



**Faculty of Engineering
Department of Electrical and Electronics Engineering**

EE 402 FINAL REPORT

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SMART CHARGING ALGORITHMS FOR ELECTRIC VEHICLES

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APPROVAL PAGE

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ABSTRACT

The increasing deployment of electric vehicles in urban and industrial environments has amplified the need for intelligent charging management systems that can dynamically allocate power based on real-time vehicle conditions. Traditional fixed-distribution methods fall short in addressing the complexity introduced by diverse SOC levels, battery capacities, and user-defined priority classes.

This study presents a modular, simulation-based EV charging management framework developed in MATLAB App Designer. The system enables dynamic power allocation among multiple vehicles by evaluating their SOC levels, VIP status, and maximum charging intake. It supports multiple charging stations—both AC (single-socket) and DC (dual-socket)—and automatically assigns vehicles to available sockets using a priority-based logic. The simulation engine adapts in real time to evolving conditions, determining whether immediate AC assignment or delayed DC assignment yields faster charging outcomes.

The framework incorporates additional algorithmic layers that allow for infrastructure planning. It can compute the optimal number of AC/DC stations needed to charge a given number of vehicles under cost and coverage constraints, or inversely, calculate the maximum number of vehicles that can be supported with a fixed number of stations and limited time. Furthermore, the system can simulate large-scale scenarios to identify the configuration that minimizes the overall charging duration.

Simulation results confirm that the proposed approach provides significant advantages over static strategies by improving both fairness and operational efficiency. The integrated graphical user interface enables parameter input, real-time monitoring, and visual tracking of SOC evolution. The design is scalable and flexible, allowing for future integration with renewable energy systems, multi-fleet coordination, and smart grid platforms.

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LIST OF SYMBOLS AND ABBREVIATIONS

AC Alternating Current

App Application Interface

DC Direct Current

EV Electric Vehicle

kWh Kilowatt-hour

kW Kilowatt

SOC State of Charge

VIP Vehicle Importance Priority

1 INTRODUCTION

The global rise in electric vehicle adoption has made the efficient management of charging infrastructure a critical challenge, particularly in urban environments. Conventional charging systems often rely on static energy allocation methods that fail to account for real-time variables such as State of Charge, battery capacity, or user priority levels [1], [2]. As a result, such systems suffer from low energy efficiency and create imbalances in access to charging services, especially in shared or public stations. This has led to an increasing demand for adaptive and intelligent charging algorithms capable of responding to dynamic scenarios [3].

This project presents a multi-layered simulation framework developed in MATLAB App Designer, which aims to address these challenges through the design and implementation of four key algorithmic structures. The system simulates complex real-time conditions where multiple vehicles interact with multiple AC and DC stations. Each vehicle is defined by parameters such as SOC, battery capacity, VIP priority level, and maximum allowable charging power. Using these inputs, the system dynamically evaluates socket availability, charging needs, and optimal allocation strategies [4], [5].

One of the primary mechanisms within the system enables real-time power distribution among vehicles by analyzing their SOC, urgency, and available socket types. As vehicles complete charging, the system instantly reallocates newly available sockets to the next vehicle in line based on a calculated priority score. Beyond operational flow control, the system also supports forward-planning functionalities, including the ability to calculate the optimal number and type of charging stations required to serve a given number of vehicles under a cost-efficiency constraint [6], [7].

In reverse scenarios, the simulation allows users to determine how many vehicles can be supported by a fixed number of AC and DC stations. This is calculated by considering total available power, average battery demand, SOC distributions, and time limits. Through this dual perspective—both infrastructure-to-vehicle and vehicle-to-infrastructure planning—the system operates not just as a power allocator, but also as an analytical decision support tool [8].

All components of the simulation are integrated into an interactive graphical user interface, allowing users to define input parameters, initiate simulations, and monitor real-time SOC progression through charts and result tables. The system architecture is modular and scalable, making it applicable not only to small test environments but also to large-scale planning scenarios involving fleet management or industrial facilities [9], [10].

In summary, this work proposes a comprehensive and flexible EV charging simulation framework that combines real-time power allocation with planning-oriented optimization. By incorporating adaptive logic, cost-awareness, and simulation-based testing capabilities, the system contributes to the growing need for intelligent EV charging infrastructure aligned with smart grid principles and sustainable mobility strategies.

2 METHODOLOGY

This section outlines the methods and computational approaches developed to evaluate the performance of electric vehicle charging infrastructure. The objective is to quantitatively determine the system's capacity, operational efficiency, and limitations under different station configurations and vehicle profiles.

The calculation models used in this study are based on both user-defined input parameters and potential system scenarios. These models provide analyses from multiple perspectives, including maximum vehicle capacity, minimum station requirements, and dynamic power distribution. The ultimate goal is to support decision-making processes and provide practical insights for real-world planning scenarios.

The following subsections provide detailed explanations of the algorithms, simulation logic, scenario generation methods, output tables, graphical analyses, and application interface developed within the scope of this methodology.

2.1 Problem Formulation

The explosive growth in the number of electric vehicles (EVs) has introduced significant engineering challenges in charging infrastructure capacity planning and power distribution strategies. In scenarios involving multiple vehicles and stations operating simultaneously, ensuring efficient utilization of available resources while achieving various operational objectives becomes a complex task. This challenge results in a multi-dimensional optimization problem that spans from real-time power allocation to long-term station capacity planning.

- **Priority-Based Power Allocation:** Dynamically prioritizing vehicles according to VIP level and SOC value, and applying proportional power distribution in DC stations.
- **Station Requirement Based on Vehicle Count:** Determining the minimum number of AC/DC

stations required, along with the associated total cost, to fully charge a given number of vehicles within a defined time frame.

- **Maximum Vehicle Capacity Based on Station Count:** Calculating the maximum number of vehicles that can be charged within a given time frame using a fixed number of AC/DC stations.
- **Minimum Total Charging Time:** Developing a power allocation plan that enables all vehicles to reach 100 percent SOC in the shortest possible time under the given vehicle and station configuration.

All four of these problem dimensions must be addressed under varying input parameters and operational scenarios. This ensures that the available infrastructure capacity can be accurately determined while improving the overall efficiency of the charging process.

2.2 Proposed Solution

In this study, a simulation-based smart charging management system was developed to address four main problem dimensions within a single adaptable framework. The system is designed to dynamically allocate available charging power in real time based on vehicle-specific parameters and station configurations. It was implemented in MATLAB using App Designer, providing an interactive environment for defining input parameters, running simulations, and monitoring results.

For station requirement by vehicle quantity, the system calculates the minimum number of AC/DC stations required to fully charge all vehicles within the defined time constraints and estimates the associated installation cost.

For maximum vehicle capacity based on station count, it determines the highest number of vehicles that can be fully charged within the given time frame, considering station type, capacity, and operational constraints.

For minimum total charging time, the system applies an optimization-based allocation strategy that distributes available power to ensure all vehicles reach full charge in the shortest possible time.

For priority-based power allocation, vehicles are dynamically ranked according to VIP level and SOC value, with DC station power distributed proportionally according to these rankings to maximize overall system performance.

By integrating these four functionalities into a single adaptable simulation environment, the system provides a comprehensive decision-support tool for evaluating and improving EV charging infrastructure performance under various operational scenarios.

2.3 System Structure

The developed system is based on a modular structure that follows the operational logic of a single station. The operation of each station consists of three main steps: collecting data from connected vehicles, processing this data through the algorithm, and distributing power based on the calculated results. Inputs include the vehicles' SOC levels, VIP status, battery capacities, and the station's available power capacity. These inputs are evaluated by the decision-making engine to generate the most suitable power allocation plan for the current conditions.

The generated power allocation plan determines the amount of power each connected vehicle will receive. These power values are then used to update SOC levels at each time step. This process continues in real time until one of the vehicles either completes charging or disconnects from the station, enabling the system to respond quickly to changes in operational conditions.

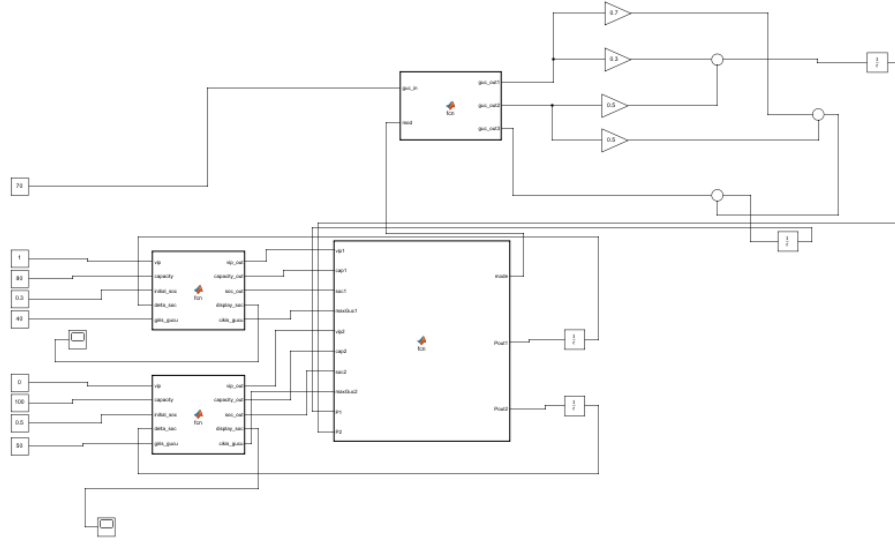


Figure 1: System block diagram of the proposed charging system.

This structure is applied identically to all stations in the system. The differences between modes arise only in the calculation logic, while the general operational workflow of the station remains unchanged. This allows the system to be easily adapted to different operational scenarios, and when new power distribution strategies are introduced, only the decision-making stage needs to be updated without altering the core infrastructure.

2.4 Research Approach

In this study, a simulation-based experimental approach was adopted to evaluate the performance of electric vehicle charging infrastructure under different operational conditions. This method enables a comparative analysis of how the system behaves under various input parameters.

Simulation scenarios were created by combining different values of variables such as the number of vehicles, the number of stations, station type, station power capacity, initial SOC levels of vehicles, VIP levels, and battery capacities. Each scenario was executed in line with predefined objectives, and the system's performance was analyzed accordingly.

The objectives of these scenarios include determining the minimum number of stations required to fully charge all vehicles, calculating the maximum number of vehicles that can be charged with a

fixed number of stations, minimizing the total charging time, and evaluating the impact of priority-based power allocation strategies.

This approach reveals the system's response to different operational situations, providing valuable input for infrastructure capacity planning and the development of power distribution algorithms.

2.5 Methods and Tools

In this study, MATLAB R2021b and App Designer were utilized to develop, simulate, and visualize an electric vehicle charging management system. MATLAB served as the core environment for implementing the algorithms, performing calculations, and processing simulation data. App Designer provided the platform for collecting user inputs, initiating the simulations, and displaying the results in a visual and interactive format.

The development process was carried out entirely within MATLAB, ensuring seamless integration between the computational logic and the user interface. This allowed the system to execute simulations, apply different operational scenarios, and present outputs without the need for external tools. By combining MATLAB's strong computational capabilities with the interactive features of App Designer, the project was able to incorporate multiple problem dimensions within a unified simulation framework.

2.5.1 MATLAB R2021b

MATLAB R2021b was used as both the development and simulation environment in this project. The coding process was implemented entirely with user-developed functions using core MATLAB programming structures such as loops, conditional statements, and matrix operations. No external libraries or toolboxes were used.

The system performs the calculations for the different problem dimensions defined in the project, processing input parameters to update SOC values, calculate power distribution, and generate scenario-based outputs. MATLAB also produces simulation results in the form of tables and graphical plots. The computational logic and algorithmic steps for the modes will be explained in detail in later sections.

2.5.2 App Designer

App Designer is MATLAB's integrated graphical user interface development tool and was used in this project to enable interaction between the user and the system. Through this interface, users can enter vehicle and station parameters, start the simulation, and view the basic results.

The interface directly transfers input data to the MATLAB algorithms and presents the computation results in the form of graphs and tables. The design and components of the interface will be described in detail in later sections. .

2.6 System Design and Implementation

The developed system is designed to execute multiple independent algorithms. These algorithms can be selected and run through the user interface, with each one structured to address a different problem dimension. The system operates in three main stages: receiving input data, executing the selected algorithm, and presenting the results to the user.

During the input stage, key parameters related to vehicles and stations are entered by the user. These include the initial SOC value, battery capacity, VIP level, number of vehicles, number of stations, station type, and station power capacity. These values serve as common inputs for all algorithms.

Once the input data is collected, the user selects the desired algorithm from the interface. The system then applies that algorithm's calculation logic and mathematical model to perform power allocation, update SOC values, and generate results in line with the defined objectives.

Finally, the output stage presents results specific to the chosen algorithm's problem dimension. These may include SOC variation graphs, total charging times, station utilization rates, or indicators such as minimum cost.

This structure enables the system to evaluate different scenarios independently and allows new algorithms to be added without altering the existing framework.

2.7 System Operation Flow

The developed system is designed so that the four different algorithms operate completely independently. Each algorithm is structured to address a specific problem dimension and applies its own calculation method. However, from a technical perspective, there are similarities in their code structures and process sequences. These similarities stem from the repetition of certain common steps that form the general operational logic of the system.

This shared flow begins with transferring user-provided data into the system. Next, the necessary preparations are made to ensure the simulation runs correctly, after which the algorithm selected by the user is executed. The algorithm applies its own calculation model to perform power allocation, updates SOC values according to time steps, and produces outputs relevant to its problem dimension. In the final stage, these outputs are presented to the user in the form of graphs, tables, or statistical indicators.

This approach allows different scenarios to be executed using their unique logic while following a similar process order, ensuring that the system remains modular and easily expandable.

2.7.1 Data Collection

Although each of the four algorithms in the system focuses on a different problem dimension, the fundamental parameters used in their calculations are largely common. Regardless of which algorithm is executed, the required data for that specific algorithm is collected from the user through the graphical interface. These parameters define the initial conditions of the simulation, ensure the system operates correctly, and directly affect the reliability of the results. Accurate and complete data entry is critical for the flawless execution of the algorithm's logic and for the validity of the simulation outputs. The parameters generally used across the algorithms are as follows:

- State of Charge: The initial battery charge level of the vehicles.
- Battery capacity: The total energy storage capacity of the vehicles.
- VIP level: The priority classification of the vehicles.

- Number of vehicles: The total number of vehicles included in the simulation.
- Number of stations: The total number of available charging stations.
- Station type: Whether the stations operate as AC or DC.
- Station power capacity: The maximum charging power available at the stations.
- Ambient temperature: The surrounding environmental temperature that may affect charging efficiency.
- Simulation time: The total duration over which the charging process will be simulated.

These parameters may be used in different combinations depending on the algorithm. Fields that are not required for a particular scenario remain unfilled, and only the values necessary for the selected algorithm are included in the calculations. Providing parameters in a complete and consistent manner plays a crucial role in ensuring the smooth progress of the simulation process, reducing the likelihood of errors, and increasing the reliability of the results.

2.7.2 Data Processing and Transformation

Before the simulation can proceed to the execution phase, the collected input data must be refined and transformed into a format that the system can process efficiently. This stage ensures that all parameters are standardized, relevant calculations are completed, and the data is fully prepared for subsequent computational steps. By doing so, potential inconsistencies are eliminated, and the algorithm is provided with accurate and ready-to-use values. The operations carried out in this scope are as follows:

- Determination of SOC values: For each vehicle, the initial State of Charge (SOC) is taken from the percentage format and recorded in the system.
- Determination of station numbers: Based on user input, the number of AC and DC stations is defined in the system.
- Determination of socket numbers: For AC stations, a single socket is defined, while for DC stations, two sockets are assigned, and the total socket count is calculated.

- Determination of priority order: Using VIP level and SOC information, the charging priority order of vehicles is established.
- Calculation of required energy: For each vehicle, the amount of energy to be charged is calculated based on its capacity and current SOC value.

As a result of these steps, all fundamental data required by the system during the algorithm execution phase is defined and prepared for processing. This ensures that allocation, distribution, and simulation calculations in the following stages can be carried out smoothly.

2.7.3 Output Generation

Before the simulation results are finalized, they must be converted into clear and analyzable outputs that can be effectively interpreted by the user. This stage involves presenting the processed data through visual and tabular components, each designed for a specific analytical purpose. By doing so, the operational performance of the system, infrastructure utilization, and vehicle charging processes can be examined in detail. The outputs generated in this scope are as follows:

- Histogram (axis): Used to visualize the distribution of different scenarios and the missing energy levels of vehicles, enabling the identification of the energy ranges in which the system operates most intensively.
- SOC change graph (axis): Displays the change in each vehicle's State of Charge over time, allowing the monitoring of charging progress and rate for each vehicle.
- Table – Number of stations: Lists the number of AC and DC stations used in the simulation, assisting in evaluating existing infrastructure capacity.
- Table – Cost and number of stations: Presents the total cost and quantity of each station type, allowing the assessment of the economic impact of different infrastructure configurations.
- Table – Vehicle-to-station connections: Indicates which station each vehicle is connected to, providing a clear view of vehicle–station assignments within the system.
- Table – Vehicle completion times: Lists the time at which each vehicle's charging process is completed, supporting the analysis of charging distribution efficiency.

- Edit Field – Total charging time: Shows the total time required for all vehicles to complete charging, serving as a critical metric for evaluating overall system performance.
- Table – Initial SOC values: Lists the State of Charge for each vehicle at the start of the simulation, clarifying the initial conditions of the charging process.

These outputs enable a detailed examination of the system’s overall performance, ensuring that design and optimization decisions can be based on reliable and well-structured data.

2.8 Application Design

This section presents the graphical user interface of the software developed using MATLAB App Designer. A separate tab has been created for each algorithm, with the interface layout and input components adapted to the requirements of the corresponding computational process. In each tab, dedicated input fields, tables, and graphical axes are arranged to facilitate structured data entry and parameter configuration before running the simulation.

This section only displays the empty interface layouts, without including simulation results. The purpose is to present the arrangement and functions of the input components in each tab with the support of figures.

2.8.1 Dynamic Power Distribution

This interface is specifically designed for scenarios where dynamic power distribution is performed among multiple vehicles connected to the same charging station. It offers a structured and user-friendly layout that allows users to easily input vehicle and station parameters. The interface supports the complete and accurate entry of all necessary data before simulation, enabling the algorithm to operate smoothly. Thus, users can conveniently manage critical information such as vehicle charge statuses, priority levels, and station capacities.

The interface includes components for entering technical data as well as visual arrangements that enhance user experience. Users can easily specify the number of vehicles and their initial SOC values, as well as define station power capacities and VIP levels. This setup facilitates accurate and efficient modeling of complex power distribution scenarios, thereby increasing the effectiveness of

the simulation.

2.8.2 Station Selection Based on Vehicle Count Interface

This interface is developed to enable users to calculate the required number of charging stations and their associated costs based on the size of their vehicle fleet. Its user friendly and organized design supports complete and accurate input of fleet size and station parameters.

The interface facilitates the entry of critical data such as total vehicle count, preferred station types like alternating current or direct current, and the power capacity of each station. Additionally, cost information for each station type can be input to allow economic analysis. This enables users to preview infrastructure needs and costs for various scenarios, supporting more informed decision making.

Such comprehensive data entry setup allows for effective infrastructure planning during the simulation preparatory phase.

2.8.3 Maximum Vehicle Support per Fixed Station Setup Interface

This interface is developed to determine the maximum number of vehicles that can be supported based on the fixed number and power capacities of existing alternating current and direct current charging stations. It offers a comprehensive and user friendly platform that enables users to optimize their fleet size by efficiently utilizing available infrastructure resources.

The interface supports detailed input of fixed station counts, power ratings, and the charging requirements of vehicles. This allows users to easily calculate the maximum number of vehicles that can be accommodated under different infrastructure scenarios and realistically assess system capacity.

This design facilitates accurate and effective fleet capacity planning during the preparatory phase of the simulation. It serves as a critical tool for users to optimize infrastructure investments and fleet management strategies.

2.8.4 Minimum Charging Time and Dynamic Assignment Interface

This interface enables the dynamic assignment of vehicles with varying charge levels and priority ranks to charging stations and sockets. It offers a comprehensive and user friendly platform that allows users to input critical parameters such as vehicle charge status, priority levels, and station capacities accurately and completely.

The interface is designed to meet the complex requirements of the dynamic assignment algorithm. It allows users to easily configure vehicle prioritization, monitor charging processes, and manage the replacement of completed vehicles with new ones.

This setup maximizes the efficient use of system resources while aiming to minimize the total charging time for all vehicles. Additionally, the provision of dynamic transitions between vehicles ensures that the simulation is conducted in a realistic and effective manner.

2.9 Operational Analysis Modes

This section provides a comprehensive examination of various operational modes and algorithms designed to manage electric vehicle charging processes. Each mode incorporates specialized strategies optimized for different fleet sizes, vehicle priority levels, charging infrastructure constraints, and performance objectives.

These analysis modes aim to maximize the efficient utilization of charging station capacity while minimizing vehicle charging times. The modes have been developed and implemented to adapt to a wide range of real-world scenarios.

Within this section, the operational principles, algorithmic approaches, and application conditions of each mode are thoroughly analyzed, demonstrating the system's flexibility and performance capabilities. This establishes a solid foundation for optimal decision-making processes in electric vehicle charging management.

The system calculates the change in State of Charge during the charging process using the following

fundamental formula:

$$\Delta SOC = \frac{P}{C \times 3600} \quad (1)$$

where ΔSOC represents the incremental increase in the State of Charge over one second, P denotes the charging power in watts, and C is the battery capacity expressed in watt-hours. The factor 3600 converts hours into seconds to maintain consistent units.

This formula allows the dynamic updating of the battery's charge level throughout the simulation and ensures consistent and accurate calculation of SOC changes across all algorithms. Thus, the charging behavior of vehicles is modeled precisely over time.

2.10 Dynamic and Priority-Based Power Distribution Algorithm

This algorithm is designed to dynamically, efficiently, and fairly distribute the available power resources between two electric vehicles connected to the same charging station. The algorithm continuously monitors the instantaneous battery state of charge, VIP priority level, and charging status of both vehicles. Based on this information, it optimizes and updates the power allocation in real time.

According to the prioritization logic, vehicles with higher priority are allocated power preferentially, while the other vehicle utilizes the remaining power as effectively as possible. Additionally, when a vehicle completes charging and leaves the system, all remaining power is automatically redirected to the other vehicle. This dynamic power management ensures maximum utilization of power resources and contributes to reducing charging times.

The real-time adaptation capability of the algorithm is critically important, especially in environments with limited infrastructure resources and varying vehicle demands. In the two-vehicle scenario, the system's ability to respond quickly and continuously update power distribution supports battery health preservation and enhances user satisfaction.

2.10.1 Environmental Factors

Environmental factors play a decisive role in the charging process of electric vehicles, influencing both efficiency and battery health. When combined with the technical capacity of the charging infrastructure, these factors directly impact the system's power distribution decisions. In the designed algorithm, external conditions such as temperature and station type are of critical importance for reducing or extending charging times, as well as for preserving battery lifespan.

The system obtains environmental data directly from user inputs and internet-based sources. This ensures that the decision-making process is based not only on the technical specifications of the vehicles but also on the prevailing environmental conditions. By incorporating these parameters, the algorithm maintains a dynamic rather than static power distribution structure, enabling the implementation of the most suitable charging scenario under any given circumstances.

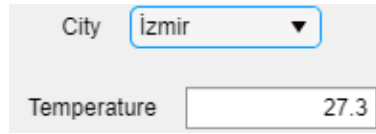
The image shows a portion of a web application interface. It features two input elements on a light gray background. The first is a dropdown menu labeled 'City' with a blue border and a downward arrow, showing 'İzmir' as the selected option. Below it is a text input field labeled 'Temperature' with a gray border, containing the numerical value '27.3'.

Figure 2: City temperature.

The interface displays the selected city along with its real-time temperature. This data is retrieved from an online source and directly integrated into the algorithm's decision-making process. Since temperature is a factor that significantly affects charging performance, the system uses this information to optimize power distribution strategies according to the current environmental conditions. In this way, both charging efficiency and battery health are preserved.

The type of charging station is a decisive parameter in the system's power distribution strategy. In the user interface, selecting the station type defines the capacity of the charging infrastructure. The selected station type directly affects the algorithm's maximum power allocation and prioritization logic. For example, DC stations generally have higher power capacity, which can significantly reduce the charging times of priority vehicles. In contrast, AC stations have lower power capacity and may require longer charging times.

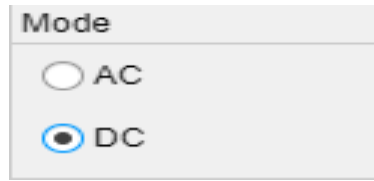


Figure 3: System mode selection.

The selected station type is immediately taken into account by the algorithm during the charging process. This information, combined with real-time temperature data, allows the system to adapt its power distribution strategy to both infrastructure capacity and environmental conditions. By doing so, the algorithm ensures that available resources are utilized efficiently while meeting the specific needs of each connected vehicle.

2.10.2 Priority Assignment Logic

In this system, power distribution is not merely based on equal sharing but also dynamically adjusted according to each vehicle's condition and urgency. For every vehicle, the system evaluates the VIP level, current SOC value, and charging connection status. Using these parameters, a real-time priority score is calculated, and vehicles are ranked accordingly.

Vehicles with high VIP levels — such as ambulances, police cars, or service vehicles used in critical missions — are always given top priority in the system. Additionally, vehicles with SOC values below 5 percent are granted temporary priority. As a result, an emergency vehicle with a low SOC level can receive dual priority based on both its VIP status and critical battery condition.

This approach not only reduces charging times but also increases overall system efficiency and contributes to battery health. Power allocation based on priority ensures optimal use of limited resources. The algorithm block responsible for handling this decision-making process is illustrated below.

```

if    vip == 2 && soc < 0.05
    category = 6;
elseif soc < 0.05
    category = 5;
elseif vip == 2
    category = 4;
elseif vip == 1 && soc < 0.05
    category = 3;
elseif vip == 1
    category = 2;
else
    category = 1;
end
socInverted = round((1 - soc) * 100);

```

Figure 4: Priority scores.

The algorithm block shown above illustrates how priority scores are assigned to each vehicle and how the system makes decisions based on these scores. Vehicles with a high VIP level or a SOC value below 5 percent are automatically prioritized, ensuring faster response in emergency situations or when the battery level is critically low.

This mechanism enhances both user satisfaction and system reliability. Moreover, the dynamic ranking based on priority scores allows the charging process to be continuously re-evaluated, strengthening the system's ability to respond in real time.

2.10.3 Dynamic Power Management

This section explains the operation of the dynamic algorithm that distributes power resources in real time between vehicles connected to the same charging station. The main goal is to continuously update the power allocation based on each vehicle's charging needs and priority level to ensure the most efficient scenario.

The algorithm constantly monitors each vehicle's SOC, VIP priority level, and connection status. Based on this data, higher power is allocated to vehicles with higher priority. Vehicles with elevated status—such as ambulances, police cars, or those purchased with premium access—are evaluated with higher priority by the system.

In addition, vehicles with an SOC below 5 percent are considered to have an urgent charging need and are temporarily prioritized. This shows that the system reacts not only to predefined priorities but also to real-time conditions. Thus, power is effectively directed based on both planned priorities and emergency needs.

If both vehicles have the same priority level, the system shares the power equally between them. However, this balance is updated as SOC levels change. When one vehicle completes charging or disconnects from the station, the algorithm automatically redirects all available power to the remaining vehicle, switching to single-vehicle mode. This transition occurs automatically without requiring user intervention.

Thanks to this flexible structure, the system accelerates the charging process, optimizes power resource usage, and contributes to preserving battery health by making real-time decisions based on continuously updated data.

2.10.4 Visualization and Monitoring

This section illustrates how the developed algorithm distributes power between two electric vehicles by tracking their state of charge over time. The SOC curves clearly demonstrate how the algorithm reacts to different vehicle priorities and SOC levels during the charging process.

First, the SOC progression of each vehicle is displayed separately. This allows an independent observation of how power distribution affects each vehicle throughout the simulation. After that, both vehicles are shown on the same graph to enable a comparative analysis. At this point, it becomes easy to observe when one vehicle completes its charging and the full available power is redirected to the remaining vehicle.

These visual representations play a key role in understanding the system's real-time decision-making and adaptive behavior throughout the charging period.

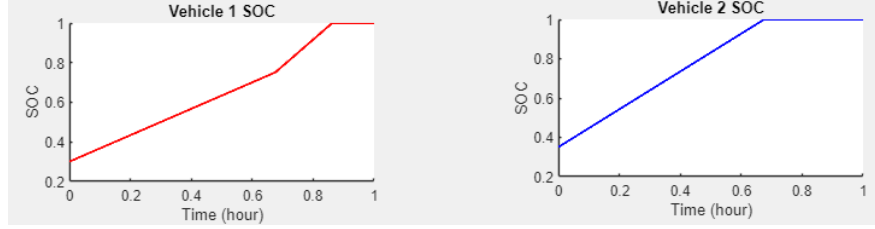


Figure 5: Vehicles graph.

Each graph above shows the individual SOC progression of one vehicle. By observing them separately, it becomes easier to analyze how each vehicle responds to dynamic power distribution. The charging slope visibly changes when a vehicle receives more power due to the other vehicle completing its charging or having a lower priority. This enables clear interpretation of how the algorithm adapts in real time to the changing status of each vehicle.

In addition to separate monitoring, both vehicles' SOC progression can be tracked on a single graph. This combined visualization offers a holistic view of the charging dynamics, revealing how the power is reallocated during the charging process.

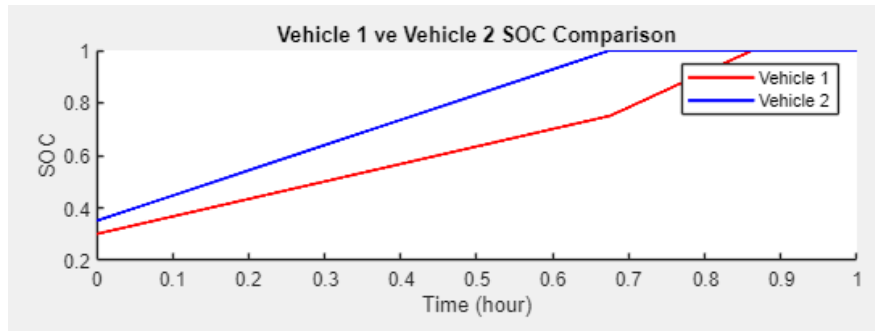


Figure 6: Vehicles graph comparison.

The shared SOC graph clearly illustrates the dynamic behavior of the system. The slope differences between the two vehicles help identify priority-based power allocation moments. When one vehicle completes charging, the other benefits from the full available power, resulting in a steeper increase

in its SOC curve.

2.10.5 Interface Overview with Input Configuration

In this section, the MATLAB App Designer interface of the developed algorithm is presented. Before running the simulation, all required user inputs have been filled in. The interface clearly demonstrates how the algorithm is parameterized and what information the user is expected to provide.

In the interface image below, sample input values for two vehicles are shown. The simulation has not been executed; only the initial state of the interface with filled-in input fields is displayed. The following parameters have been entered into the system:

- SOC values
- Battery capacities (kWh)
- Station power (kW)
- VIP levels.

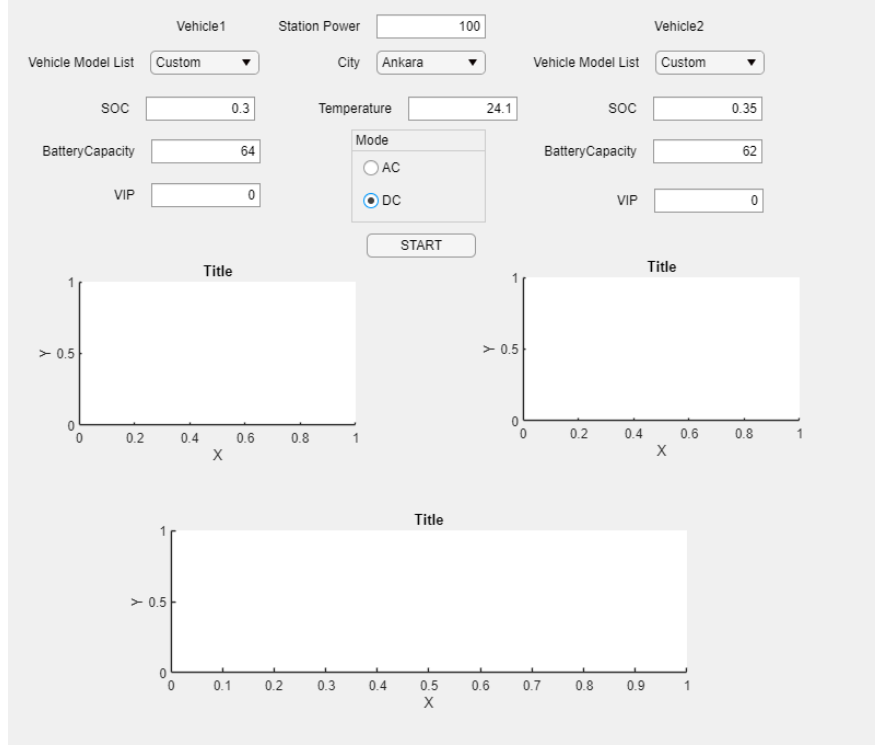


Figure 7: Dynamic and Priority-Based Power Distribution Algorithm Interface Overview.

The figure above includes all necessary user inputs. This screen represents the initial system configuration and visually displays all parameters required for the algorithm to operate. The charts and tables are left empty, as this section focuses solely on the data input phase.

2.11 Station Selection by Vehicle Count Algorithm

With the increasing adoption of electric vehicles, properly planning charging infrastructure has become a critical issue. For businesses that manage a specific fleet of vehicles, determining the minimum number of required charging stations in advance is a key engineering challenge. The goal is to ensure sufficient charging capacity while avoiding unnecessary infrastructure costs.

The algorithm developed in this section aims to meet the system's needs with the minimum number of AC and DC charging stations, based on the total number of vehicles and the maximum allowed charging duration. Using inputs such as the vehicle class (from which battery capacity is automatically determined), charging time, and station power levels, the algorithm calculates the energy demand under various scenarios. Based on these demands, suitable station configurations are generated.

The system creates scenarios with different initial charge levels and visualizes the total energy requirement for each scenario using a histogram. Two threshold levels are defined: one that covers 50 percent of all scenarios and another that covers 80 percent. Recommended station configurations for each threshold are presented in two separate tables, along with the total cost information.

This algorithm can be used as part of decision-support systems by enabling cost-effective comparisons between different charging strategies.

2.11.1 Vehicle Class System and Battery Capacity

One of the core components of this algorithm is determining the battery capacity based on the selected vehicle class. Depending on the user's selection, the system assumes that all vehicles share the same battery capacity. This approach significantly improves the speed and consistency of the overall calculations. The defined vehicle classes and their corresponding battery capacities are listed below:

- Passenger Vehicle Battery Capacity 60kWh
- Commercial Vehicle Battery Capacity: 90kWh
- Forklift Battery Capacity: 30kWh
- Custom Battery Capacity: In this option, the user manually enters a battery capacity value instead of selecting from predefined classes.

In this setup, all vehicles are treated as identical in terms of energy demand, based on the selected class. This simplifies the calculation process and ensures structural consistency throughout the simulation.

2.11.2 Input Parameters

This algorithm operates based on specific input values provided by the user to determine the optimal charging station configuration for a given number of vehicles. All values are entered through the MATLAB App Designer interface. These parameters form the basis for energy demand calculations

and scenario generation. The key input parameters used in the system are listed below:

- Number of Vehicles: The total number of electric vehicles to be charged.
- Battery Capacity (kWh): Automatically set based on the selected vehicle class. For the Custom option, it must be entered manually.
- Vehicle Class: Determines the battery capacity of each vehicle based on the selected class.
- Maximum Duration: Defines the time limit within which all vehicles are expected to be fully charged.

After these parameters are entered, the system calculates the total energy requirement under multiple SOC scenarios and proceeds to determine the minimum number of required stations accordingly. The precision of these inputs plays a critical role in ensuring the reliability of the final station assignment results.

2.11.3 Station Capacity and Allocation Logic

This section introduces the charging station models that can be used based on the number of vehicles and the target charging duration. The system supports both AC and DC charging types, each with its own capacity and cost structure.

First, the AC and DC station models used in the system are listed, followed by representative images of each. After the visuals, this section explains how the stations are integrated into the charging infrastructure and how the total station requirement is calculated.

AC and DC stations are evaluated separately, and then combined configurations are explored to identify the minimum-cost solution. The calculation algorithms operate scenario-based, and the total number of required stations is determined according to input values such as the number of vehicles, battery capacity, and charging time.

To determine which stations could be used in the system, a variety of AC and DC models with different power and capacity levels were examined. Based on this evaluation, a set of station models

was selected for inclusion. The models used on the AC and DC sides are listed separately below.

AC Charging Station Models Used in the System

- Vestel EVC04 – 22kW
- Schneider EVH4S11NC – 22kW
- Piller – 7.4kW

These AC models were selected based on the system's power requirements and cost constraints. Each model offers a different charging capacity and cost level, allowing for flexible deployment in a variety of scenarios. While some models are ideal for low-cost use cases, others provide higher charging speeds at a higher cost. The selected models strike a balance between performance and cost, making them suitable for both public and private fleet charging operations.



Figure 8: AC station Vestel EVC04 22kW.

The image above shows a representative AC charging station model used in the system. In real-world implementations, different variations of this model may be used depending on availability and compatibility.

Following the AC station models, the DC charging stations used in the system are presented below. These models are typically preferred in scenarios where high charging power and shorter durations are required.

- TommaTech – 60kW
- Tunçmatik Pro – 90kW
- Star Charge – 120kW

These DC charging station models were selected to meet high-demand charging scenarios where shorter charging times are critical. Each model offers a different power level and cost, enabling the system to simulate a range of configurations under time-constrained conditions. DC stations are typically equipped with two sockets, allowing simultaneous charging of two vehicles. The selected models provide fast and efficient energy transfer and are commonly used in commercial or high-traffic areas.



Figure 9: DC station Tunçmatik Pro 90kW.

The image above shows a representative DC charging station model used in the system. Depending on the infrastructure design and requirements, other variants of this model may also be deployed.

AC Station Calculation Logic

The number of AC stations is calculated based on the scenario-specific energy demand. In each

scenario, the total energy required to charge all vehicles is determined. This value is calculated using the number of vehicles, battery capacity, and the given SOC levels. Since all vehicles are assumed to have the same battery capacity, the system generates a clear energy demand for each scenario.

The total energy that a single AC station can deliver is obtained by multiplying its power capacity by the user-defined charging duration. AC stations are considered single-socket, meaning each station can serve only one vehicle at a time. This assumption increases the practicality and realism of the system.

For each scenario, the required number of AC stations is calculated by dividing the total energy demand by the energy that one AC station can supply. All scenarios are evaluated separately, and the system presents the minimum number of AC stations required to meet the 50 percent and 80 percent scenario coverage thresholds.

DC Station Calculation Logic

The number of DC stations is calculated based on the total energy demand and the available charging time. In each scenario, the total missing energy required by all vehicles is summed to determine the system's overall energy need. Since all vehicles are considered identical, this value is calculated directly using battery capacity and SOC levels.

DC stations are considered dual-socket, meaning they can charge two vehicles simultaneously. Therefore, the total energy that one DC station can deliver within the given time is calculated by multiplying its power by the duration and then accounting for both sockets. This total capacity is compared to the system's energy requirement for each scenario.

The minimum number of DC stations is determined by dividing the total energy demand by the total energy that a dual-socket DC station can provide. This process is repeated for each SOC scenario, and the system presents the minimum number of DC stations required to meet the 50 percent and 80 percent scenario coverage thresholds.

Combined Structure and Cost-Based Selection

In this system, calculations are not limited to a single station type. Mixed structures using both AC and DC stations are also evaluated. For each scenario, different combinations of AC and DC stations are tested to determine whether the total energy demand can be met within the given duration. These combinations are assessed based on both energy capacity and time constraints.

For each combination, the system calculates the total number of required stations and the associated cost. The cost calculation considers the number of stations and the unit price of each selected model. The resulting data allows for comparison between different charging infrastructure strategies.

After evaluating all scenarios, the system selects the combination with the lowest total cost that satisfies either the 50 percent or 80 percent scenario coverage thresholds. This approach enhances system efficiency by optimizing both infrastructure capacity and economic feasibility.

In this section, the AC and DC charging station models used in the system were introduced, and the method for calculating the required number of stations per scenario was explained. Calculations were performed separately for each scenario, and the minimum number of stations needed to meet the 50 percent and 80 percent scenario coverage thresholds was determined.

Additionally, mixed structures combining both AC and DC stations were evaluated, and the configuration with the lowest total cost among the valid options was selected as the recommended solution. All these calculations were carried out to ensure that the system provides the most efficient charging infrastructure from both technical and economic perspectives.

2.11.4 Scenario-Based Demand Calculation

Each vehicle in the system is assumed to have a different initial SOC level. Therefore, instead of using a fixed SOC value, the system generates a scenario base that accounts for multiple possible states per vehicle. The goal is to analyze all potential situations the system may encounter and perform station capacity planning accordingly.

Each vehicle is modeled to take one of the predefined SOC group values. This creates a structure

that includes a large number of different combinations and reflects more realistic system behavior. Calculations based on this structure have the ability to represent thousands of distinct cases rather than relying on a single assumption.

SOC Grouping Logic

The system considers the SOC range from 0 to 100. However, using this full range directly increases computational complexity and makes data control more difficult. To address this, the SOC range is divided into 10 equal groups, each represented by an average SOC value.

Each group spans a 10-unit interval. For example, the range 0–10 corresponds to an average SOC of %5; 10–20 becomes %15, and so on.

The representative SOC values are:

%5, %15, %25, %35, %45, %55, %65, %75, %85, %95

With this approach, each vehicle can be modeled with one of 10 discrete SOC levels, allowing for realistic and computationally efficient scenario generation.

SOC Grouping Logic

Each scenario represents different initial state-of-charge (SOC) levels for the vehicles in the system. Therefore, the energy deficit for each vehicle is calculated based on its current SOC. The energy deficit is defined as the difference between the battery capacity and the current charge level.

$$E_{\text{deficit}} = C \times (1 - \text{SOC}) \quad (2)$$

- E_{deficit} : Energy required to fully charge a single vehicle (kWh),
- C : Battery capacity of the vehicle (kWh),
- SOC: Current state of charge expressed as a decimal between 0 and 1.

For each scenario, the total energy deficit is obtained by summing the deficits of all vehicles:

$$E_{\text{total}} = \sum_{i=1}^N E_{\text{deficit},i} \quad (3)$$

where N is the total number of vehicles.

This total energy deficit serves as a critical input for charging infrastructure planning. The capacity and number of stations are determined based on these values to ensure the system can meet the energy demand in each scenario. This approach helps prevent outages and waiting times caused by insufficient capacity.

Furthermore, the total energy deficits calculated across various SOC scenarios allow evaluation of the infrastructure's flexibility and robustness. By considering this diversity during planning, an efficient and cost-effective charging system can be developed that meets real-world conditions. This optimizes resource usage and ensures uninterrupted charging availability for vehicles.

Scenario Count and Combination Calculation

Each vehicle in the system can take one of several SOC (state-of-charge) groups. Therefore, the total number of scenarios representing all possible SOC distributions depends on the number of vehicles and the number of SOC groups. These scenarios are necessary to comprehensively analyze different initial conditions and energy requirements of the system.

$$\text{Total Number of Scenarios} = \binom{n + r - 1}{r} \quad (4)$$

where: - n = number of SOC groups. - r = number of vehicles.

- The combinations are *with repetition*, meaning each SOC level can be assigned to multiple vehicles.
- The combinations are *unordered*, so the order of SOC levels among vehicles does not matter.
- This formula represents the total count of possible SOC distributions.
- Due to computational complexity, all scenarios are not directly calculated; instead, sampling and statistical methods are employed.

For example, with 20 vehicles and 10 SOC groups, the total number of scenarios is:

$$\binom{10 + 20 - 1}{20} = \binom{29}{20} = 10,015,005 \quad (5)$$

This number represents the total count of different SOC combinations.

However, the calculations using coverage coefficients mentioned earlier do not fully align with this scenario count. Coverage coefficients are used as a simplified and summarized representation of all possible scenarios. This approach reduces computational load and provides a practical solution.

2.11.5 Histogram-Based Scenario Visualization

In scenario-based analyses, each vehicle is assumed to enter the system with a different initial State of Charge (SOC). This assumption results in a wide distribution of energy deficits across scenarios. The histogram provides a visual representation of these varying energy demands by grouping them and displaying how many scenarios fall within each energy range.

This visual distribution helps identify which energy levels are most common and how often the system is likely to encounter certain energy requirements. Detecting frequently recurring energy demands contributes significantly to efficient charging station capacity planning. Additionally, identifying outlier scenarios provides insight into how the infrastructure should prepare for peak loads.

By considering the entire distribution rather than relying solely on average values, this histogram-based approach enables more realistic and robust planning that better reflects real-world conditions.

X-Axis Description

In histogram charts, the x-axis represents the total energy deficit (in kWh) calculated for each scenario. This value is obtained by summing the individual energy deficits of all vehicles in a given scenario, based on their initial SOC levels and battery capacities.

Each scenario results in a specific total energy demand. The x-axis of the histogram displays these various energy demand levels across all possible combinations. This allows for a clear analysis of how energy needs are distributed in the system.

The values on the x-axis are sorted from low to high, each representing a specific energy band. This visual structure provides insights into which energy levels are more common and which are rare, helping to identify the most likely infrastructure loads.

Y-Axis Description

In histogram charts, the y-axis shows the number of scenarios that result in a specific energy deficit value. In other words, it represents the frequency of occurrence for each total energy demand level.

This value reveals which energy demand levels are more frequently encountered in the system. For example, the energy deficit with the highest y-axis value corresponds to the most common scenario in the simulation.

With this visual representation, it becomes easier to distinguish between rare and frequent cases. This insight is especially valuable for infrastructure planning, allowing focus on the most probable energy demand ranges to ensure efficient system design.

%50 and %80 Coverage Thresholds

On the histogram, two vertical lines are displayed: one represents the 50% coverage level, and the other indicates the 80% coverage level. These lines serve as reference points for evaluating how much energy capacity is required to meet the demands of a significant portion of scenarios.

- The 50% coverage line shows the minimum energy capacity needed for the system to successfully fulfill energy requirements in at least half of the scenarios. This is especially useful in systems with limited resources and is considered the baseline for basic functionality.

- The 80% coverage line represents a more robust planning target, ensuring that the system can operate effectively under a broader range of conditions. This threshold is often used for designing more resilient and reliable infrastructures.

Together with the histogram, these coverage lines offer clear visual insight into how well the system can perform under various energy demands. This helps decision-makers prioritize their investments and design systems that are both cost-effective and operationally efficient.

Scenario-based energy deficit calculations result in large datasets that represent every possible combination of vehicle SOC values. However, interpreting such raw numerical data is not practical. To address this, a histogram is used to visually display the frequency distribution of energy deficits across all scenarios.

This method helps identify the most common energy demand levels, understand how charging infrastructure is utilized under various conditions, and detect extreme scenarios that may cause system overload. Histogram-based visualizations are effective not only for technical analysis but also for communicating results to decision-makers in a clear and intuitive format.

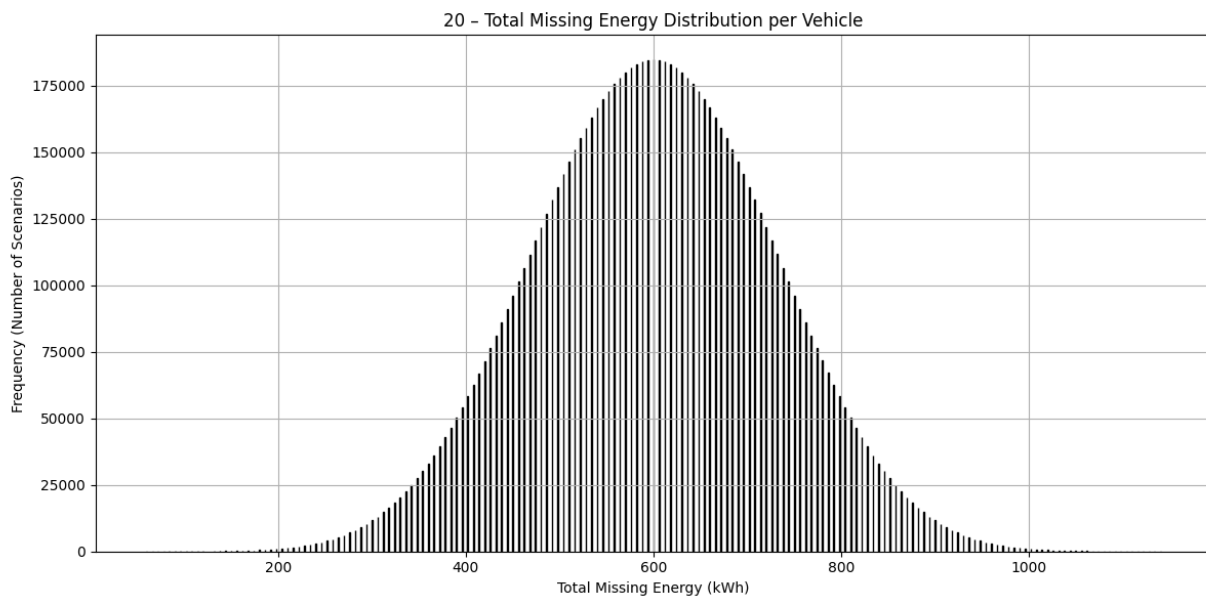


Figure 10: Histogram for 20 Vehicles.

- X-Axis: Represents the energy deficit levels (in kWh) across different SOC scenarios.
- Y-Axis: Shows the number of scenarios corresponding to each energy level.

%50 and %80 Vertical Lines:

- These reference lines indicate the target coverage levels for the charging infrastructure.
- Scenarios falling to the left of the lines are considered to be within system capability.
- Scenarios falling to the right of the lines represent potentially critical demand situations.
- The peak of the histogram reflects the most frequent energy deficit level, highlighting the typical system load.
- Overall, the distribution tends to resemble a bell curve, indicating a near-normal distribution of total energy requirements.

Histogram analysis demonstrates the importance of evaluating not just a single case, but a wide range of possible demand scenarios when planning charging infrastructure. Identifying the frequency of high-demand cases supports better decisions about scaling system capacity and designing more flexible operational strategies.

As a result, histogram-based visualization is not only a tool for simplifying complex datasets, but also a key component in building a sustainable, adaptive, and efficient charging ecosystem. It enables planners to allocate resources wisely and ensure that vehicles can always access reliable charging, even under peak conditions.

2.11.6 Output Tables and Interpretation

This section explains how the results obtained from the station planning process are presented in table format. At this stage, no actual numerical results are provided. Instead, the structure of the tables, their purpose, and the type of information they contain are clearly defined. This ensures that the reader can better understand how the results will be organized and interpreted in the following sections.

During the analysis, scenarios were created based on different coverage thresholds, and suitable station configurations were determined accordingly. As a result, two separate tables have been prepared. Each table contains station alternatives that meet a specific coverage level, along with the associated cost data.

Purpose and Distinction of the Two Tables

During station planning, two distinct scenarios were considered in order to evaluate how the infrastructure performs under different adequacy levels. These scenarios target 50% and 80% coverage thresholds respectively.

- The first table includes only those station configurations that achieve at least 50% coverage. It is suitable for systems aiming to deliver acceptable performance at minimal cost.
- The second table presents configurations that meet the more ambitious 80% coverage level. These setups are recommended for systems requiring higher service quality and broader charging availability.

The difference between these two tables allows for an effective cost-performance comparison and provides decision-makers with optimization alternatives at varying levels of service expectation.

Table Structure and Column Descriptions

The following tables present the details of recommended charging station configurations under two different planning objectives 50% and 80% scenario coverage. These configurations have been derived from analyzing the energy demands and charging requirements of the system under a wide variety of SOC-based scenarios. By comparing different infrastructure setups, planners can assess trade-offs between cost and performance across varying levels of system adequacy.

Each row represents a specific station model and its associated parameters. The columns in the tables are as follows:

- Station Type (AC/DC/DC+AC)

- Station Model
- Power Capacity (kW)
- Quantity
- Total Cost

With this structure, it becomes possible to clearly analyze how each configuration differs in terms of infrastructure requirements and budget constraints. The explicit categorization of AC and DC station types allows for quick identification of trade-offs between speed, cost, and availability. Especially, changes in station types and quantities across different scenarios provide valuable insights into system planning needs, enabling more informed decisions in real-world deployment strategies.

2.11.7 Application Interface

This section presents the MATLAB App Designer interface of the developed simulation system, captured after all user inputs have been entered but before the simulation has been initiated. The image clearly demonstrates how the system is configured and what data is required from the user. This screenshot is included to document the functionality of the user interface and to enhance the technical completeness of the report.

The interface screenshot below displays the state of the application just before the simulation begins. The screen includes essential user inputs such as vehicle class, number of vehicles, battery capacity, maximum charging power, and total time. All relevant data has been entered, and the system is ready to proceed with the calculations.

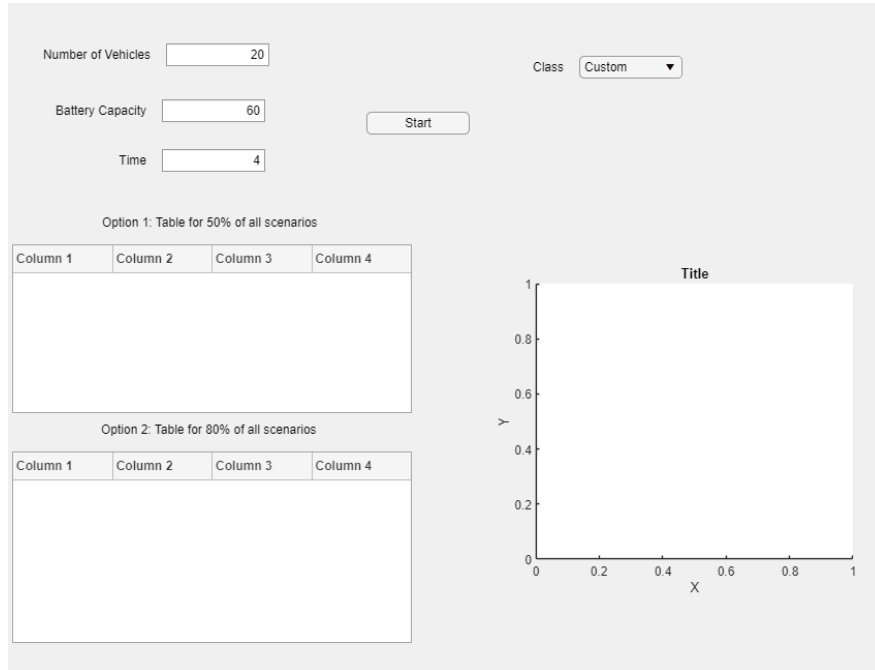


Figure 11: Station Selection by Vehicle Count Algorithm Interface.

This visual clearly demonstrates the functional layout of the user interface, the input fields, and how the core planning parameters are systematically collected to initiate scenario-based calculations.

As this screen represents the initial stage of the simulation, it reflects the foundational structure upon which all subsequent analyses and calculations are built. The data gathered at this point plays a critical role in enabling the system to generate accurate and adaptive infrastructure planning results.

2.12 Optimal Vehicle Capacity Algorithm

The sustainability of an electric vehicle charging infrastructure is not only determined by how quickly vehicles are charged, but also by how many vehicles the system can support with a fixed number of charging stations. The aim of this section is to calculate the maximum number of vehicles that can be fully charged within a given time frame using a specified number of AC and DC stations.

The calculations take into account key parameters such as battery capacity, charging time, station power, and vehicle class, helping to define the operational boundaries of the system. Additionally, multiple scenario results are generated based on different coverage levels, allowing a deeper analysis of the system's flexibility and scalability.

2.12.1 Vehicle Class System and Battery Capacity

To effectively represent the charging demands of various types of vehicles, this study categorizes them into four main classes: passenger, commercial, load-carrying, and forklift vehicles. Each class is assigned a specific battery capacity that reflects real-world operational scenarios. This classification allows for a more realistic modeling of how different types of vehicles impact the charging infrastructure.

The battery capacities for each vehicle class are defined as follows:

- Passenger Vehicle Battery Capacity 60 kWh
- Commercial Vehicle Battery Capacity 90 kWh
- Forklift Battery Capacity 30 kWh
- Custom Battery Capacity In this option, the user manually enters a battery capacity value instead of selecting from predefined classes.

These values serve as a foundation for all capacity-related calculations. With this setup, the maximum number of vehicles that can be supported for each class can be evaluated individually based on the available infrastructure.

2.12.2 Input Parameters

The primary objective of this algorithm is to determine the maximum number of electric vehicles that can be supported within a given charging infrastructure. Specifically, in scenarios where the number of AC and DC stations is fixed, it becomes crucial to estimate how many vehicles can be efficiently charged within a limited time frame. To achieve this, the algorithm requires several operational and technical input parameters from the user. These parameters directly influence the system's capacity calculations and form the basis for running simulation scenarios under different conditions.

- Time (hours): The total duration within which all vehicles are expected to be fully charged.
- Number of AC Stations: Represents the available number of AC charging stations (each with a single socket).

- Number of DC Stations: Indicates the number of DC stations available (each with two sockets)
- AC Station Power (kW): Maximum charging power of a single AC station
- DC Station Power (kW): Total power capacity delivered by one DC station.
- Battery Capacity (kWh): Defined based on the selected vehicle class.
- Vehicle Class: Defines the type of vehicle selected.

Based on the input parameters provided, the algorithm evaluates multiple configuration scenarios to identify the optimal number of vehicles that can be charged successfully within the defined constraints. This process not only enhances resource utilization but also enables strategic infrastructure planning by highlighting system limits and potential bottlenecks. Ultimately, the approach contributes to designing a flexible, scalable, and cost-efficient charging system aligned with real-world operational requirements.

2.12.3 Output Tables

This section explains the structure of the output tables generated by the algorithm. These tables present the maximum number of vehicles that can be charged within a defined time period, based on fixed AC and DC station counts. Each table corresponds to a scenario meeting either 50% or 80% of the demand coverage. While the actual table values will be shown in the results section, this part focuses solely on structural explanation.

By understanding the columns listed below, it becomes easier to evaluate the system's charging capacity and the contribution of each station type.

Table Rows:

- Number of Vehicles Charged by AC Stations
- Number of Vehicles Charged by DC Stations
- Total Number of Vehicles Charged

This structure enables a clear comparison of the individual and combined contributions of AC and DC stations. It also supports strategic planning by highlighting how different station configurations can meet varying levels of demand.

The sample table below illustrates the general structure of the output. It does not represent actual data but provides a template for how the final results will be organized.

Table 1: Sample table structure representing vehicle charging distribution.

Charging Type	Number of Vehicles
Number of Vehicles Charged by AC Stations	9
Number of Vehicles Charged by DC Stations	20
Total Number of Vehicles Charged	29

With this structure, the individual and combined charging capabilities of AC and DC stations can be clearly analyzed. This allows for a comparative evaluation of the system's efficiency under different station configurations. The tables aim to provide insight into planning flexibility through different coverage ratios.

2.12.4 Output Tables

This section explains the structure and purpose of the histograms that represent the distribution of the maximum number of vehicles supported under fixed station configurations. Although the visual itself is not included here, it will be presented and discussed in the results section.

Two distinct histograms were prepared to compare how the system performs under different coverage thresholds:

- The first histogram represents the energy deficit threshold that covers 50% of all scenarios.
- The second histogram is based on a broader threshold that covers 80% of scenarios.

These visualizations allow planners to consider the variability of possible outcomes, not just the average result.

Axis Descriptions:

- X-Axis: Energy deficit (kWh)
- Number of scenarios with that specific energy deficit (Frequency)

Each histogram includes a vertical dashed line:

- In the first histogram, this line marks the point where 50% of all scenarios fall to the left side of the distribution.
- In the second histogram, the line indicates the 80% coverage threshold, again with all scenarios to the left representing that proportion of the total.

This histogram-based analysis provides a comparative view of the system's performance under different coverage levels. By clearly showing the supported vehicle count next to each coverage threshold, the visualization delivers valuable insights for infrastructure planning. The histograms, along with detailed interpretations, will be included in the results section.

2.12.5 Application Interface

This section visually presents how the algorithm is integrated into the application via a snapshot of the user interface. The interface shown reflects the state just before the simulation starts. All required input parameters have been entered by the user, but the simulation has not yet been executed. This snapshot clearly demonstrates the structure and logic behind the input phase of the algorithm.

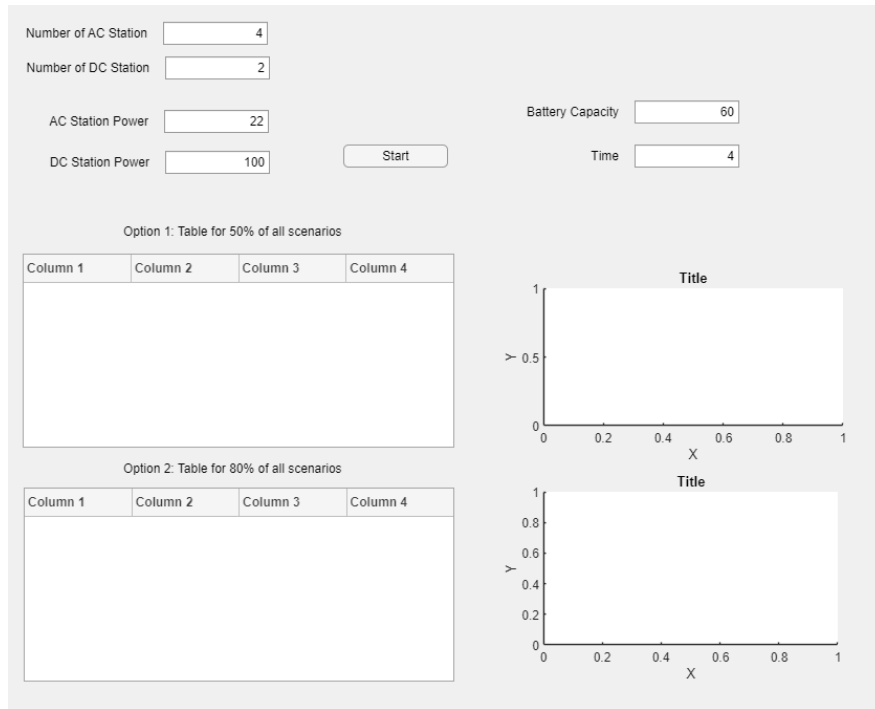


Figure 12: Vehicle Count Estimation Based on Station Configuration Interface.

The displayed interface clearly shows which parameters the system requires from the user. All fields are filled, and the system is ready to run. This image captures the system's state just before it processes real-time simulation data.

- Vehicle Class Selection: Four different predefined vehicle classes
- Battery Capacity (kWh): Battery size of each vehicle
- Charging Time (hours): All vehicles are expected to be charged within this time
- Number of AC Stations: Number of available single-socket AC stations
- Number of DC Stations: Number of available dual-socket DC stations
- AC Station Power (kW): Maximum output power per AC station
- DC Station Power (kW): Total output power per DC station

These input fields are essential for the algorithm to function accurately. The parameters entered by the user allow the system to simulate scenarios and determine the maximum number of vehicles

that can be supported. Each parameter directly influences the outcome of the simulation.

This interface layout provides a visual complement to the algorithm's logic. It effectively illustrates what data is required from the user and how the system will process it. Displaying this pre-simulation state helps users understand the operational framework of the algorithm before any execution begins.

2.13 Minimum Charging Time and Dynamic Assignment Algorithm

In systems with a high density of electric vehicles, effectively managing the available charging infrastructure is essential for optimizing total operation time. The algorithm developed in this section provides a priority-based and dynamic assignment strategy that ensures multiple vehicles are charged in the shortest possible time across a mix of AC and DC stations. Unlike static allocation models, this system evaluates both the current state of the infrastructure and future implications at each decision point, enabling intelligent, time-efficient scheduling.

At the beginning of the simulation, the user provides the following inputs: total number of vehicles, battery capacity, the number and power ratings of AC and DC stations, initial SOC (State of Charge) values, and VIP priority levels. SOC values are randomly generated but can be manually adjusted, while VIP levels are user-defined. Based on these parameters, each vehicle is assigned a priority score and sorted accordingly.

Vehicles are assigned to available sockets in order of their priority scores. The core strategy is defined by the following logic:

If there are available sockets in the system:

- The vehicle is immediately assigned to a free socket.
- DC sockets are prioritized since they typically enable faster charging.

If all sockets are occupied:

- The vehicle must wait until the earliest socket becomes available.

- However, the algorithm does not simply wait; it also considers the type of the upcoming socket (AC or DC).

A comparison is made: If DC Waiting Time + DC Charging Time < Immediate AC Charging Time

- then, the system chooses to wait and assign the vehicle to the DC socket.
- Otherwise, the vehicle is immediately assigned to an available AC socket.

This decision-making process is evaluated dynamically for each vehicle, as:

- Socket availability changes in real time,
- Vehicles reach 100% SOC and release sockets,
- The priority queue remains fixed, but assignments are recalculated live.

Through this approach, the system does not aim to charge each vehicle at maximum speed individually, but rather to maximize the overall system efficiency by optimally utilizing the infrastructure.

At the end of the simulation, the following data is presented for each vehicle:

- Assigned station and socket,
- Charging start time,
- Charging duration,
- Charging completion time,
- Total system-wide charging time (based on the last vehicle to finish charging)

This algorithm goes beyond previous fixed-distribution models by providing a smart, flexible, and optimization-driven structure. In high-demand vehicle environments, such dynamic decision-making mechanisms significantly enhance the system's performance and reliability.

2.13.1 Input Parameters

In order for the simulation to operate correctly, the user must provide several key parameters through the interface. These parameters define both the energy demand of the vehicles and the physical limitations of the charging infrastructure. The input screen allows for structured and user-friendly data entry.

- **Number of Vehicles:** Total number of vehicles included in the simulation.
- **Battery Capacity [kWh]:** Common battery capacity assigned to each vehicle.
- **AC Station Count:** Number of single-socket AC charging stations.
- **DC Station Count:** Number of dual-socket DC charging stations.
- **AC Station Power [kW]:** Maximum power supplied by each AC socket.
- **DC Station Power [kW]:** Total power available at each DC station (shared between 2 sockets).
- **SOC Values [%]:** Initial state-of-charge values of vehicles at the beginning of the simulation. Randomly generated, but editable by the user.
- **VIP Levels:** Priority level assigned to each vehicle:
 - 0 = Normal
 - 1 = VIP
 - 2 = Critical / VIP+

Once the simulation begins, each vehicle is assigned a priority score based on these inputs, and the system's charging schedule is shaped accordingly. Among all parameters, the VIP level and SOC values play a key role in determining the assignment order.

2.13.2 Priority Assignment

The core factor in assigning vehicles to charging stations is the priority score calculated for each vehicle. This score is determined by combining the vehicle's VIP level and its current state of charge. This mechanism ensures that vehicles with urgent needs and higher priority are placed

earlier in the queue.

- A priority score is calculated for each vehicle:

$$\text{priorityScore} = \text{VIP} \times 100 + (1 - \text{SOC}) \quad (6)$$

- Higher VIP levels increase the score. Among vehicles with the same VIP level, lower SOC means higher priority.
- Vehicles are sorted in descending order based on priority score (higher score = higher priority).
- Vehicles are placed in a queue according to this sorted order.
- As sockets become available, assignments are made following this priority queue.

This scoring mechanism ensures that the most critical vehicles are processed first, contributing to overall time minimization. The same score continues to guide decisions even when vehicles are waiting or being reassigned.

2.13.3 Simulation Output Table

Before the simulation begins, the system generates a structured table based on the number of vehicles entered by the user. Each row corresponds to one vehicle, and initial SOC values are randomly assigned while VIP levels can be adjusted manually by the user. The table layout visually represents the simulation framework and helps users verify the input data before execution.

At this stage, only the following three columns are filled: Vehicle, SOC (%), and VIP Level. Other columns such as Assigned Station, Start Time (min), Charging Time (min), and Finish Time (min) are left empty. These columns exist to show the full table structure and are intended to be filled during the simulation process.

Vehicle	SOC (%)	VIP Level	Assigned Station	Start Time (min)	Charging Time (min)	Finish Time (min)
Vehicle 1	28	0	-	-	-	-
Vehicle 2	5	0	-	-	-	-
Vehicle 3	10	0	-	-	-	-
Vehicle 4	83	0	-	-	-	-
Vehicle 5	70	0	-	-	-	-
Vehicle 6	32	0	-	-	-	-

Figure 13: Initial table with SOC and VIP values only.

As shown in the screenshot, the vehicles are listed in the table with their corresponding SOC and VIP values. However, no assignments or timing data are present at this point. The table serves only as a structural preview and does not yet include any operational data.

In addition to the table, a separate Total Time (min) Edit Field is displayed below. This field remains empty prior to the simulation and is only a placeholder within the interface.

2.13.4 Application Interface

The following interface screenshot shows the complete application view before the simulation has been started. All necessary user inputs have been entered, including the number of vehicles, battery capacity, AC and DC station counts, and their respective power values. Additionally, the table displaying vehicle SOC values and VIP levels is also visible.

This screen represents the system in a fully prepared but non-executed state.

NumberofACStation

NumberofDCStation

ACStationPower BatteryCapacity

DCStationPower

NumberofVehicles TotalTime

Vehicle	SOC (%)	VIP Level	Assigned Station	Start Time (min)	Charging Time (min)	Finish Time (min)
Vehicle 1	65	0	-	-	-	-
Vehicle 2	71	0	-	-	-	-
Vehicle 3	76	0	-	-	-	-
Vehicle 4	28	0	-	-	-	-
Vehicle 5	68	0	-	-	-	-
Vehicle 6	66	0	-	-	-	-
Vehicle 7	17	0	-	-	-	-

Figure 14: Minimum Charging Time and Dynamic Assignment Algorithm Interface.

As seen in the interface, all relevant fields have been filled and the system is ready for execution. However, the simulation has not been launched yet. No vehicle has been assigned to any socket, and timing calculations have not been triggered. This screen serves as a snapshot of the configuration phase, ensuring that the system setup can be reviewed and confirmed prior to starting the simulation.

2.14 Limitations and Assumptions

The algorithm developed in this study operates under a set of predefined assumptions and does not aim to perfectly replicate all real-world conditions. In order to ensure analytical clarity and maintain computational efficiency, several simplifications were made during the modeling process.

First, all vehicles are assumed to have the same battery capacity. Although different vehicle models may have varying battery sizes and charging characteristics in real-world applications, this project uses a uniform capacity value for calculation. Additionally, the maximum charging power that each vehicle can draw is considered constant and independent of SOC level or charging curve behavior.

Charging stations are modeled such that AC stations have one socket and DC stations have two sockets. Effects such as power degradation, energy losses due to cable length or infrastructure load,

and delays during connection/disconnection phases are not included in the simulation. While most environmental variables like voltage fluctuations and ambient conditions were ignored, temperature was partially considered in specific models where its impact on station efficiency was relevant.

Throughout the simulation, it is also assumed that all sockets operate at full efficiency, and vehicle assignments and transitions occur instantaneously without delay.

3 RESULTS AND DISCUSSIONS

In this section, the overall performance of the four developed algorithms is evaluated. The system, implemented within the MATLAB App Designer environment, was tested under various scenarios based on vehicle priority levels, SOC values, and station configurations. Each algorithm was simulated individually according to its specific purpose, and the results are presented through graphs and tables.

Through the conducted tests, the system's flexibility, efficiency, and applicability to real-world scenarios were observed. The details of the results are discussed under the following subsections.

3.1 Results

For each of the four algorithms, the system behavior was analyzed based on the outcomes of the simulations. The focus was placed on key performance indicators such as total charging time, energy distribution, required number of stations, and vehicle capacity.

The following sections provide a detailed overview of test scenarios and the results obtained for each algorithm.

3.1.1 Dynamic and Priority-Based Power Distribution Algorithm Results

Test Scenario 1: In this test, two vehicles with similar battery capacities and initial SOC levels were simulated under a DC dual-socket configuration. However, Vehicle 2 was assigned a higher VIP level ($VIP = 1$), while Vehicle 1 had no VIP priority. The goal was to observe how the algorithm dynamically manages charging power in favor of higher-priority vehicles, and whether it can automatically switch to single-vehicle mode once one vehicle reaches full charge.

As the simulation progressed, Vehicle 2, having priority, received a larger portion of the available power and reached 100% SOC earlier than Vehicle 1. Once fully charged, the system immediately

redirected all available power to Vehicle 1 without requiring any manual intervention. This behavior demonstrates that the algorithm successfully handles both priority-based distribution and automatic mode switching, which are crucial for optimizing charging time and station efficiency in real-world applications.

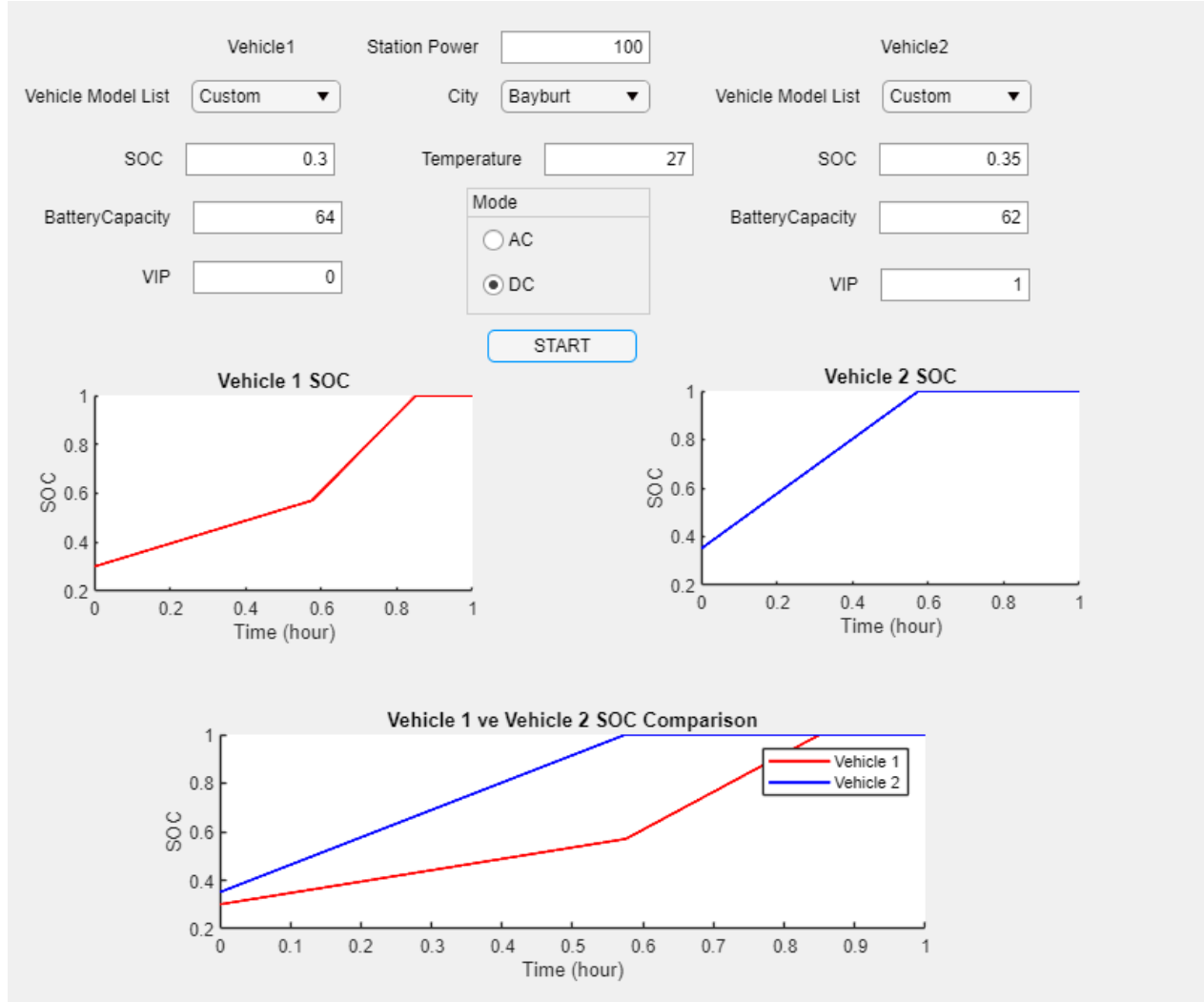


Figure 15: SOC vs Time.

The figure above shows the SOC progression of both vehicles. It is clearly observed that Vehicle 2 has a steeper slope, indicating faster charging due to its VIP status. After reaching full SOC, the curve flattens, while the slope of Vehicle 1 increases, reflecting the system's transition to single-vehicle mode. This confirms the adaptive and intelligent behavior of the developed algorithm under real-time simulation conditions.

Test Scenario 2:

In this test scenario, two vehicles with equal priority levels are considered. Initially, one of the vehicles has a state of charge (SOC) below 5 percent, while the other starts with a higher SOC level. According to the algorithm logic, when a vehicle's SOC is below 5 percent, it receives 70 percent of the total available power, and the remaining 30 percent is allocated to the other vehicle — regardless of VIP levels. Once the SOC of the critical vehicle reaches 5 percent, the system automatically switches to equal power distribution, since both vehicles have the same priority.

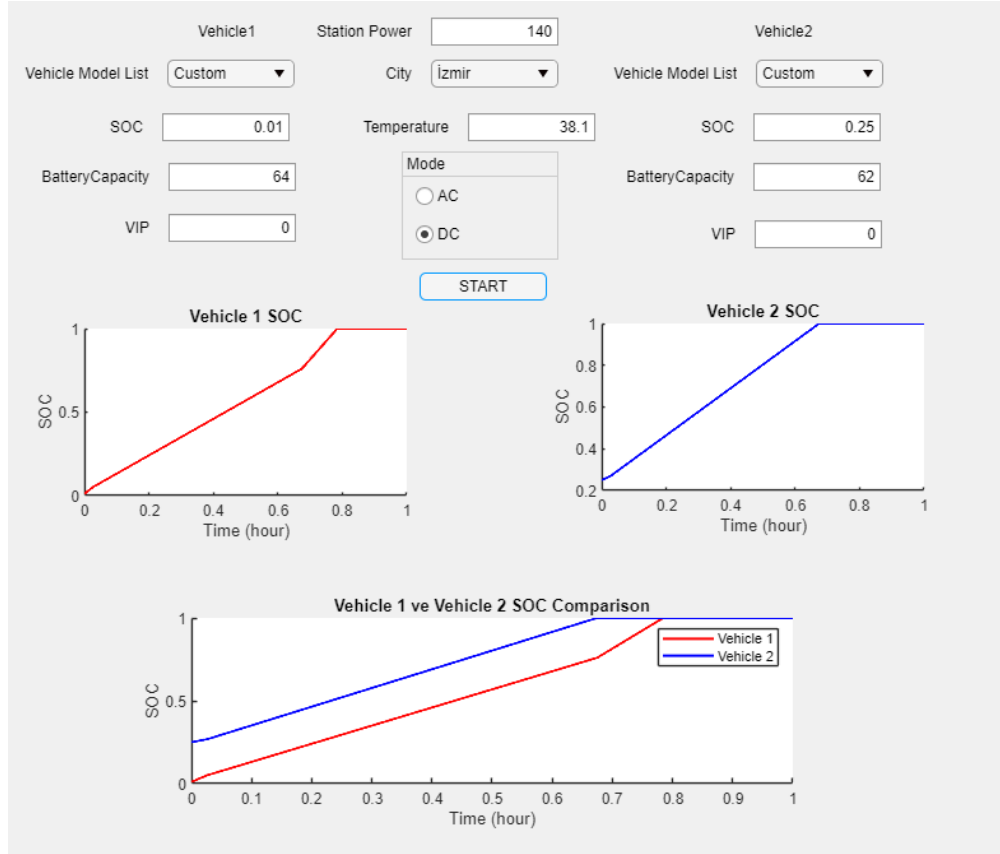


Figure 16: Priority override below 5 percent SOC.

As shown in the figure, the vehicle with initially low SOC receives more power at the beginning, which results in a steeper SOC increase. After reaching 5 percent SOC, the charging rates of both vehicles become similar, indicating the transition to equal power distribution.

This behavior confirms that the algorithm successfully prioritizes vehicles in critical condition and dynamically switches the power allocation mode based on SOC thresholds.

3.1.2 Station Selection by Vehicle Count Algorithm

Test Scenario 1:

In this test, the algorithm was used to identify the most cost-efficient AC and DC charging station configuration capable of charging 20 vehicles. The goal was to determine the minimum number of stations required while ensuring that the majority of SOC distribution scenarios could be covered within the given time limit. The system considered both AC stations, which include one socket, and DC stations, which have two sockets.

The simulation generated two different tables based on scenario coverage. The first table includes configurations that cover at least 50% of all potential SOC scenarios, while the second table targets 80% scenario coverage. Each configuration is evaluated for cost, and the results are listed in order of increasing total cost, with the most economical solution presented first.

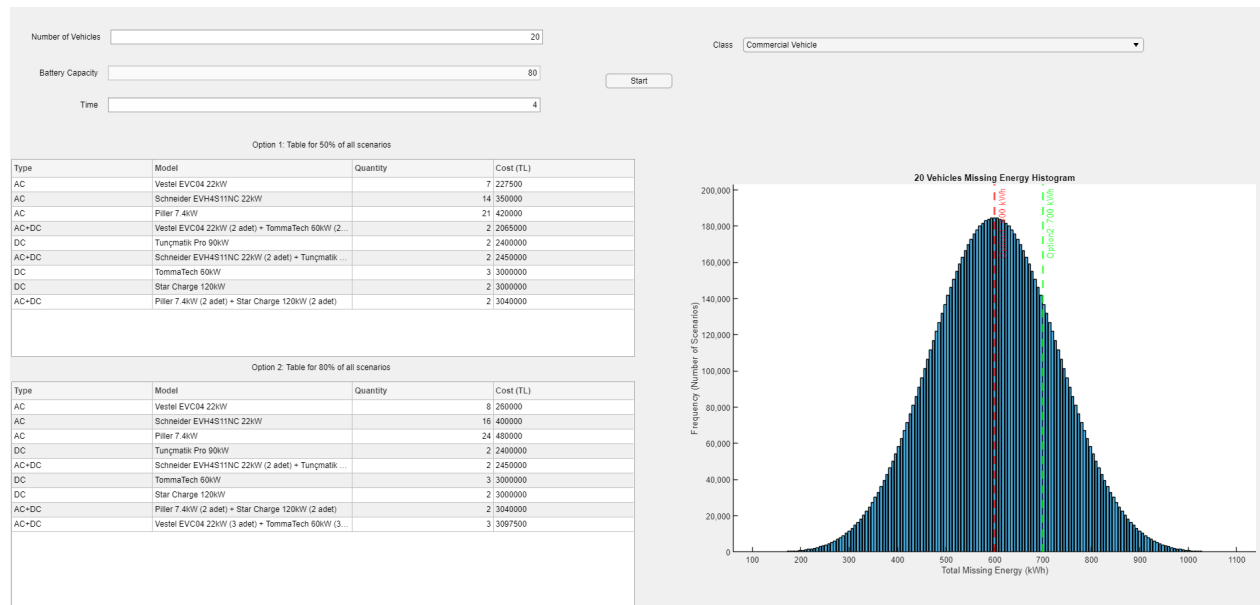


Figure 17: Station Configuration Tables for 50 percent and 80 percent Scenario Coverage.

To improve readability, the relevant sections are magnified and presented below the main image.

Option 1: Table for 50% of all scenarios			
Type	Model	Quantity	Cost (TL)
AC	Vestel EVC04 22kW	7	227500
AC	Schneider EVH4S11NC 22kW	14	350000
AC	Piller 7.4kW	21	420000
AC+DC	Vestel EVC04 22kW (2 adet) + TommaTech 60kW (2...	2	2065000
DC	Tunçmatik Pro 90kW	2	2400000
AC+DC	Schneider EVH4S11NC 22kW (2 adet) + Tunçmatik ...	2	2450000
DC	TommaTech 60kW	3	3000000
DC	Star Charge 120kW	2	3000000
AC+DC	Piller 7.4kW (2 adet) + Star Charge 120kW (2 adet)	2	3040000
Option 2: Table for 80% of all scenarios			
Type	Model	Quantity	Cost (TL)
AC	Vestel EVC04 22kW	8	260000
AC	Schneider EVH4S11NC 22kW	16	400000
AC	Piller 7.4kW	24	480000
DC	Tunçmatik Pro 90kW	2	2400000
AC+DC	Schneider EVH4S11NC 22kW (2 adet) + Tunçmatik ...	2	2450000
DC	TommaTech 60kW	3	3000000
DC	Star Charge 120kW	2	3000000
AC+DC	Piller 7.4kW (2 adet) + Star Charge 120kW (2 adet)	2	3040000
AC+DC	Vestel EVC04 22kW (3 adet) + TommaTech 60kW (3...	3	3097500

Figure 18: Test 1 - Table listing AC/DC station counts with associated total cost.

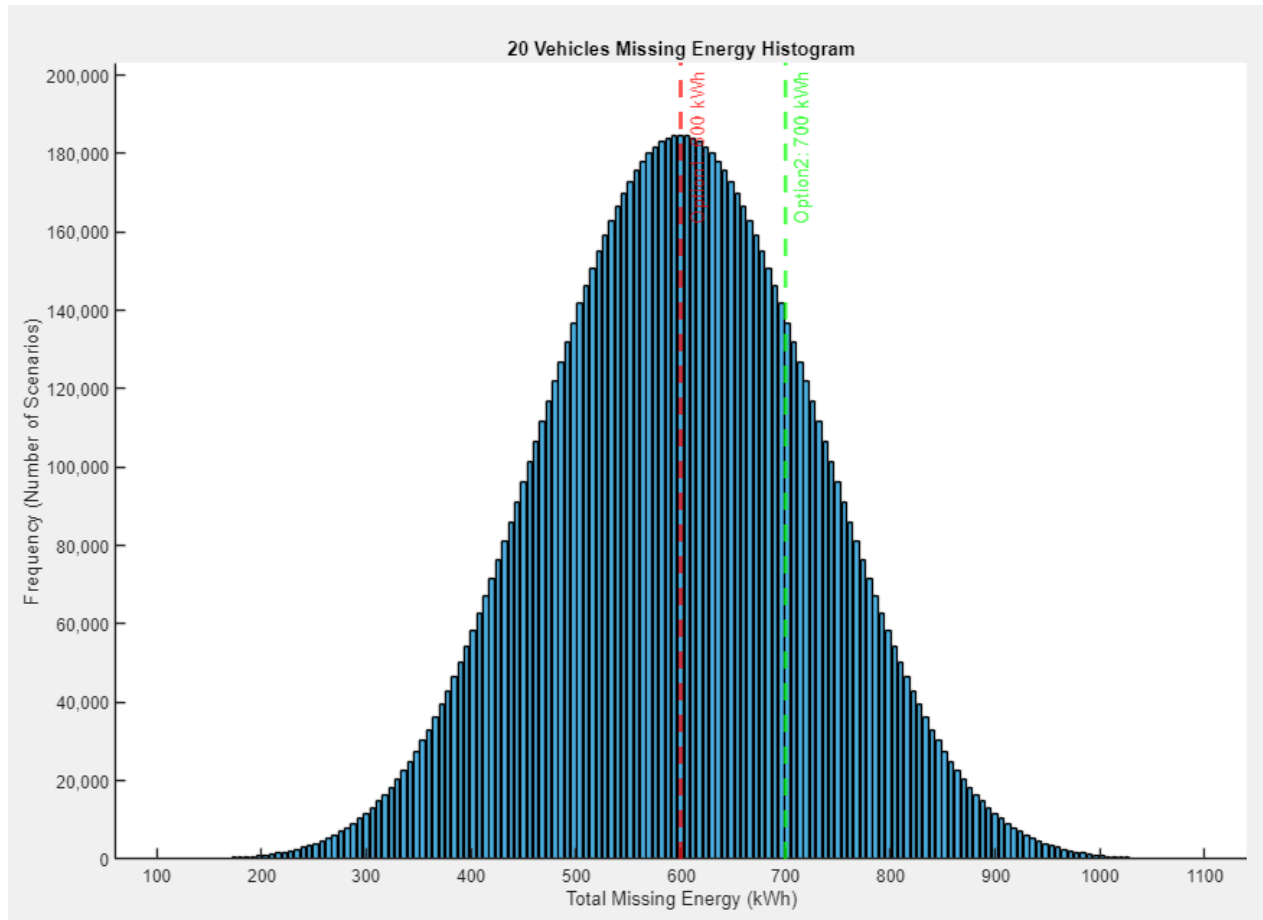
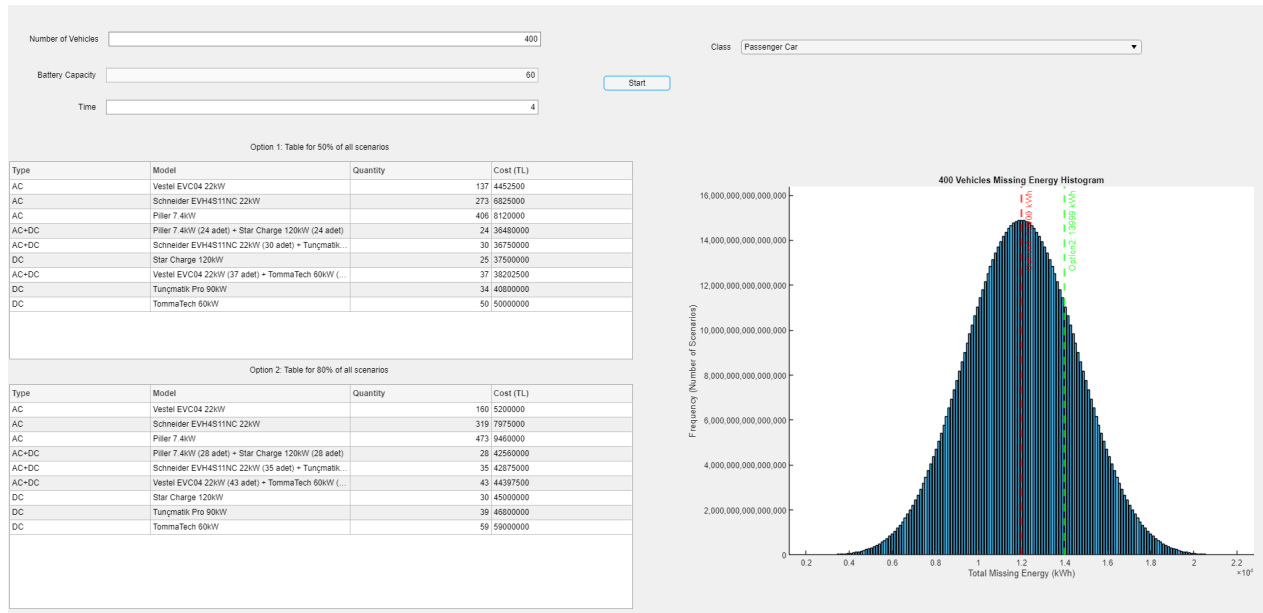


Figure 19: Test 1 - Histogram showing dual coverage thresholds.

Results show that configurations involving a limited number of DC stations supported by several AC stations offer significant cost advantages, especially for the 50% scenario coverage level. As expected, the configurations covering 80% of scenarios require more stations, leading to higher total cost. However, this trade-off provides flexibility for system designers to choose between economic and comprehensive solutions based on their operational needs.

Test Scenario 2:

In this test, the algorithm was applied to determine the maximum number of vehicles that can be charged within a 4-hour time frame, given a fixed number of AC and DC stations. The test scenario assumes 400 passenger-class vehicles, each with a 60 kWh battery capacity. The objective was to identify how many vehicles could be supported realistically under typical SOC distributions.



400 Vehicles Missing Energy Histogram

Figure 20: Station Configuration Tables for 50% and 80% Scenario Coverage.

To improve readability, the relevant sections are magnified and presented below the main image.

Option 1: Table for 50% of all scenarios			
Type	Model	Quantity	Cost (TL)
AC	Vestel EVC04 22kW	137	4452500
AC	Schneider EVH4S11NC 22kW	273	6825000
AC	Piller 7.4kW	406	8120000
AC+DC	Piller 7.4kW (24 adet) + Star Charge 120kW (24 adet)	24	36480000
AC+DC	Schneider EVH4S11NC 22kW (30 adet) + Tunçmatik...	30	36750000
DC	Star Charge 120kW	25	37500000
AC+DC	Vestel EVC04 22kW (37 adet) + TommaTech 60kW (...)	37	38202500
DC	Tunçmatik Pro 90kW	34	40800000
DC	TommaTech 60kW	50	50000000
Option 2: Table for 80% of all scenarios			
Type	Model	Quantity	Cost (TL)
AC	Vestel EVC04 22kW	160	5200000
AC	Schneider EVH4S11NC 22kW	319	7975000
AC	Piller 7.4kW	473	9460000
AC+DC	Piller 7.4kW (28 adet) + Star Charge 120kW (28 adet)	28	42560000
AC+DC	Schneider EVH4S11NC 22kW (35 adet) + Tunçmatik...	35	42875000
AC+DC	Vestel EVC04 22kW (43 adet) + TommaTech 60kW (...)	43	44397500
DC	Star Charge 120kW	30	45000000
DC	Tunçmatik Pro 90kW	39	46800000
DC	TommaTech 60kW	59	59000000

Figure 21: Test 2 - Table showing required AC/DC stations and total installation cost.

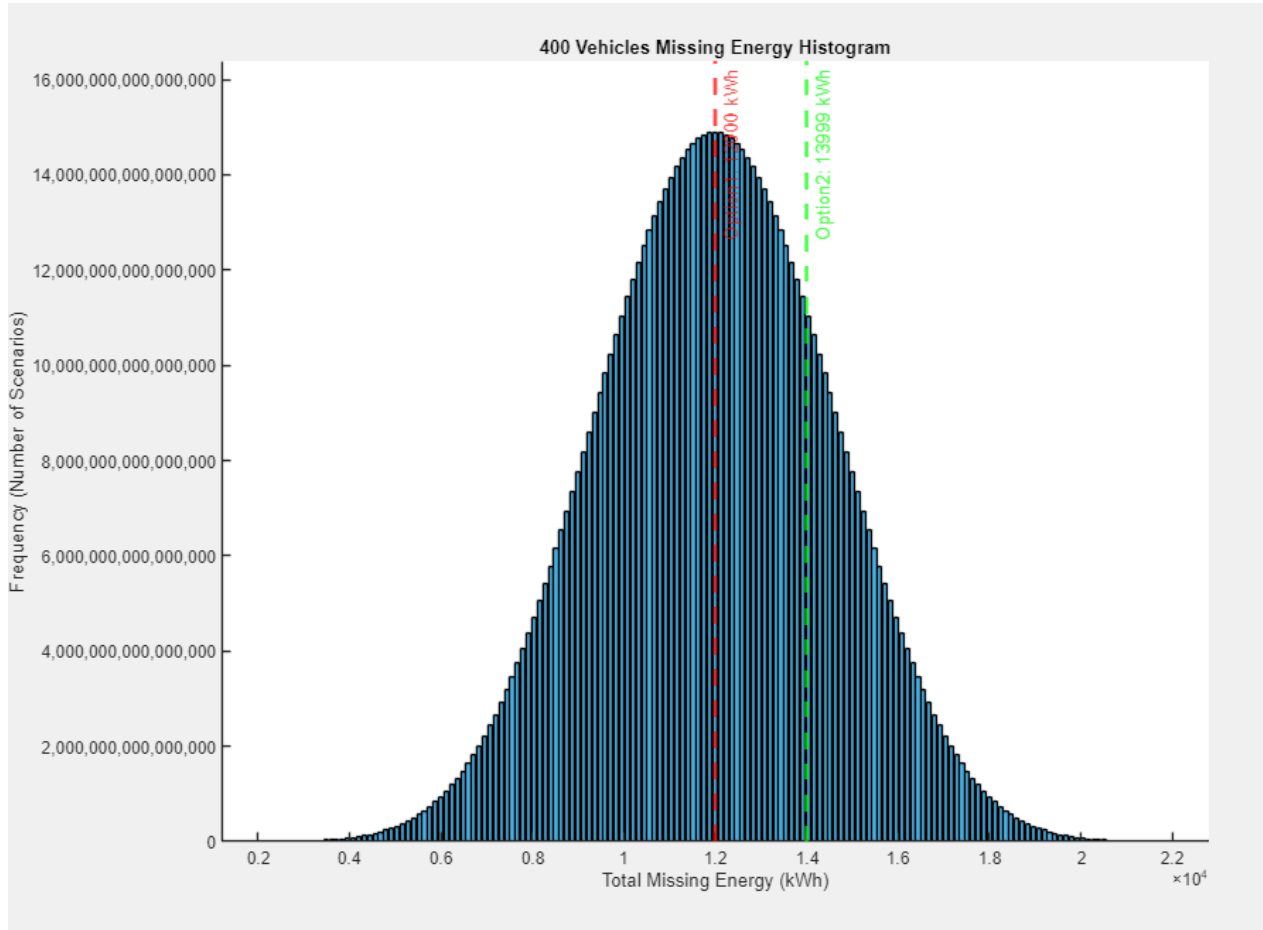


Figure 22: Test 2 - Histogram with two coverage reference lines.

Based on the simulation results, the system was able to compute total capacity under different configurations. The outcome helps infrastructure planners understand how many vehicles can be served with limited charging resources, offering guidance for optimal station setup in constrained environments.

3.1.3 Optimal Vehicle Capacity Algorithm

Test Scenario 1:

In this scenario, the algorithm was used to calculate the maximum number of vehicles that can be charged within a given time frame under a fixed number of AC and DC stations. Each AC station includes a single socket, whereas DC stations offer dual-socket configurations. The input parameters also included power capacity for each station, battery capacity per vehicle, and total available charging time.

Two separate tables were generated based on the statistical SOC distributions across possible scenarios. The first table shows the maximum number of vehicles that can be served under 50 percent of SOC demand scenarios, while the second table reflects the values for 80 percent coverage. These outputs help decision-makers understand how many vehicles their infrastructure can realistically support under different levels of uncertainty.

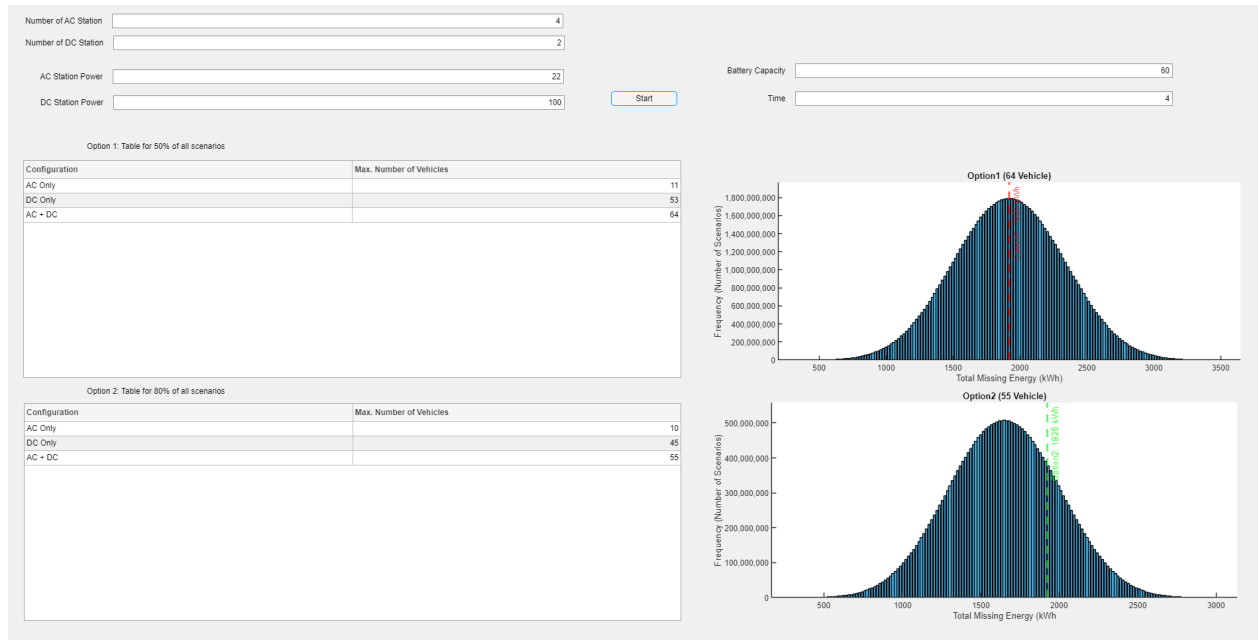


Figure 23: Maximum Vehicle Capacity Tables for 50 percent and 80 percent Scenario Coverage.

To improve readability, the relevant sections are magnified and presented below the main image.

Option 1: Table for 50% of all scenarios	
Configuration	Max. Number of Vehicles
AC Only	11
DC Only	53
AC + DC	64
Option 2: Table for 80% of all scenarios	
Configuration	Max. Number of Vehicles
AC Only	10
DC Only	45
AC + DC	55

Figure 24: Test 1 - Close-up of results table for AC/DC vehicle capacity.

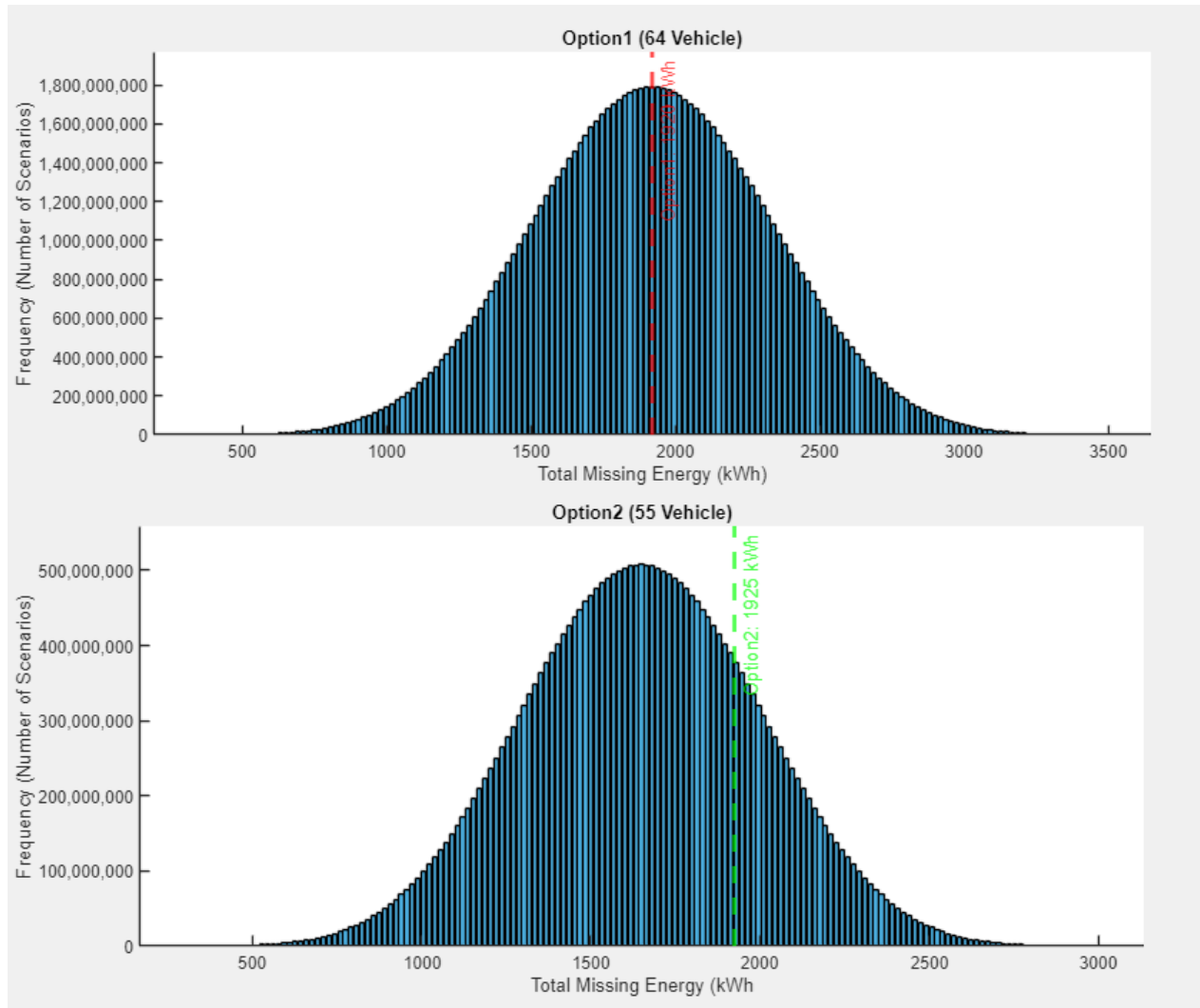


Figure 25: Test 1 - Zoom-in on histogram of AC/DC vehicle capacity.

Results indicate that, under a fixed station configuration, DC stations allow for a significantly higher number of supported vehicles due to their dual-socket and high-power design. The total vehicle capacity naturally decreases as the scenario coverage increases from 50% to 80%, given the wider variance in energy demands. These insights are essential for infrastructure planning, especially when aiming for high system utilization and future scalability.

Test Scenario 2:

In this test, a different configuration was applied compared to the previous scenario. The system was tested using 8 AC stations and 1 DC station, aiming to evaluate how many vehicles could be effectively charged within the given time constraints. Each AC station includes a single socket,

while the DC station has two sockets. The battery capacity and other parameters remain the same as before.

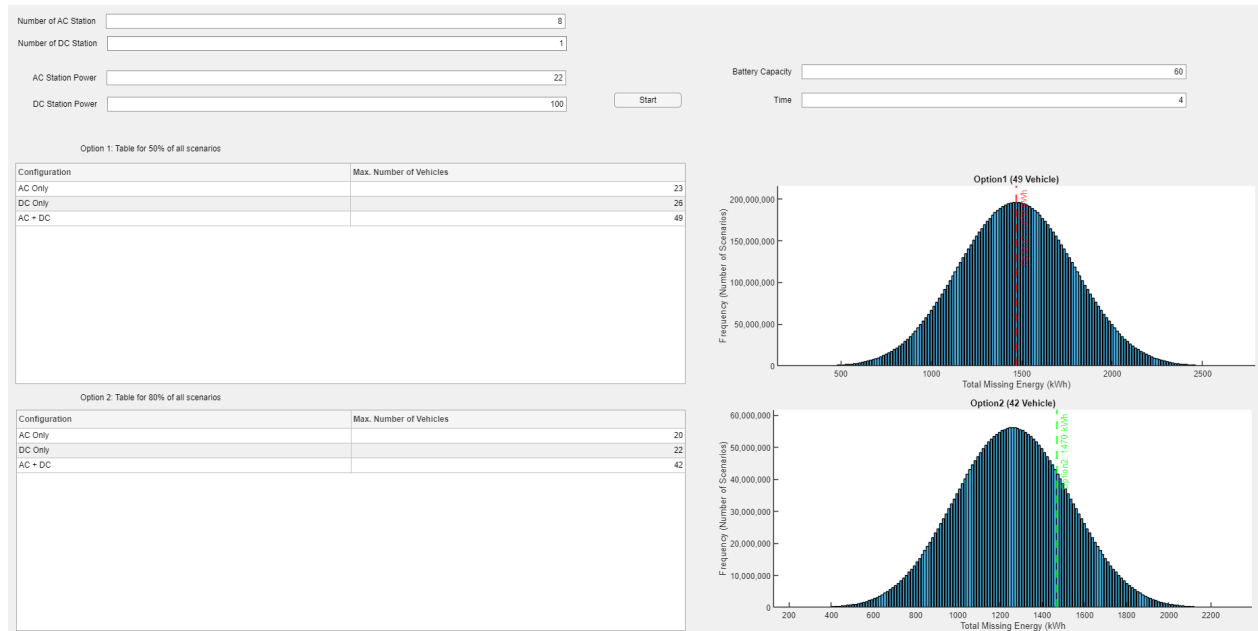


Figure 26: Maximum Vehicle Capacity Tables for 50 percent and 80 percent Scenario Coverage.

To improve readability, the relevant sections are magnified and presented below the main image.

Option 1: Table for 50% of all scenarios	
Configuration	Max. Number of Vehicles
AC Only	23
DC Only	26
AC + DC	49
Option 2: Table for 80% of all scenarios	
Configuration	Max. Number of Vehicles
AC Only	20
DC Only	22
AC + DC	42

Figure 27: Test 2 - Zoom-in on results table of vehicles supported by AC/DC stations.

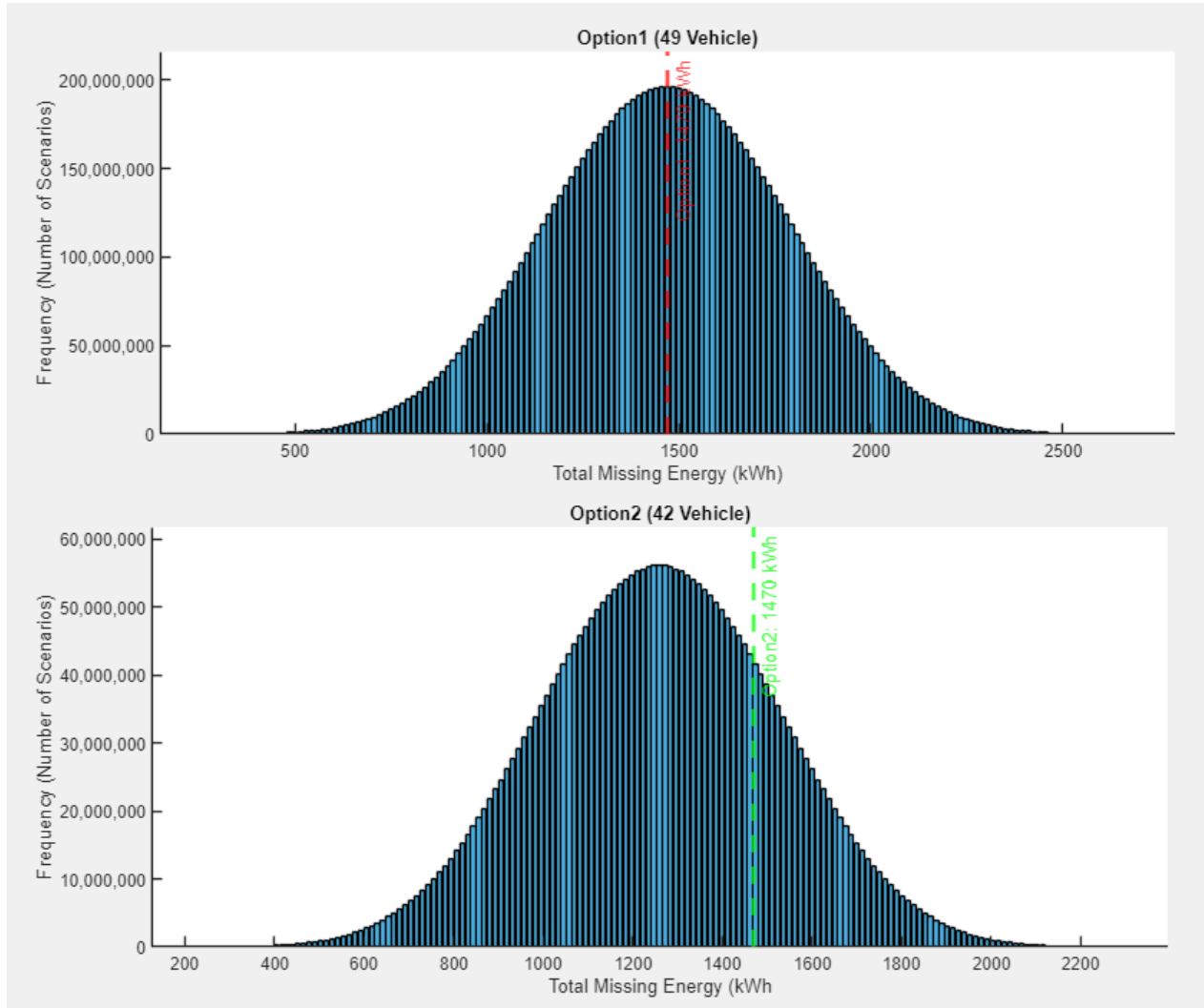


Figure 28: Test 2 — Close-up of histograms comparing AC/DC vehicle support.

3.1.4 Minimum Charging Time and Dynamic Assignment Algorithm

Test Scenario 1:

In this test, the developed algorithm was applied to a scenario involving 17 electric vehicles with varying SOC levels and VIP priorities. The goal of the simulation was to minimize the total charging time by dynamically assigning vehicles to available AC and DC station sockets over time. The assignment logic prioritizes vehicles based on VIP level and SOC values, ensuring optimal use of available charging infrastructure.

The test was conducted using both AC (single-socket) and DC (dual-socket) stations. As vehicles completed charging and vacated their sockets, waiting vehicles were assigned dynamically based

on priority scores. This real-time reassignment mechanism allowed for the reduction of idle time and maximized resource utilization.

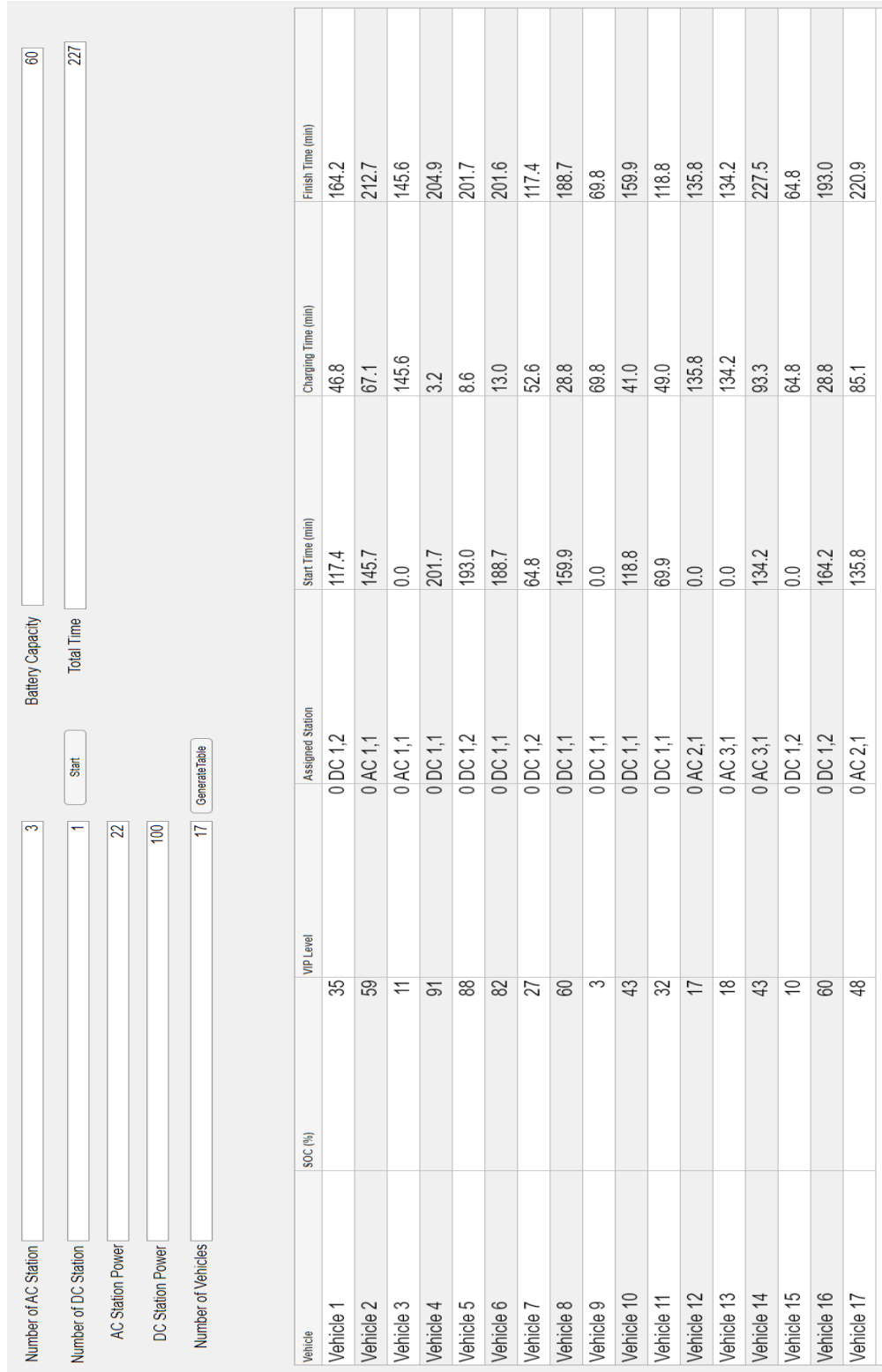


Figure 29: Charging Timeline and SOC Progression for 17 Vehicles.

To improve readability, the relevant sections are magnified and presented below the main image.

Number of AC Station	3	Battery Capacity	60
Number of DC Station	1	Start	Total Time 231
AC Station Power	22		
DC Station Power	100		
Number of Vehicles	20	GenerateTable	

Figure 30: Test 1 - Zoom-in on input fields for vehicle and station parameters.

Vehicle	SOC (%)	VIP Level	Assigned Station	Start Time (min)	Charging Time (min)	Finish Time (min)
Vehicle 1		35	0 DC 1,2	117.4	46.8	164.2
Vehicle 2		59	0 AC 1,1	145.7	67.1	212.7
Vehicle 3		11	0 AC 1,1	0.0	145.6	145.6
Vehicle 4		91	0 DC 1,1	201.7	3.2	204.9
Vehicle 5		88	0 DC 1,2	193.0	8.6	201.7
Vehicle 6		82	0 DC 1,1	188.7	13.0	201.6
Vehicle 7		27	0 DC 1,2	64.8	52.6	117.4
Vehicle 8		60	0 DC 1,1	159.9	28.8	188.7
Vehicle 9		3	0 DC 1,1	0.0	69.8	69.8
Vehicle 10		43	0 DC 1,1	118.8	41.0	159.9
Vehicle 11		32	0 DC 1,1	69.9	49.0	118.8
Vehicle 12		17	0 AC 2,1	0.0	135.8	135.8
Vehicle 13		18	0 AC 3,1	0.0	134.2	134.2
Vehicle 14		43	0 AC 3,1	134.2	93.3	227.5
Vehicle 15		10	0 DC 1,2	0.0	64.8	64.8
Vehicle 16		60	0 DC 1,2	164.2	28.8	193.0
Vehicle 17		48	0 AC 2,1	135.8	85.1	220.9

Figure 31: Test 1 - Results table: station assignments and charging times.

Simulation results showed that the dynamic assignment strategy significantly reduced the overall charging duration compared to static allocation. Vehicles with critical SOC or higher priority were charged first, and the system automatically transitioned between multi-vehicle and single-vehicle modes as needed. The time logs captured throughout the process confirmed that this approach ensures fairness, flexibility, and responsiveness in a multi-station EV charging environment.

3.2 Discussion

While the simulation-based results indicate strong performance across all four developed algorithms, several limitations should be acknowledged:

- The priority-based power allocation algorithm assumes that all vehicles provide accurate SOC and VIP data. In real-world applications, this data may not always be reliably available or updated in real time.
- In the station selection algorithms, the cost calculations are based on fixed assumptions about

station installation prices and efficiency, which may vary across regions and technologies.

- The maximum vehicle capacity algorithm simplifies some dynamics by assuming consistent charging behavior among vehicles, which may not fully capture real-time environmental or technical variations.
- The minimum charging time algorithm performs well in simulation but may require more advanced scheduling logic in scenarios with more than 30 vehicles or when integrated with renewable energy systems.

These limitations offer opportunities for future improvements, such as real-time data integration, support for variable energy sources, or adaptive learning-based optimization.

4 CONCLUSIONS AND FUTURE WORKS

In this study, a modular and scenario-based simulation system was developed to enable smart charging management for electric vehicles (EVs). Designed using MATLAB App Designer, the system supports various operational scenarios involving both AC (single-socket) and DC (dual-socket) charging stations.

Four different algorithms were developed and implemented as part of the project:

- A dynamic power allocation algorithm based on SOC and VIP priority levels,
- An algorithm that determines the optimal number of AC/DC stations according to the number of vehicles with minimum cost,
- A reverse algorithm that calculates the maximum number of vehicles that can be supported given a fixed number of stations,
- A dynamic scheduling algorithm that ensures the minimum total charging time through real-time assignments.

Simulation results show that these algorithms provide significant improvements in fairness, efficiency, and cost compared to static power distribution strategies. The system prioritizes vehicles with lower SOC or higher VIP level, allowing more efficient use of the charging infrastructure.

However, the system has some limitations. It assumes that VIP and SOC data are reliably available in real time, which may not always be the case in real-world applications. Additionally, the cost of stations is calculated based on fixed values and does not account for regional or hardware variations. Some physical parameters such as charging efficiency and battery behavior are modeled under ideal conditions.

Future Work:

The following improvements are recommended to further enhance the system:

- Integration with communication protocols such as OCPP or MQTT to enable real-time data collection for SOC and VIP status.
- Inclusion of renewable energy sources (e.g., solar power) to improve environmental sustainability.
- Implementation of AI-based or heuristic optimization algorithms to further optimize charging time and cost.
- Development of a web-based interface to enable remote access and management.
- Expansion of the system to support larger fleets and more complex behaviors, such as variable arrival times and multi-depot logistics.

Additionally, testing the system on a real EV fleet would be a significant step to validate its accuracy and scalability. With proper adaptations, the system can be applied to different vehicle types (e.g., buses, forklifts, trucks) and infrastructure setups. Thanks to its modular structure, the system can be easily expanded according to future requirements.

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APPENDICES

Appendix-A

SOC Scenario Histogram (20 Vehicles)

```
Energy20 = [60.0, 66.0, 72.0, 78.0, 84.0, 90.0, ...
            96.0, 102.0, 108.0, 114.0, 120.0, 126.0, ...
            132.0, 138.0, 144.0, 150.0, 156.0, 162.0, ...
            168.0, 174.0, 180.0, 186.0, 192.0, 198.0, ...
            204.0, 210.0, 216.0, 222.0, 228.0, 234.0, ...
            240.0, 246.0, 252.0, 258.0, 264.0, 270.0, ...
            276.0, 282.0, 288.0, 294.0, 300.0, 306.0, ...
            312.0, 318.0, 324.0, 330.0, 336.0, 342.0, ...
            348.0, 354.0, 360.0, 366.0, 372.0, 378.0, ...
            384.0, 390.0, 396.0, 402.0, 408.0, 414.0, ...
            420.0, 426.0, 432.0, 438.0, 444.0, 450.0, ...
            456.0, 462.0, 468.0, 474.0, 480.0, 486.0, ...
            492.0, 498.0, 504.0, 510.0, 516.0, 522.0, ...
            528.0, 534.0, 540.0, 546.0, 552.0, 558.0, ...
            564.0, 570.0, 576.0, 582.0, 588.0, 594.0, ...
            600.0, 606.0, 612.0, 618.0, 624.0, 630.0, ...
            636.0, 642.0, 648.0, 654.0, 660.0, 666.0, ...
            672.0, 678.0, 684.0, 690.0, 696.0, 702.0, ...
            708.0, 714.0, 720.0, 726.0, 732.0, 738.0, ...
            744.0, 750.0, 756.0, 762.0, 768.0, 774.0, ...
            780.0, 786.0, 792.0, 798.0, 804.0, 810.0, ...
```

```

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888.0, 894.0, 900.0, 906.0, 912.0, 918.0, ...
924.0, 930.0, 936.0, 942.0, 948.0, 954.0, ...
960.0, 966.0, 972.0, 978.0, 984.0, 990.0, ...
996.0, 1002.0, 1008.0, 1014.0, 1020.0, 1026.0, ...
1032.0, 1038.0, 1044.0, 1050.0, 1056.0, 1062.0, ...
1068.0, 1074.0, 1080.0, 1086.0, 1092.0, 1098.0, ...
1104.0, 1110.0, 1116.0, 1122.0, 1128.0, 1134.0, ...
1140.0];

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11, 15, 22, 30, 41, 54, ...
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318, 393, 488, 597, 730, 883, ...
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2964, 3453, 4018, 4646, 5361, 6152, ...
7048, 8029, 9131, 10335, 11673, 13125, ...
14730, 16459, 18356, 20391, 22603, 24963, ...
27516, 30218, 33121, 36181, 39442, 42858, ...
46480, 50247, 54215, 58321, 62612, 67025, ...
71613, 76293, 81126, 86030, 91053, 96112, ...
101263, 106406, 111604, 116756, 121915, 126983, ...
132021, 136912, 141727, 146355, 150854, 155117, ...
159214, 163024, 166627, 169907, 172935, 175606, ...
178001, 180001, 181700, 182991, 183957, 184500, ...
184717, 184500, 183957, 182991, 181700, 180001, ...
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132021, 126983, 121915, 116756, 111604, 106406, ...

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101263, 96112, 91053, 86030, 81126, 76293, ...
71613, 67025, 62612, 58321, 54215, 50247, ...
46480, 42858, 39442, 36181, 33121, 30218, ...
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14730, 13125, 11673, 10335, 9131, 8029, ...
7048, 6152, 5361, 4646, 4018, 3453, ...
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1069, 883, 730, 597, 488, 393, ...
318, 252, 201, 157, 123, 94, ...
73, 54, 41, 30, 22, 15, ...
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