*, 43–49.

Lajunen, A. (2018). Lifecycle costs and charging requirements of electric buses with different charging methods. *Journal of Cleaner Production*, *172*, 56–67. https://doi.org/10.1016/j.jclepro.2017.10.066

Liang, Y., Fei, X., Li, J., He, X., & Gu, H. (2022). Location of Electric Vehicle Charging Piles Based on Set Coverage Model. *World Electric Vehicle Journal*, *13*(5), 77. https://doi.org/10.3390/wevj13050077

Lim, K. L., Speidel, S., & Bräunl, T. (2022). A comparative study of AC and DC public electric vehicle charging station usage in Western Australia. *Renewable and Sustainable Energy Transition*, *2*, 100021. https://doi.org/10.1016/j.rset.2022.100021

Lin, Y., Zhang, K., Shen, Z.-J. M., & Miao, L. (2019). Charging Network Planning for Electric Bus Cities: A Case Study of Shenzhen, China. *Sustainability*, *11*(17), 4713. https://doi.org/10.3390/su11174713

Liu, X., Liu, X., Zhang, X., Zhou, Y., Chen, J., & Ma, X. (2023). Optimal location planning of electric bus charging stations with integrated photovoltaic and energy storage system.

Computer-Aided Civil and Infrastructure Engineering, *38*(11), 1424–1446. https://doi.org/10.1111/mice.12935

Madhavan, K. K., M S, R., & H L, S. (2025). Hybrid metaheuristic algorithm for optimal EV and PV placement in real-time networks. *Engineering Research Express*, *7*(2), 025363. https://doi.org/10.1088/2631-8695/addd61

McCabe, D., & Ban, X. (Jeff). (2023). Optimal locations and sizes of layover charging stations for electric buses. *Transportation Research Part C: Emerging Technologies*, *152*, 104157. https://doi.org/10.1016/j.trc.2023.104157

Meishner, F., & Uwe Sauer, D. (2020). Technical and economic comparison of different electric bus concepts based on actual demonstrations in European cities. *IET Electrical Systems in Transportation*, *10*(2), 144–153. https://doi.org/10.1049/iet-est.2019.0014

Mirjalili, S., & Lewis, A. (2016). The Whale Optimization Algorithm. *Advances in Engineering Software*, *95*, 51–67. https://doi.org/10.1016/j.advengsoft.2016.01.008

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey Wolf Optimizer. *Advances in Engineering Software*, *69*, 46–61. https://doi.org/https://doi.org/10.1016/j.advengsoft.2013.12.007

Nazari-Heris, M., Mirzaei, M. A., Asadi, S., Mohammadi-Ivatloo, B., Zare, K., & Jebelli, H. (2021). A hybrid robust-stochastic optimization framework for optimal energy management of electric vehicles parking lots. *Sustainable Energy Technologies and Assessments*, *47*, 101467. https://doi.org/10.1016/j.seta.2021.101467

Olsen, N., & Kliewer, N. (2022). Location Planning of Charging Stations for Electric Buses in Public Transport Considering Vehicle Scheduling: A Variable Neighborhood Search Based Approach. *Applied Sciences*, *12*(8), 3855. https://doi.org/https://doi.org/10.3390/app12083855

Orji, I. J. (2024). Adopting electric bus for improving efficiency in the local public transport sector: Analysis of facilitating conditions and their nonlinear relationships. *Transportation Research Part A: Policy and Practice*, *180*, 103967. https://doi.org/10.1016/j.tra.2024.103967

Ramingwong, S., Sampattagul, S., & Jintana, J. (2025). Economic Viability of Electric Bus Adoption for Public Transportation in Thailand: A Monte Carlo Simulation Approach. *Logistics*, *9*(2), 60. https://doi.org/10.3390/logistics9020060

Ray, G. C., Hufford, G. L., Overland, J. E., Krupnik, I., McCormick-Ray, J., Frey, K., & Labunski, E. (2016). Decadal Bering Sea seascape change: consequences for Pacific walruses and indigenous hunters. *Ecological Applications*, *26*(1), 24–41. https://doi.org/10.1890/15-0430

Rogge, M., Wollny, S., & Sauer, D. (2015). Fast Charging Battery Buses for the Electrification of Urban Public Transport—A Feasibility Study Focusing on Charging Infrastructure and Energy Storage Requirements. *Energies*, *8*(5), 4587–4606. https://doi.org/10.3390/en8054587

Saldanha-da-Gama, F. (2022). Facility Location in Logistics and Transportation: An enduring relationship. *Transportation Research Part E: Logistics and Transportation Review*, *166*, 102903. https://doi.org/10.1016/j.tre.2022.102903

Sarda, J., Patel, N., Patel, H., Vaghela, R., Brahma, B., Bhoi, A. K., & Barsocchi, P. (2024). A review of the electric vehicle charging technology, impact on grid integration, policy consequences, challenges and future trends. *Energy Reports*, *12*, 5671–5692. https://doi.org/10.1016/j.egyr.2024.11.047

Serra, D., & Marianov, V. (1998). The p-median problem in a changing network: the case of Barcelona. *Location Science*, *6*(1–4), 383–394. https://doi.org/10.1016/S0966-8349(98)00049-7

Shariatzadeh, M., Lopes, M. A. R., & Henggeler Antunes, C. (2025). Electric vehicle users' charging behavior: A review of influential factors, methods and modeling approaches. *Applied Energy*, *396*, 126167. https://doi.org/10.1016/j.apenergy.2025.126167

Srinivasa, K. G., Venugopal, K. R., & Patnaik, L. M. (2007). A self-adaptive migration model genetic algorithm for data mining applications. *Information Sciences*, *177*(20), 4295–4313. https://doi.org/10.1016/j.ins.2007.05.008

Tang, C., Xue, H., Ceder, A. (Avi), & Ge, Y.-E. (2024). Optimal variable vehicle scheduling strategy for a network of electric buses with fast opportunity charging. *Transportmetrica A: Transport Science*, *20*(3). https://doi.org/10.1080/23249935.2023.2182611

Tessler, M. E., & Traut, E. J. (2022). Hurricane resiliency methods for the New York City electric bus fleet. *Transportation Research Part D: Transport and Environment*, *105*, 103255. https://doi.org/10.1016/j.trd.2022.103255

Trojovský, P., & Dehghani, M. (2023). A new bio-inspired metaheuristic algorithm for solving optimization problems based on walruses behavior. *Scientific Reports*, *13*(1), 8775. https://doi.org/10.1038/s41598-023-35863-5

Unterluggauer, T., Rich, J., Andersen, P. B., & Hashemi, S. (2022). Electric vehicle charging infrastructure planning for integrated transportation and power distribution networks: A review. *ETransportation*, *12*, 100163. https://doi.org/10.1016/j.etran.2022.100163

Vansola, B., . M., & Shukla, R. N. (2022). Set cover model-based optimum location of electric vehicle charging stations. *Current Science*, *123*(12), 1448. https://doi.org/10.18520/cs/v123/i12/1448-1454

Veisi, M., Naderian, H., & Karimi, M. (2025). Optimal charging station placement of electric vehicles in the smart distribution network based on the mixed integer linear programming. *International Journal of Electrical Power & Energy Systems*, *168*, 110675. https://doi.org/10.1016/j.ijepes.2025.110675

Vepsalainen, J., Baldi, F., Lajunen, A., Kivekas, K., & Tammi, K. (2018). Cost-Benefit Analysis of Electric Bus Fleet with Various Operation Intervals. *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 1522–1527. https://doi.org/10.1109/ITSC.2018.8569583

Wang, X., Dong, X., Zhang, Z., & Wang, Y. (2024). Transportation carbon reduction technologies: A review of fundamentals, application, and performance. *Journal of Traffic and Transportation Engineering (English Edition)*, *11*(6), 1340–1377. https://doi.org/10.1016/j.jtte.2024.11.001

Wang, X., Yang, J., Teng, X., Xia, W., & Jensen, R. (2007). Feature selection based on rough sets and particle swarm optimization. *Pattern Recognition Letters*, *28*(4), 459–471. https://doi.org/10.1016/j.patrec.2006.09.003

Wu, X., Feng, Q., Bai, C., Lai, C. S., Jia, Y., & Lai, L. L. (2021). A novel fast-charging stations locational planning model for electric bus transit system. *Energy*, *224*, 120106. https://doi.org/10.1016/j.energy.2021.120106

Xu, M., Song, Q., Xi, M., & Zhou, Z. (2023). Binary arithmetic optimization algorithm for feature selection. *Soft Computing*, *27*(16), 11395–11429. https://doi.org/10.1007/s00500-023-08274-x

Xu, Y., Zhang, J., Wang, P., & Lu, M. (2021). Research on the Bi-Level Optimization Model of Distribution Network Based on Distributed Cooperative Control. *IEEE Access*, *9*, 11798–11810. https://doi.org/10.1109/ACCESS.2021.3051464

Xue, Z., Liu, W., Liu, C., & Chau, K. T. (2025). Critical Review of Wireless Charging Technologies for Electric Vehicles. *World Electric Vehicle Journal*, *16*(2), 65. https://doi.org/10.3390/wevj16020065

Yang, X.-S. (2010). *Nature-inspired metaheuristic algorithms.* Luniver press.

Yang, X.-S. (2013). *Metaheuristic Optimization: Nature-Inspired Algorithms and Applications* (pp. 405–420). https://doi.org/10.1007/978-3-642-29694-9_16

Yin, W., Liang, W., & Ji, J. (2024). Study on charge and discharge control strategy of improved PSO for EV. *Energy*, *304*, 132061. https://doi.org/10.1016/j.energy.2024.132061

Zeb, M. Z., Imran, K., Khattak, A., Janjua, A. K., Pal, A., Nadeem, M., Zhang, J., & Khan, S. (2020). Optimal Placement of Electric Vehicle Charging Stations in the Active Distribution Network. *IEEE Access*, *8*, 68124–68134. https://doi.org/10.1109/ACCESS.2020.2984127

Zhang, X., Nie, S., He, M., & Wang, J. (2021). Charging system analysis, energy consumption, and carbon dioxide emissions of battery electric buses in Beijing. *Case Studies in Thermal Engineering*, *26*, 101197. https://doi.org/10.1016/j.csite.2021.101197

Zhang, Y., Kamargianni, M., Cheng, L., De Vos, J., & Cao, M. (2024). Evaluating the accessibility of on-street household electric vehicle charging stations in London: Policy insights from equity analysis across emission zones. *Energy Policy*, *195*, 114375. https://doi.org/10.1016/j.enpol.2024.114375

Zhou, B., Wu, Y., Zhou, B., Wang, R., Ke, W., Zhang, S., & Hao, J. (2016). Real-world performance of battery electric buses and their life-cycle benefits with respect to energy consumption and carbon dioxide emissions. *Energy*, *96*, 603–613. https://doi.org/10.1016/j.energy.2015.12.041

Zhou, G., Dong, Q., Zhao, Y., Wang, H., Jian, L., & Jia, Y. (2023). Bilevel optimization approach to fast charging station planning in electrified transportation networks. *Applied Energy*, *350*, 121718. https://doi.org/10.1016/j.apenergy.2023.121718

Zhou, Y., Ong, G. P., & Meng, Q. (2023). The road to electrification: Bus fleet replacement strategies. *Applied Energy*, *337*, 120903. https://doi.org/10.1016/j.apenergy.2023.120903