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Enhancing Campus Mobility: Simulated Multi-Objective Optimization of Electric Vehicle Sharing Systems Within an Intelligent Transportation System Frameworks

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ABSTRACT This research optimizes an electric vehicle (EV) sharing system for a university campus, focusing on different demand patterns and peak times within an Intelligent Transportation System (ITS) framework. The main objectives are to reduce the number of unserved demands and operational costs. A simulation model was developed in MATLAB, utilizing the Non-dominated Sorting Genetic Algorithm (NSGA-II), a powerful multi-objective optimization technique that balances conflicting objectives to achieve the best trade-offs for operational efficiency. In addition to conventional decision variables, dynamic dual relocation thresholds and charge levels are introduced as decision variables to enhance optimization. The study compares two scenarios: Equally Distributed Demand (EDD) and Non-Equally Distributed Demand (NEDD), customized for the University Putra Malaysia (UPM) campus. Findings indicate that the NEDD scenario, which concentrates on specific demand areas, effectively decreases unserved demands and operational costs. Additionally, a station-specific approach expanded the solution space, improving adaptability and resulting in notable reductions in operational costs and smaller but meaningful improvements in unserved demands, especially during peak periods. By setting station-specific relocation thresholds and charge levels, resources were deployed efficiently, minimizing unnecessary relocations. The use of dynamic values for dual relocation thresholds and charge-to-work levels further optimized the process, reducing operational costs significantly, with a lesser impact on unserved demands across both scenarios. This research offers valuable insights into the implementation of EV sharing systems in educational institutions, emphasizing the advantages of focused resource allocation and the integration of dynamic decision variables.

INDEX TERMS NSGA-II, multi-objective optimization, EV sharing system, smart campus, car sharing system, vehicle relocation, charging strategies, ITS.

I. INTRODUCTION

EVs are revolutionizing the transport sector, providing a greener alternative to conventional internal combustion engines. This shift has been necessitated by the pressing need to reduce greenhouse gas emissions and address the growing concerns about climate change. Governments and organizations around the world have acted on ambitious goals of cutting emissions; hence, EVs are in place for part of the future solution to transportation [1], [2]. Besides their environmental benefits, EVs would be great contributors to improve ITS, enabling smoother traffic flow and thus preventing congestion, which in turn raises overall transportation efficiency [3].

Existing studies have emphasized operational efficiencies and cost savings associated with EV sharing systems. For instance, the availability of vehicle stations and the proximity of the stations to the customer destination points are some of the paramount issues that influence the service quality. Also, the infrastructure and operational costs of those systems are driven by multiple elements that include fleet size, number of stations, and vehicle chargers or timely availability of vehicles at strategic positions [4], [5], [6], [7]. Most research on EV sharing systems has focused intensely on operational efficiencies in urban areas, highlighting fleet management strategies, charging infrastructure, and mitigating environmental factors like weather and public transit availability [4], [8]. However, these studies may neglect certain challenges that can be more specific to environments with both concentrated and variable human demand, such as that of university campuses [9].

University campuses, with high population density dominated by short trips, are an ideal location for the siting of an EV sharing system due to the controlled environment and predictable travel patterns by students, faculty, and staff [10]. Implementing EV sharing systems on campuses presents a unique opportunity to promote sustainable transportation while catering to the specific mobility needs of the campus community [11]. However, optimizing these systems in small-scale environments like university campuses poses significant challenges, particularly due to the diverse distribution of demand [12], which lead into the needed relocation vehicle that can serve more demands without using alarm to have threshold relocation of vehicles in the supplier station maybe lead to unbalance system then user dissatisfaction, Moreover, the need for vehicles to charge adds to the waiting times for relocation, which, in turn, increases operational costs. Using a decision variable to manage charge levels and optimize vehicle availability can help address this issue effectively [13].

Recent studies have explored the feasibility of shared electric mobility systems specifically in campus settings, considering various vehicle types such as electric cars, e-bikes, and scooters. Carrese et al. (2017) investigated the implementation of an electric car-sharing system at Roma Tre University, focusing on factors that influence service uptake, such as user behavior [10]. Galatoulas et al. (2018) studied such economic feasibility in the possible demand and costs for establishing an electric vehicle sharing system for academic communities, highlighting economic feasibility [15]. A study was conducted for university Malay (UM) in 2021 as presented by Yin et al. to understand the pattern of usage and to identify the various factors that determine the shared transport systems, involving electric scooters. As such, they identified a few key factors influencing the usage patterns: daily travel modes, road features, age, and weather conditions. [11]. Bitencourt et al. (2024) analyzed operational strategies of the optimal shared e-bike system on campus, focusing on user-based and operator-based relocation schemes with the ability to balance out demand effectively. Integration of other smart campus technologies such as photovoltaic systems and dynamic energy costs was considered [15]. By reading these studies, insight into issues of adoption, feasibility, and sustainability regarding shared electric mobility services at university campuses can be gained. However, they gave more emphasis to feasibility, behavioral aspects, and environmental sustainability than to the operational optimization strategies which could be used for the improvement of user satisfaction and operational cost, such as vehicle relocation or dynamic charging.

Within reputation and benefit, UPM University initiated an EV sharing program within the campus with the motive of establishing a name as a smart campus, saving time for traveling students and staff. This paper accordingly represents the results of a collaborative joint research by KYUTECH, Japan, and UPM in designing an optimal one-way EV sharing system with reservations for transportation within the internal campus using single-seat COMS cars made by Toyota Auto Body.

This study contributes by developing a simulation model for an EV sharing system suited to UPM campus by considering decision variables of dual relocation threshold and charge to work in two different demand distribution scenarios (NEED, EDD), Detailed descriptions of these scenarios are provided in the (4. Results and Discussion section). In this work, NSGA-II has been utilised as an optimization tool to balance dual objectives (minimizing operational costs and reducing unserved demands). Additionally, A novel station-specific approach is also implemented to expand the solution space and enhance resource allocation at individual stations, thereby using dynamic values for dual threshold relocation and charge level to work at each station based on the needed amount, providing more granular levels of optimization. Comparing the performance of the EV system in EDD and NEDD scenarios, the present work has provided some insight into the most efficient management strategies related to shared EVs in a campus environment. By using dynamic values of the decision variables can enhance the optimization in both the large-scale scenario (EDD) and the small-scale scenario (NEDD). Results obtained from this research will fill in the existing gaps in literature and create a useful framework for the future implementation of EV-sharing systems in similar contexts.

II. RELATED WORK

A. EV SHARING SYSTEMS IN URBAN ENVIRONMENTS

Numerous studies have examined the design and implementation of EV sharing systems in urban areas regarding customer satisfaction, vehicle utilization, infrastructure needs, relocation strategies, and optimizing charging strategy. For instance, Hua et al. (2019) examined operational cost strategies as a critical indicator by highlighting vehicle utilization and customer satisfaction [16]. Similarly, according to Jung et al. (2017), establishing an EV sharing system in a densely populated location is difficult and necessitates efficient car distribution through robust charging infrastructure [17]. Several studies for relocation and charging strategies have been developed that can provide better availability and operational costs for the vehicles in the urban environment. For example, Caggiani et al. (2020) look at vehicle-to-grid- technology to optimize the management of energy and the availability of vehicles [18]. Additionally, Boyacı et al. developed two optimization models: a multi-objective mixed-integer linear programming (MILP) model for one-way EV sharing systems with reservation, and an extended multi-objective mixed-integer multi-level programming (MMILP) model that integrates vehicle and personnel relocation. These models focused on balancing user satisfaction, operational costs [4], [8].

B. EV SHARING SYSTEMS ON UNIVERSITY CAMPUSES

In contrast to urban settings, university campuses present unique challenges, including limited space, concentrated demand during specific hours, and the need for sustainable solutions that align with green initiatives. Recent studies have specifically examined these challenges and offered tailored solutions for campus environments, focusing on different types of electric vehicles such as electric cars, e-bikes, and e-scooters.

At Roma Tre University, Carrese et al. (2017) suggested EV sharing system with an emphasis on the behavioral factors influencing its adoption. Using both revealed and stated preference surveys, they developed a model that predicted modal shifts driven by attitudes such as environmental awareness ("Green Attitude") and openness to shared services ("Sharing Attitude"). These factors were found to significantly impact the choice of electric cars within the university community [10]. The university community's mode choice, particularly for electric cars, was found to be highly influenced by important variables including "Green Attitude" and "Sharing Attitude," which were highlighted in this study.

Similarly, the possible demand and expenses of starting an EV sharing business aimed at academic communities were also investigated by Galatoulas et al. (2018). In order to determine the economic viability of deploying such systems in academic settings, they carried out comprehensive surveys to evaluate mobility needs and examined the expenses of the fleet and infrastructure [14]. By investigating the usage of shared electric scooters at UM, Moosavi et al. (2022) expanded on this line of investigation. Using machine learning models to forecast usage trends, they discovered a number of important parameters affecting usage, including road features, weather, demographics, and daily travel modes [11]. Their results emphasized how crucial it is to comprehend the unique needs of each community when creating sustainable mobility solutions, especially for e-scooters.

Furthermore, at the University of Tennessee, Knoxville, Ji et al. (2014) investigated a completely automated electric bike (e-bike) sharing system. They assessed system dependability under various configurations by simulating different demand situations, emphasizing the significance of battery management and charging procedures to preserve service availability [19]. In order to maximize the sustainability of the e-bike sharing system, the study showed how well off-board battery charging and swappable batteries work to guarantee reliable service.

Moreover, Yin et al. (2021) investigated the factors that motivate service sharing in Ningbo University and the usage patterns of shared transportation in high-education zones. They discovered that the adoption rates of electric vehicles and shared bikes in university regions were highly impacted by socioeconomic variables, vehicle density, and service fees. They found that socioeconomic factors, vehicle density, and service costs significantly influenced the adoption rates of shared bikes and electric vehicles in university areas [9]. Their study revealed a knowledge gap about how to efficiently balance supply and demand, which is crucial for campus environments with distinct mobility patterns, especially for electric cars and bikes.

Piazza et al. (2021) also contributed to this area by investigating the optimal design for a combined electric mobility service and an energy system based on renewable energy in an Italian university campus. They presented a mixed-integer linear programming model that defines the optimal configuration of shuttles, bikes, and cars with the purpose of meeting campus needs, while integration of renewable energy solutions underlines synergies with electric mobility and energy supplies at the local level [20]. Furthermore, Bitencourt et al. (2024), studied user-based and operator-based relocation schemes to balance demand and integrated dynamic energy tariffs, providing a basis for understanding charging and relocation strategies in campus environments, particularly for electric bikes costs [15].

C. RESEARCH GAPS IN LITERATURE

Despite extensive research on EV-sharing systems in urban areas, there is a significant research gap regarding how the specific demand of the university campus is met. Some other unique problems exist with the university campus such as the non-uniform distribution of demand, limited space, and concentrated demand at certain locations, which are often not considered in the prevailing models assuming even distribution of demand. While relocation strategies with dual thresholds, along with charging levels, are rarely considered as simultaneous decision variables, allowing dual threshold relocations enables some of the vehicles to be located around essential serving stations with the surplus relocating through the system toward demand areas, which is an essential requirement for efficiency in EV sharing systems. Meanwhile, charge level can be a decision variable to reduce operational cost and improve service availability through better optimization of vehicle usage and reduction of downtime for charging.

Bitencourt et al. (2024) addressed research related to EV sharing system in university by relocation and charging strategies using a user-based e-bike relocation optimization model and an operator-based e-bike relocation optimization model [15]. Similarly, Piazza et al. present a mixed-integer linear programming model to integrate electric shuttles, electric bikes, and cars with renewable energy sources [20]. However, both studies had their limitations in accommodating concentrated and fluctuating demand patterns typical on university campuses, in particular to electric cars. Their limitations restricted the reliability of static or predictive models that lacked flexibility for dynamic changing of the outputs with changing demands.

Most methods presently in existence are rather static and have failed to consider this dynamic nature, so critical at university settings where demand is highly concentrated and time-of-day-dependent. This paper fills the research gaps by presenting a new dynamic optimization model, incorporating dual threshold relocation strategies and adaptive charging of EV, fitted to the unique demand profile and space constraints found on university campuses. It optimizes vehicle relocation and charging together to achieve further improvement in system efficiency, reduction of operating costs, and higher customer satisfaction than the previous studies that did not consider campus-specific dynamic operational optimization.

III. METHODOLOGY

This section describes the modeling, simulation, and optimization methodology for the electric vehicle sharing system on a university campus. The whole structure is divided into three major parts: (1) Model Description-naming the structure of the EV sharing system including its environment, vehicles, stations, and operational processes; (2) Simulation Model-which simulates the performance of the system in order to calculate unserved demands and operational costs with generated data; and (3) Optimization Techniques-by using NSGA-II in two different ways: one is with uniform decision variables across all of the stations, and another is with station-specific approach in order to enhance system adaptability.

A. MODEL DESCRIPTION

This section introduces the EV sharing system adapted to university campus demands and focuses on the determination of served demands and operational costs. The system characteristics are adapted from the large-scale city optimization framework developed by Boyaci [4], designed for Nice, France. Key adaptations include modifications to demand modeling, station placement, and fleet size, tailored to the unique spatial and usage patterns of a campus environment. This adaptation ensures that the system meets the specific needs of a university, characterized by concentrated demand in certain hotspots and unique operational challenges.

1) ENVIRONMENTS INFORMATION

Using Google Maps, we obtained a map of the UPM campus to identify the station locations based on key areas such as major faculties, offices, and food courts, which attract the highest concentration of people. This approach mirrors the Roma Tre University EV sharing project, where stations were strategically placed near key facilities to serve students and staff efficiently [10]. The environmental information covers the UPM university area, with dimensions of 3894 meters in height and 4372 meters in width. After determining the station locations on the map, we created a graph representing the environment, including the stations and routes, as depicted in Fig. 1.

2) STATIONS

Stations are strategically placed throughout the campus to ensure maximum coverage and accessibility. Stations are located at key points such as building entrances, cafeterias, and other common areas. This strategy is inspired by similar implementations in the University of Tennessee e-bike sharing project, where station placement was optimized to ensure accessibility and maximize system reliability by serving areas with the highest demand, such as key campus facilities [19]. Parking spots for stations are equal. Stations are equipped with charging infrastructure to ensure that EVs can be charged between uses, maintaining the system's operational efficiency, number of parking spots and charging stations are not considered.

3) VEHICLE

The fleet of EVs is the core component of the sharing system. Each vehicle is designed to meet the transportation needs of the university campus. Initially, vehicles were distributed equally to each station.

4) COVERAGE ZONE

The coverage zone defines the geographical area that each station can effectively serve. This ensures that most demands fall within a station's serviceable area of a station, reducing waiting times and improving service reliability. Stations are placed to maximize coverage and accessibility, ensuring that key areas of the campus are within the coverage zones of one or more stations.

5) OPERATIONS

a) Charging operations: The charging process begins by identifying vehicles that need to be charged [12], i.e., those whose battery levels have dropped below the Threshold Level to Charge. These vehicles are removed from the service list and moved to the chargingVehicles list (as shown in fig. 2, 1). During the charging process, the system monitors battery levels, and vehicles exceeding the Charge Level to Work as a decision variable can temporarily be used to serve demands if needed. These vehicles are returned to the charging process after completing their assigned trips, ensuring minimal interruption to the charging cycle (as shown in fig. 2, 2). Once fully charged, the vehicles are moved back to the available Vehicles table, ready to be deployed again (as shown in fig. 2, 3). This dynamic system optimizes vehicle availability and

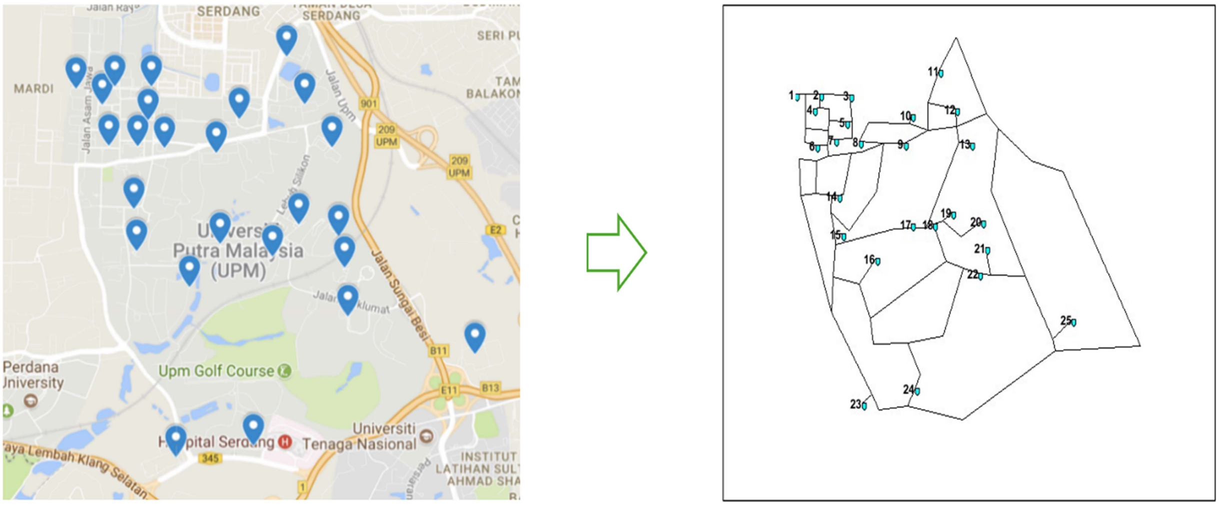

FIGURE 1. Identification of stations based on faculty locations and buildings on the university campus, and conversion of the campus map into a graph.

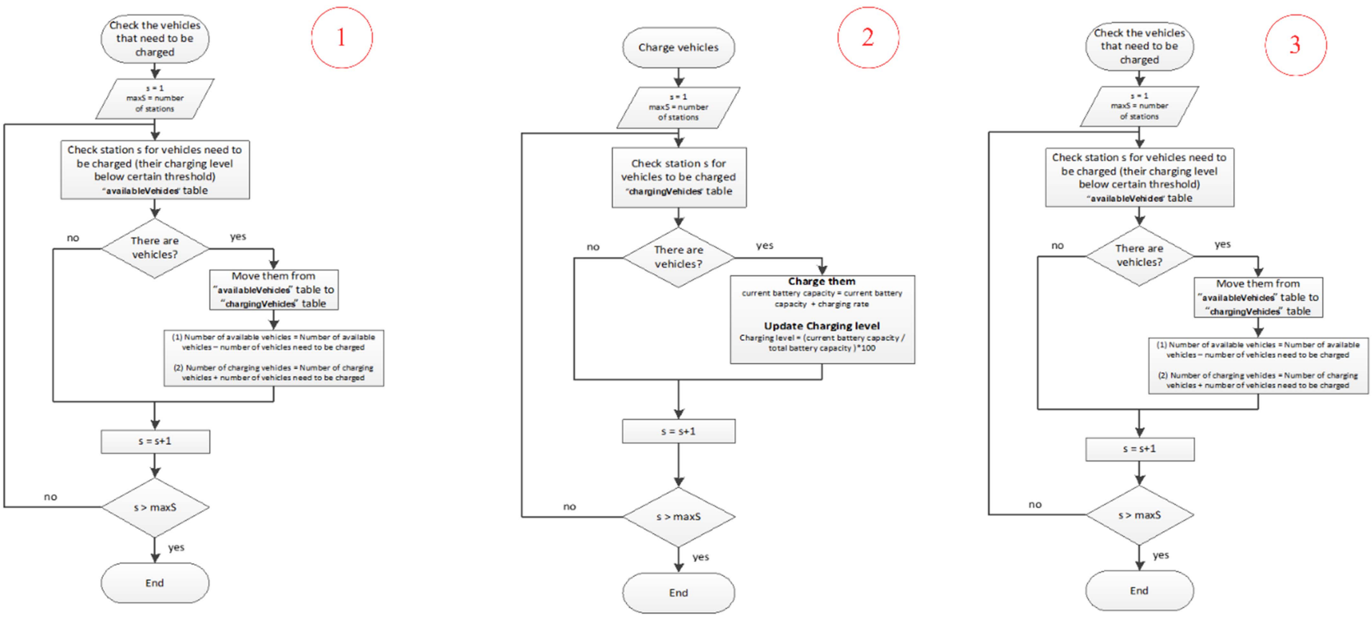

FIGURE 2. Charging operations.

charging efficiency, ensuring that vehicles are almost available when demand arises while maintaining efficient battery management.

Parameters used for simplification in a simulation and optimization can be seen in Table 1. Note herein that all the values are scaled for simplicity and do not directly relate to any real-world specifications of EVs. For your reference only, 100 joules scaled approximately corresponded to a real-world value of about 0.000028 kWh. With this scaling, the relations for energy consumption, charging, and available vehicles hold across different scales of parameters. This dynamic system optimizes vehicle availability and charging efficiency while maintaining effective battery management.

b) Relocation algorithm: The relocation algorithm is designed to ensure efficient distribution of electric vehicles (EVs) across the campus, responding dynamically to fluctuating demand throughout the day. This approach was inspired by similar research conducted for one-way electric car-sharing systems, which used a dynamic threshold-based method to

TABLE 1. Fixed Vehicle Parameters

Constant	Value
Battery capacity	100 [joule]
Energy consumption rate	0.01 [joule/meter]
Charging assumption rate	10 [joule/time interval] (optimization)
	0.0111 [joule/time interval] (simulator)
Vehicle assumption average speed	15 [meter/sec]

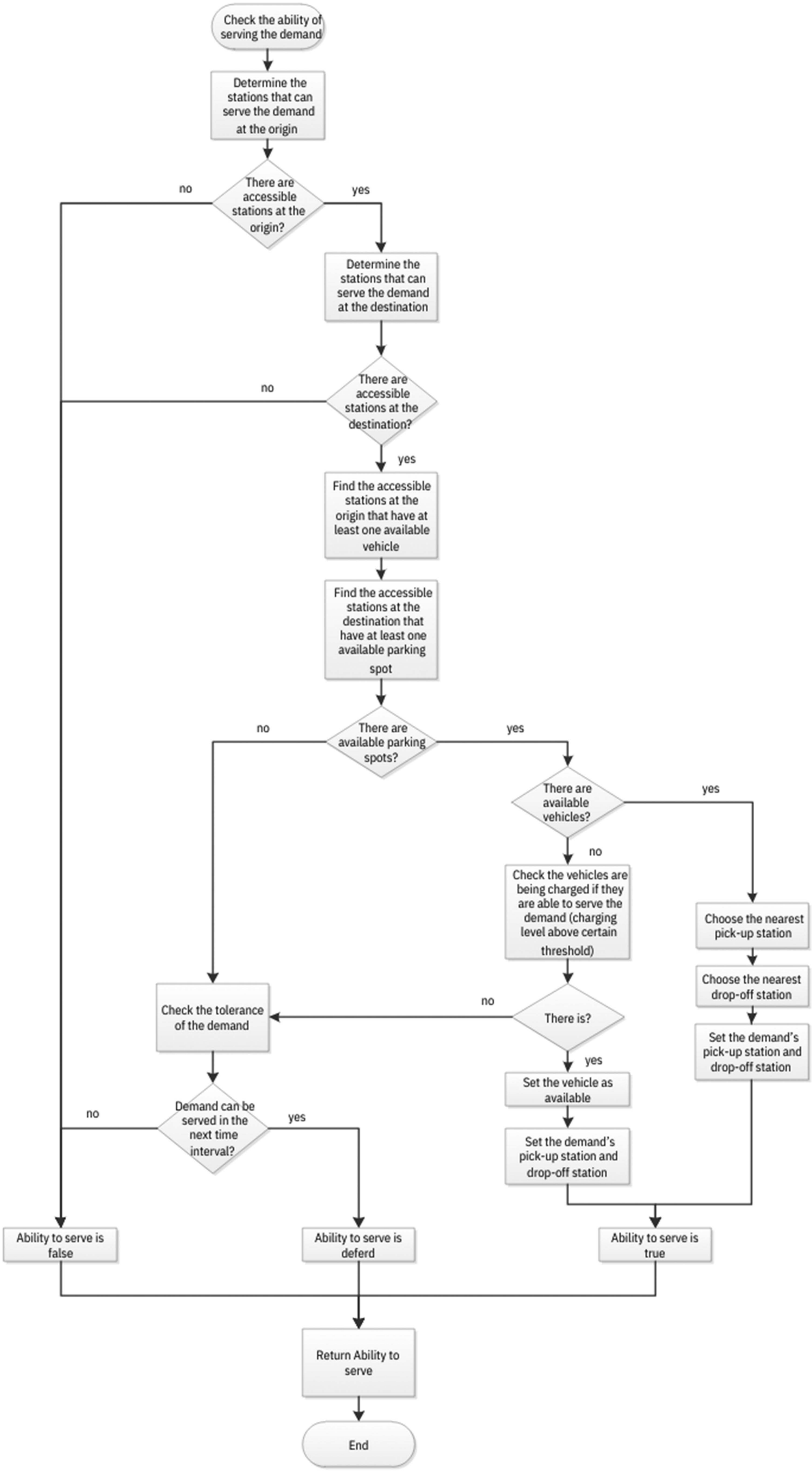

FIGURE 3. **Serving demands for EV sharing system with reservation.**

optimize vehicle relocation and minimize inefficiencies in vehicle distribution [21]. However, unlike the urban-focused approach, which primarily dealt with broader urban mobility challenges, our relocation algorithm is specifically tailored to a university campus environment, addressing unique operational needs such as concentrated demand during peak academic hours and the availability of campus staff for relocations. This process relies on two key thresholds. The first, referred to as Relocation-Threshold-1, signals when a station's vehicle count drops below a critical level, indicating that more vehicles are needed at that location to meet demand. On the other hand, Relocation-Threshold-2 marks the point at which a station has more vehicles than it requires, prompting the system to redistribute the surplus to under-supplied stations. The algorithm continuously monitors vehicle levels at each station, comparing them to these thresholds to determine whether relocations are necessary. When a station triggers Threshold 1, the system identifies nearby stations exceeding Threshold 2, facilitating the transfer of surplus vehicles. To manage these transfers, employees working in two shifts (8 AM-2 PM and 2 PM-8 PM) are responsible for executing relocations. However, if employee availability becomes a limiting factor, such as when one station lacks sufficient staff, the system applies the same relocation logic to employees, reassigning staff from stations with extra personnel to those requiring assistance. Since the EVs used in the system are one-seat vehicles, relocating employees poses an additional logistical challenge. To address this, different modes of transport, such as the shuttle, are used to move employees between stations, ensuring they are available where needed. This approach helps maintain optimal vehicle and personnel distribution throughout the day. By balancing vehicle availability across stations and relocating employees as required, the algorithm enhances the system's responsiveness, reducing unserved demands and ensuring efficient fleet operation across the campus network.

c) Employee: Employees play a crucial role in maintaining and operating the EV sharing system. Employees work in shifts to ensure continuous operation of the system. They are responsible for tasks such as relocating EVs, maintaining vehicles, and assisting users. Their presence ensures the smooth operation of the system, particularly during high-demand periods.

B. SIMULATION MODEL

The simulation aims to run the EV sharing system model to calculate the number of unserved demands and the operational cost of the system. This is based on generated demand data over a 12-hour period, from 8 AM to 8 PM, which represents the most active working hours within a university setting. The simulation helps assess the effectiveness of the model under different demand scenarios, using various statistical distributions to simulate realistic conditions [19].

1) GENERATED DEMAND

The demand generation process is essential for simulating the operational dynamics of our electric vehicle (EV) sharing system, due to the lack of real data. This involves generating demands over a 12-hour period using a combination of Poisson, Uniform, and Normal distributions to accurately reflect temporal and spatial variations typical of an EV sharing system on a university campus.

Poisson Distribution: This distribution is used to model the number of demands generated per unit of time. It is well-suited for events that occur independently and sporadically over time, which is characteristic of demand occurrences in an EV sharing system. The Poisson distribution is defined by:

$$\mathbf{P}\left(\mathbf{K}\right)=\frac{\boldsymbol{\lambda}^{\mathbf{k}}\mathbf{e}^{-\boldsymbol{\lambda}}}{\mathbf{k}!} \tag{1}$$

where $P(K)$ is the probability of exactly K demands occurring in each interval, λ is the average number of generated demands (set to 4 demands per minute), and K is the actual number of demands occurring in that interval.

Uniform Distribution: This distribution is employed to generate random spatial coordinates for the origin and destination of each demand. By ensuring that every point within the specified area has an equal probability of being selected, it provides a fair and unbiased spatial distribution. The Uniform distribution is defined by:

$$\mathbf{f}\left(\mathbf{X}\right)=\frac{1}{\mathbf{b}-\mathbf{a}},\ \mathbf{a}\leq\mathbf{x}\leq\mathbf{b} \tag{2}$$

where f(X) is the probability density function for the variable X , X represents a randomly generated coordinate within the environment's bounds, and a, b denote the lower and upper limits of the area.

Normal Distribution: This distribution models the tolerance for each demand, capturing realistic variations where most values cluster around a mean with some standard deviation. The Normal distribution is defined by:

$$\mathbf{f}\left(\mathbf{x}\right)=\frac{1}{\boldsymbol{\sigma}\sqrt{2\boldsymbol{\pi}}}\mathbf{e}^{-\frac{(\mathbf{x}-\boldsymbol{\mu})^2}{2\sigma^2}} \tag{3}$$

where f(x) is the probability density function for tolerance time x, mean tolerance (μ) of 10 minutes and a standard deviation (σ) of 3 minutes.

By combining these three distributions, we effectively replicate a realistic demand environment for the EV sharing system, where the Poisson distribution controls demand frequency, the Uniform distribution assigns unbiased spatial coordinates, and the Normal distribution captures realistic user wait tolerance. This method enables an effective simulation of demand patterns in a campus environment, allowing for a thorough evaluation of system performance in the absence of real-world data.

The morning peak hour demand in the NEDD scenario, for instance, was based on common observations of high mobility near university gates during the start of regular academic weekdays. Such assumptions are necessary to create realistic demand models when real data is unavailable. However, we acknowledge that these patterns may vary during weekends, holidays, or summer months, which are not fully captured in this model. The focus here is primarily on typical weekday operational dynamics during active semesters, which help address critical operational challenges.

2) SERVING DEMAND

Once the demands are generated, they need to be served to complete the process, as shown in Fig. 3. The procedure first identifies stations within the coverage zone radius that can serve the demand. Next, it determines the destination station within its coverage radius. Two conditions must be met: the source station must have at least one available vehicle, and the destination station must have at least one available parking spot. If these conditions are met, the demand is served. Otherwise, it is deferred to the next time interval or marked as unserved after 10-time intervals.

3) DECISION VARIABLES, CONSTRAINS AND FORMULATIONS

a) Decision variables: Nine variables are considered for generating and serving the demand to pick up from source stations and drop-off into the destination station which are:

- **var1:** Number of Parking Spots: Represents the total parking spots available across all stations. Sufficient parking is crucial for accommodating EVs, charging, and determining the overall system capacity.
- **var2:** Number of Vehicles: Indicates the total number of vehicles in the system, equally distributed across stations. This ensures adequate supply to meet demand.
- **var3:** Number of Employees in First Shift (8 AM-2 PM): Employees in this shift handle vehicle relocation and customer service. Efficient staffing is necessary for smooth operations and managing labor costs.
- **var4:** Number of Employees in Second Shift (2 PM-8 PM): Like the first shift, these employees continue operations, ensuring consistent service throughout the day.
- **var5:** Charge Level to Work: Specifies the minimum battery level required for a vehicle to operate. This helps manage fleet availability while balancing battery health.
- **var6:** Threshold to Charge: The battery level at which vehicles are sent for charging. This is vital for maintaining service reliability and minimizing downtime.
- **var7:** Coverage Zone Radius: Defines the area within which vehicles can operate to meet demand. This radius must be optimized to cover all significant demand areas without overstretching resources.
- **var8:** Relocation-Threshold-1: The minimum number of vehicles at a station below which relocation is stopped. This prevents over-relocation and ensures that vehicles are available to meet immediate demand.
- **var9:** Relocation-Threshold-2: The maximum number of vehicles above which vehicles are relocated to other stations. This helps in balancing vehicle distribution across the network.

We selected these variables because they are crucial for optimizing the performance of the EV sharing system. The total number of parking spots and vehicles ensures adequate capacity and service availability. Dividing employees into shifts helps manage labor costs and maintain consistent coverage. Setting the charge level to work and threshold to charge ensures vehicles are ready when needed and preserves battery life. Optimizing the coverage zone radius provides efficient service within a specific area, while relocation thresholds balance vehicle distribution, preventing over-relocation and meeting demand at all stations. This combination of variables enhances cost operational efficiency, and user satisfaction.

b) Constraints: There are a few constraints that should be addressed to make the simulation in a good way during execution:

- Each vehicle, employee and parking spot has only one status.
- Number of total vehicles = number of parked vehicles (available and charging vehicles) + number of moving vehicles.
- Number of total employees = number of available employees + number of moving employees.
- Number of vehicles < Number of parking spots (var2 < var1)
- Number of employees in the first shift < Number of parking spots (var3 < var1)
- Number of employees in the second shift < Number of employees in the first shift (var4 < var3)
- Relocation-threshold-1<Relocation-threshold-2 (var8 < var9)
- Relocation-threshold-2< (Number of vehicles/ Number of station)

c) Formulation of objectives:

- *Number of Unserved Demands:* Unserved demands are critical in evaluating the effectiveness of the EV sharing system. This metric indicates the number of demands that the system could not fulfill.

$$\begin{aligned}&\mathbf{numUnservedDemands}\\&\quad= |\mathbf{D}| - \mathbf{numServingDemands}\end{aligned} \tag{4}$$

$$\mathbf{numServingDemands} = \sum_{\mathbf{d}\in\mathbf{D}} \sum_{\mathbf{v}\in\mathbf{V}} \mathbf{isServing_{v,d}} \tag{5}$$

Where $isServing_{v,d}$ is 1 if demand d is served, 0 otherwise. $|D|$ is the total number of generated demands

- *Operational Cost of the EV System:* The operational cost of the EV sharing system at the university includes both fixed and variable components. As a non-profit initiative, the system is part of the university's effort to enhance facilities, with no costs recouped through user or student fees.

The fixed component consists of expenses such as vehicle depreciation, insurance, maintenance, and employee salaries:

- *Employee Salary (8 RM per hour):* This rate is based on the typical hourly wage for part-time workers at Malaysian universities, such as student assistants. On-campus part-time employment generally ranges between 7 RM and 10 RM per hour, making 8 RM a reasonable middle value for roles related to operating and maintaining the EV system.

- *Fixed Vehicle Cost (5 RM per hour):* This represents the depreciation, insurance, and routine maintenance costs of the vehicles. Given that the EVs operate in a controlled environment (limited range and speed on campus), these costs are expected to be lower than those for urban fleets. The estimate was derived considering the specific conditions of campus usage, which impose less wear and tear compared to city operations.

The variable component of the operational cost includes expenses that vary depending on usage:

- *Variable Vehicle Cost (3 RM per kilometer):* This cost covers energy consumption for charging and additional maintenance that depends on distance travel. Electricity costs for EV charging in Malaysia are relatively low, and minor wear-and-tear maintenance is also considered. The 3 RM per kilometer rate accounts for charging, occasional repairs, and tire replacement, reflecting the moderate distance travelled and operational environment typical of a campus setting.

These cost parameters provide a reasonable approximation of operational expenses under typical campus conditions in Malaysia. While these values serve as an initial assessment, future models can refine these estimates if more specific data becomes available.

$$\mathbf{Operational\ Cost} = \mathbf{FixedCost} + \mathbf{VariableCost} \tag{6}$$

$$\mathbf{fixedCost} = \sum_{\mathbf{v}\in\mathbf{V}}\sum_{\mathbf{t}\in\mathbf{T}} \mathbf{fixedVehicleCost} \times \Delta\mathbf{t} + \sum_{\mathbf{t}\in\mathbf{T}} \mathbf{EmployeeSalary} \times \Delta\mathbf{t} \tag{7}$$

$$\mathbf{VariableCost} = \sum_{\mathbf{v}\in\mathbf{V}}\sum_{\mathbf{d}\in\mathbf{D}} \mathbf{isServing} \times \mathbf{distance}_{\mathbf{origin},\mathbf{destination}} \times \mathbf{variableVehicleCost} \tag{8}$$

- $Operational\ Cost$: The total cost of operating the EV sharing system.
- $fixed\ Cost$: The fixed part of the operational cost, including salaries and vehicle costs.
- $Variable\ Cost$: The variable part of the operational cost, dependent on distance and vehicle utilization.
- $v \in V$: Represents each vehicle in the fleet.
- $t \in T$: Represents each time interval considered in the simulation.
- $d \in D$: Represents each generated demand.
- *fixed Vehicle Cost:* Cost associated with each vehicle per unit time (e.g., depreciation, insurance).
- $Employee\ Salary$: Salary of employees per unit time.
- Δt: Time interval used for the calculation.
- $is\ Serving$: Indicator variable (1 if a vehicle is serving a demand, 0 otherwise).

TABLE 2. Solutions for Different Decision Variables Values

Solution	Var1	Var2	Var 3	Var 4	Var 5	Var 6	Var 7	Var 8	Var 9
1	250	200	150	100	35	20	180	3	7
2	500	375	350	300	50	30	200	6	9
3	120	100	80	60	25	15	100	2	3

- $distance_{origin,destination}$: Distance traveled by vehicle from origin to destination.
- $variable\ Vehicle\ Cost$: Cost per unit distance traveled (e.g., charging, maintenance).

Considering the fixed parameters are used to calculate the operational cost.

C. OPTIMIZATION TECHNIQUES

This section focuses on the optimization of the EV sharing system, considering two approaches with the aid of the NSGA-II in order to minimize unserved demands and operational costs while giving due consideration to achieving a balance between the different goals of the system.

1) NSGA-II OPTIMIZATION WITHOUT STATION-SPECIFIC APPROACH

In this study, we used NSGA-II to optimize EV sharing system [22]. It is one of the most powerful multi-objective optimization tools which can manage conflicting objectives to minimize operational costs in addition to reducing unserved demand. This method can ensure better access to the vehicles for the users while maintaining cost efficiency.

The key benefit of using NSGA-II is that it produces a Pareto-optimal front of solutions. A decision-maker can then choose from a set of solutions that would balance one set of objectives against others based on the need at hand. NSGA-II reaches these balanced solutions with several key steps. Fig. 4 gives the flowchart for NSGA-II:

- *Step1. Initialization population:* We start by creating a group of potential solutions, called a population. Each solution is defined by set of decision variables. For example, in our EV sharing system, these variables include the number of parking spots (var1), number of vehicles (var2), and number of employees in different shifts (var3 and var4). The initial values for these variables are chosen randomly within specified ranges, such as 250 to 500 parking spots or 100 to 250 vehicles based on Table 3.
- *Step2. Evaluation objective function:* Each solution is then evaluated using objective functions that measure its performance. For our EV sharing system, we might use two objectives: minimizing operational costs and minimizing unserved demands. For example, a solution with

TABLE 3. **Bounds of Decision Variables for NSGA-II**

Variable number	Variable symbol	Variable	Lower bound	Upper bound
1	var1	Number of parking spots	250	500
2	var2	Number of vehicles	100	250
3	var3	Number of employees in the first shift	75	200
4	var4	Number of employees in the second shift	64	150
5	var5	Charge level to work	50	80
6	var6	Threshold to charge	20	40
7	var7	Coverage zone radius	150	250
8	var8	relocation threshold 1	2	10
9	var9	relocation threshold 2	3	15

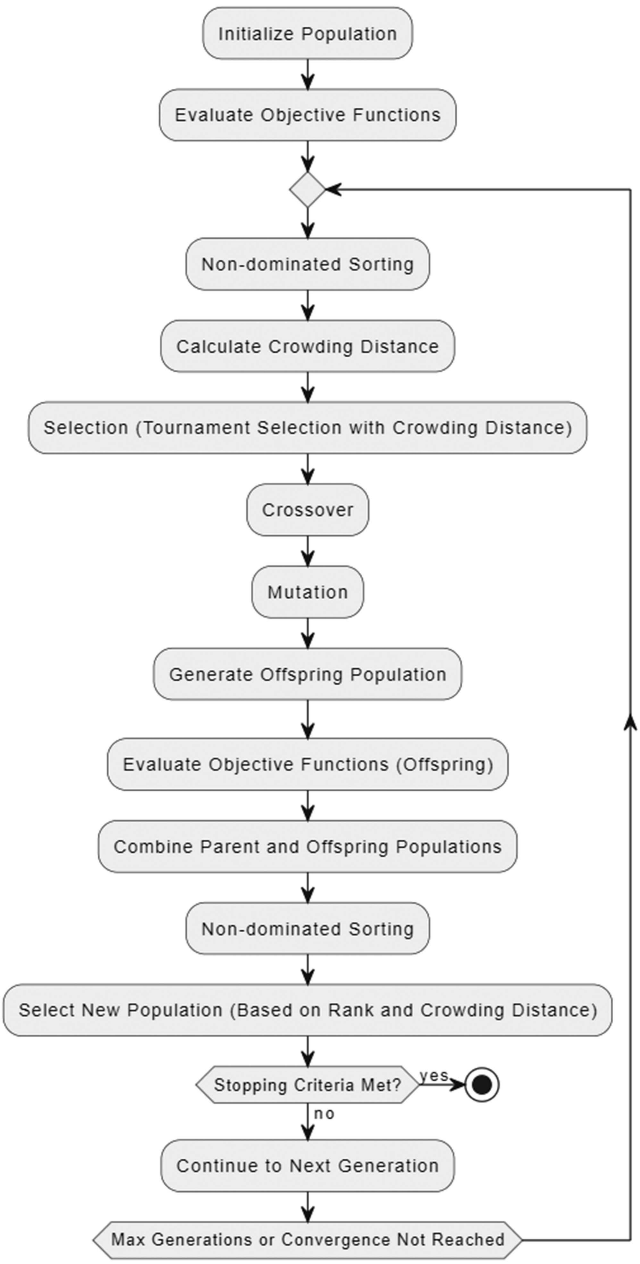

FIGURE 4. **NSGA-II flowchart.**

200 vehicles and 250 parking spots, so on for other decisions variables, will have its costs and unserved demands calculated.

- *Step3. Non-dominated Sorting:* The solutions are sorted into groups called Pareto fronts. The first front contains solutions that are not worse than any other solution in all objectives. For instance, if one solution has lower costs but the same unserved demands as another, it will be on the first front.
- *Step4. Crowding Distance Calculation:* To maintain diversity in the solutions, we calculate a crowding distance. This helps us keep solutions that are spread out and cover different parts of the possible solutions. For example, if two solutions have similar costs, but different numbers of unserved demands, they will be kept apart to explore more options.
- *Step5. Selection:* From the sorted solutions, we select a set for the next steps. This is done using a method that considers both their ranking (Pareto front) and diversity (crowding distance). For example, we might select solutions that not only have the lowest costs but also explore different levels of unserved demands.
- *Step6. Genetic Operations:* including two steps:
  - *Crossover:* We combine parts of two solutions to create new ones. For example, if one solution has 100 vehicles and another has 150, the new solution might have 125 vehicles.
  - *Mutation:* We introduce small changes to the solutions, such as changing the charge level to work (var5) from 60 to 65, to explore more possibilities.
- *Step7. Formation of a New Population:* The new solutions form a new population, which is evaluated just like the initial one. This process helps to explore the solution space more thoroughly.
- *Step8. Combination and Re-sorting:* We combine the old and new populations and re-sort them using non-dominated sorting. This helps us to see the best solutions from both the old and new groups.
- *Step9. Selection of the Next Generation:* A new set of solutions is chosen for the next generation, again using ranking and diversity measures. This cycle continues, gradually improving the solutions.

- *Step10. Stopping Criteria:* The process stops when we reach a certain number of generations, or the solutions stop improving significantly.

By following these steps, NSGA-II helps us find a set of solutions that balance different goals, like minimizing operational costs and unserved demands in our EV sharing system. This method allows decision-makers to choose the best solutions based on their specific needs.

2) NSGA-II WITH STATION-SPECIFIC APPROACH

In order to improve our optimization results, we adopted the station-specific approach for some of the decision variables, for which we greatly increased the size of the solution space. This would give more detailed information for each station and, at the same time, allow a more efficient optimization process. This means, by personalizing the optimization with respect to individual stations, we achieve higher performance even with fewer iterations and a reduced population size, saving execution time and computational resources.

For example, consider an EV sharing system with 25 stations. Without station-specific optimization, 500 vehicles would be distributed equally, with each station receiving 20 vehicles. However, using the station-specific approach, vehicles are allocated based on the unique demand at each station. For instance, a high-demand station might receive 35 vehicles, while a low-demand station might only receive 10. This tailored distribution ensures that resources are allocated more efficiently according to each station's needs.

In our EV sharing system, different stations may have varying needs, such as different numbers of vehicles required or different charging level requirements. To account for this, we made the following adjustments:

- Relocation Thresholds (T1 and T2): Previously, we used a uniform scalar value (an integer) for relocation thresholds across the entire system. In the new station-specific approach, T1 and T2 are represented as vectors, with dimensions equal to the number of stations. This means each station has its own specific threshold values, tailored to its unique demand patterns. For instance, T1 represented as $[T1_1, T1_2, \ldots., T1_{25}]$ for a system with 25 stations, and similarly for T2. Each station can have a different threshold for relocating vehicles, dynamically adjusted to reflect specific demand patterns. For example, a station near the gate needs more frequent vehicle relocations compared to another station near to the faculties or food court in the morning (starting work). So, using dynamic dual relocations threshold will help user satisfaction and an efficient cost system.
- Charge Level to Work (C): In the uniform approach, we used a single scalar value (an integer) for charge levels across all stations. In the station-specific approach, C is now represented as a vector, $[C_1, C_2, \ldots., C_{25}]$,with each value corresponding to a specific station. This allows for tailored energy usage optimization. For instance, a station with a high turnover of vehicles might have a lower charge threshold to ensure quick availability.

By using these station-specific vectors (T1, T2, C), we can better optimize the system to meet the unique demands of each station. For example, during leaving times, the vehicles at faculty stations need more service than those in gated areas. By dynamically decreasing the charge level variable (C) at these locations, we can serve more users while saving relocation time and reducing user waiting time. This targeted approach not only helps in reducing unserved demand but also lowers operational costs. The algorithm can focus on the most promising areas, significantly improving overall system efficiency and effectiveness.

IV. RESULT AND DISCUSSION

The simulation and optimization were executed using MATLAB on a computer with an Intel Core i7 processor (2.3 GHz) and 16 GB of RAM. Two scenarios were considered:

- *Equally Distributed Demand (EDD):* In this scenario, similar to large-scale demand distribution, demands are generated using a uniformly distributed random function. Both the starting point and destination of each demand are randomly chosen within the university's boundaries, without any specific focus on high-demand areas. For example, during peak hours, demand could be randomly generated near a station or in more remote areas, with destinations also chosen randomly, regardless of proximity to major stations.
- *Non-equally Distributed Demand (NEDD):* In this scenario, demands are generated based on specific, high-demand locations within the university, such as faculties or food courts. The source and destination are predetermined according to expected traffic patterns. For instance, in the morning peak hour, demands might be concentrated near the university gate as students and staff arrive, with destinations at faculty buildings. Similarly, around lunchtime, demands might originate from faculties and head towards food courts, while in the evening, demands may shift from faculty buildings to exit gates. Unlike EDD, NEDD ensures that demands are generated close to stations, reflecting the actual demand patterns within the campus.

During the demand generation phase, both scenarios (EDD and NEDD) produced 1,798 demands over a 12-hour period, from 8 AM to 8 PM. Since our EV sharing system operates as a reservation system, the origin and destination of each demand must be predetermined. In the EDD scenario, these locations are randomly determined across the campus, whereas in the NEDD scenario, demands are strategically generated near specific stations, reflecting the practical needs of the university environment.

A. SIMULATION METRICS

The primary objective of this study is to calculate the unserved demands and operational costs for the EV sharing system on

TABLE 4. **Best Solutions With Decision Variables Value for NSGA-II in EDD Without Specific Station Approach**

solution	var1	var2	var3	var4	var5	var6	var7	var8	var9	unserved demands	Operational Cost
solution1	314	164	82	81	56	37	157	2	4	1220	1.44E+04
solution2	380	133	75	69	76	28	158	2	3	1224	1.33E+04
solution3	373	157	79	72	70	28	176	2	4	760	1.72E+04
solution4	455	217	126	101	65	30	244	5	6	133	2,76E+04
solution5	384	172	99	80	67	29	246	4	5	142	2.44E+04
solution6	360	178	81	69	67	27	209	2	4	309	2.08E+04
solution7	375	154	80	72	71	28	175	2	4	810	1.69E+04
solution8	356	152	79	70	69	29	201	2	4	421	1.98E+04
solution9	394	194	86	72	62	33	166	2	4	1007	1.56E+04
solution10	356	161	81	73	67	31	190	2	4	561	1.89E+04
solution11	383	142	78	71	73	27	171	2	3	924	1.59E+04
solution12	370	161	79	71	69	27	183	2	4	672	1.78E+04
solution13	387	136	78	72	75	28	165	2	3	1079	1.47E+04

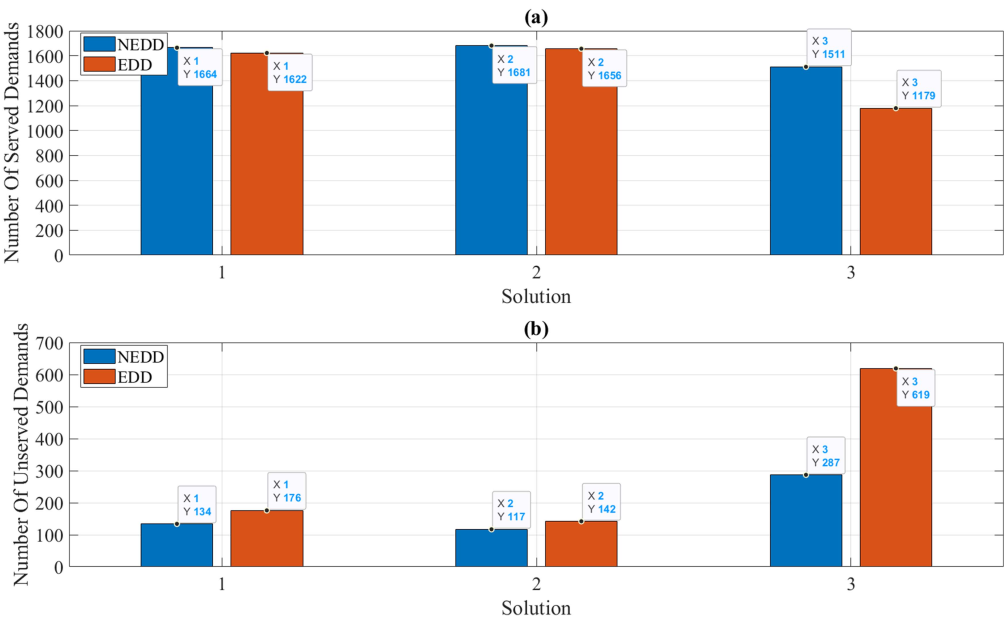

FIGURE 5. **Served and unserved demands for three solutions in both scenarios.**

the university campus. We present the results for both scenarios based on three different solutions, Table 2, to determine the most suitable approach for the university campus environment. The three solutions were logically assumed, Table 4, each representing different decision variables to calculate the operational cost and unserved demands for the EV sharing system per day. In both scenarios, the distribution of EVs is uniform, meaning the vehicle distribution is not specifically tailored.

a) *Unserved and Served Demands:* The NEDD scenario significantly outperforms the EDD scenario in minimizing unserved demands, particularly during peak hours. In Solution 3, NEDD results in 287 unserved demands, whereas EDD has 619 (Fig. 5(b)). This is due to NEDD's ability to strategically allocate vehicles to predictable high-demand hotspots, such as faculties and cafeterias. In contrast, EDD's uniform distribution means that demand can arise anywhere, requiring all stations to retain their vehicles, which leads to inefficiencies. Consequently, NEDD serves 1511 demands compared to 1179 in EDD (Fig. 5(a)), demonstrating the effectiveness of targeted resource allocation.

b) *Operational Costs:* The NEDD scenario incurs higher operational costs due to frequent relocations to meet concentrated demand at key locations (Fig. 6). For Solution 3, the cost for NEDD is 19,980.5 RM versus 17,288.4 RM for EDD. NEDD's relocation strategy focuses resources on high-demand areas, which improves service quality but increases operational cost, During peak hours. In contrast, EDD's uniform approach reduces relocation needs but often fails to meet localized peak demand, leading to more unserved trips. Thus, while NEDD requires greater resources, it ultimately

TABLE 5. Best Solutions With Decision Variables Value for NSGA-II in NEDD Without Specific Station Approach

solution	var1	var2	var3	var4	var5	var6	var7	var8	var9	unserved demands	Operational Cost
solution1	414	202	94	82	70	36	246	4	6	120	2.45E+04
solution2	343	194	133	123	58	32	162	2	4	105	2.95E+04
solution3	405	146	83	64	66	33	157	3	4	857	1.63E+04
solution4	276	147	80	75	75	27	164	3	4	495	1.98E+04
solution5	372	144	78	72	67	29	204	2	3	260	2.14E+04
solution6	354	176	84	75	56	31	160	3	5	133	2.30E+04
solution7	262	141	78	74	75	25	179	2	3	625	1.84E+04
solution8	355	142	80	66	68	29	174	2	3	754	1.70E+04
solution9	272	156	79	76	78	23	216	2	3	576	1.88E+04
solution10	405	150	78	69	63	35	247	3	4	212	2.19E+04
solution11	293	142	79	72	73	27	152	2	3	665	1.81E+04
solution12	366	144	79	70	68	29	169	2	3	368	2.03E+04
solution13	357	146	80	70	69	32	194	3	4	429	2.02E+04

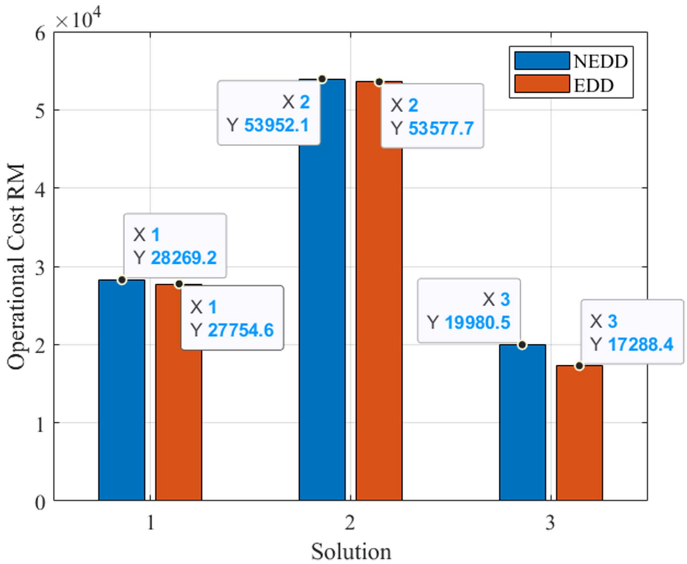

FIGURE 6. Operational cost for three solutions in both scenarios.

delivers higher service efficiency by effectively matching supply with demand.

B. NSGA-II OPTIMIZATION WITHOUT SPECIFIC-STATION APPROACH

The NSGA-II algorithm was used as a multi-objective optimization tool to minimize two key objectives: unserved demands and operational costs. Based on nine decision variables within specified bounds, NSGA-II aimed to identify optimal solutions. With a population size of 40 and 20 generations, we identified 14 optimal solutions across both scenarios.

In this optimization, the decision variables were applied uniformly, meaning each station received the same set of features. For instance, if there were 100 vehicles, each of the 25 stations would receive 4 vehicles. Similarly, a uniform charge level of 60% was applied across all stations.

The Pareto front was employed to evaluate the performance of the optimization in both scenarios, helping to identify the best solutions where one objective could not improve without compromising the other. By analyzing the Pareto front, we could assess trade-offs between objectives like minimizing unserved demands and reducing operational costs, providing a balanced view of system efficiency under both scenarios.

Unserved Demands: In the NEDD scenario, Solution 2 (Table 5) achieved the lowest unserved demands (105 out of 1798), with operational costs of 2.95E+04 RM. This result highlights the advantage of targeting high-demand areas, allowing a strategic reduction of “charge to work” (var5) and dual relocation thresholds (var8 and var9) at stations. For instance, predictable demand concentrations near faculty buildings during peak hours enable the system to allocate resources more effectively, reducing unserved demands significantly even with slightly higher operational costs. This targeted approach maximizes service quality in high-demand areas, justifying the cost increase.

In comparison, the EDD scenario’s Solution 4 (Table 4) achieved the lowest unserved demands within this scenario, with 133 out of 1798 unserved demands at an operational cost of 2.76E+04 RM. This solution showcases the limitations of the uniform distribution strategy. The random, spread-out demand pattern requires each station to retain resources for unpredictable needs, resulting in higher relocation thresholds across all stations. While this allocation achieves similar unserved demand levels as Solution 2 in NEDD, the lack of concentration in resource deployment means that high-demand areas are not adequately prioritized, leading to more unserved demands despite comparable resources. The EDD approach highlights that uniform allocation limits adaptability in addressing peak demands at specific locations.

A further comparison between Solution 4 in EDD and Solution 6 in NEDD reveals a nuanced view of unserved demands with comparable outcomes but differing costs. In Solution 6 of the NEDD scenario, unserved demands remained at 133, but fewer resources were used—176 vehicles and fewer personnel—thanks to optimized decision variables: dual relocation thresholds (Var 8 and 9 set to 3 and 5) and a lower charge-to-work level (Var 5 at 56%). This led to higher operational costs due to increased efficiency. In the EDD scenario, the same number of unserved demands (133) was achieved with 217 vehicles and more staff. However, inefficient resource utilization was evident, as higher dual relocation thresholds (Var 8 and 9 set at 5 and 6) and a higher charge-to-work level (Var 5 at 65%) resulted in underutilized vehicles, reducing operational costs but not optimizing performance.

Operational Costs: Among solutions with the lowest operational costs, NEDD Solution 3 and EDD Solution 2 illustrate key trade-offs between cost efficiency and service quality. NEDD Solution 3, with operational costs of 1.63E+04 RM, left 857 unserved demands. This solution highlights the cost-saving potential of targeting high-demand areas and adjusting relocation thresholds to limit expenses. However, the narrower service coverage meant that more demands went unmet, reflecting a trade-off in reducing operational costs at the expense of broader service reach.

In comparison, EDD Solution 2 reached the lowest operational costs of 1.33E+04 RM, with 1224 unserved demands. The broad, uniform allocation approach reduced operational costs by minimizing relocation, but the system's inability to focus on high-demand areas led to higher unserved demands. For example, during peak hours, the uniform distribution constrained the system's capacity to adjust resource allocation dynamically, impacting service quality in high-demand locations.

Finally, examining Solutions 7 and 8 provides additional insight into cost-efficient service. Solution 7 from the EDD scenario with Solution 8 from the NEDD scenario, both exhibits almost identical operational costs (169E+04 RM and 170E+04 RM, respectively). However, Solution 7 from the EDD scenario results in higher unserved demands (810) compared to the NEDD scenario (754), despite having a larger fleet (154 vehicles vs. 142). The key differences lie in the dual relocation thresholds: while threshold 1 (Var 8) remains the same at 2 for both, threshold 2 is set at 4 for EDD and 3 for NEDD. These findings demonstrate how an optimized dual relocation strategy can significantly enhance resource efficiency, reduce unserved demands, and maintain operational cost-effectiveness.

Overall Analysis: The comparison between solutions illustrates the impact of demand concentration on service quality and cost efficiency Fig. 7. Solutions within the NEDD scenario consistently demonstrated better service levels for comparable or slightly higher operational costs due to targeted resource allocation. Adjusting decision variables like "charge to work" and relocation thresholds in high-demand areas allowed NEDD to reduce unserved demands, particularly in Solutions 1,2, and 6 by concentrating resources at critical locations. This adaptability made NEDD solutions preferable for scenarios with predictable demand patterns, optimizing service delivery despite slightly higher operational expenses.

In contrast, EDD solutions like Solution 2 achieved cost efficiency through a uniform allocation approach, though at

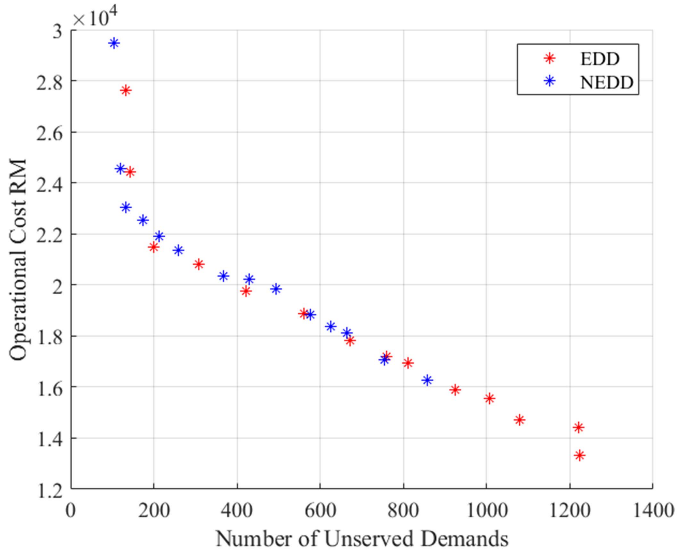

FIGURE 7. Pareto front solutions for NSGA-II in (EDD, NEDD) without specific-station approach.

the expense of service quality. Without the flexibility to respond to high-demand zones, EDD solutions required higher fleet sizes and staff numbers, resulting in a consistently higher count of unserved demands across comparable solutions. These insights reveal that while EDD is more cost-effective, NEDD's targeted strategy is more adaptable, making it preferable for maximizing service efficiency in scenarios with concentrated demand areas.

C. NSGA-II OPTIMIZATION WITH SPECIFIC-STATION APPROACH

The transition to station-specific decision variables in the NSGA-II optimization process yielded significant improvements in the EV sharing system's performance. This approach allowed us to tailor solutions more precisely to the unique conditions of each station, leading to better overall outcomes. By using NSGA-II with station-specific optimization and a population size of 20 and 40 generations, we identified 14 best solutions for both scenarios. We will present these solutions, highlighting the impact on objective functions and the effectiveness of station-specific decision variable values.

In the EDD scenario, Fig. 8. the NSGA-II without station-specific allocation (Table 4, solution 4) achieved the lowest unserved demands (131 out of 1798) and operational costs (2.76E+04), using uniform relocation thresholds (Var8) of 5 vehicles and (Var9) of 6 vehicles per station. In contrast, the station-specific NSGA-II used tailored values for each station, resulting in better optimization. For example, in Table 6, solution 3, station-specific values reduced unserved demands to 134 and operational costs to 2.40E+04. Adjusting the charge level to work (Var5) dynamically for each station, rather than uniformly at 65%, further enhanced both objectives. This

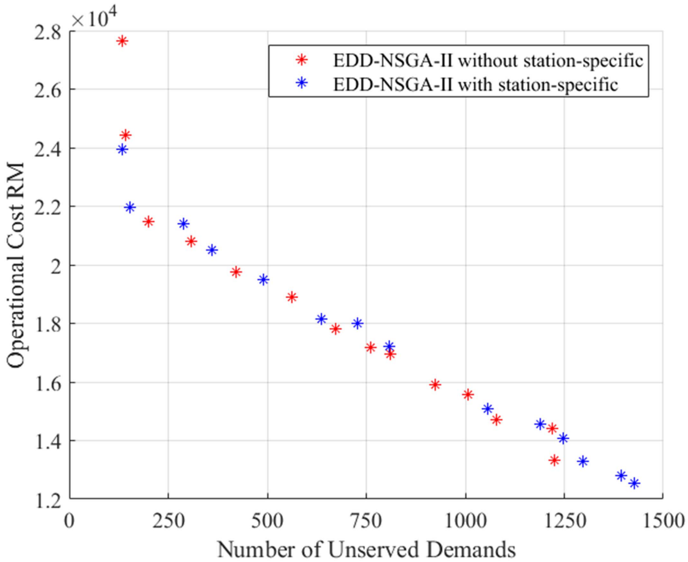

FIGURE 8. Pareto front solutions for EDD scenario for NSGA-II with & without specific-station approach.

TABLE 6. Best Solutions for EDD-NSGA-II With Specific-Station Approach

Solutions	Unserved Demands	Operational Cost
solution1	153	2.20E+04
solution2	1427	1.25E+04
solution3	134	2.40E+04
solution4	1395	1.28E+04
solution5	807	1.72E+04
solution6	1190	1.45E+04
solution7	489	1.95E+04
solution8	290	2.14E+04
solution9	1297	1.33E+04
solution10	1058	1.51E+04
solution11	727	1.80E+04
solution12	1247	1.41E+04
solution13	638	1.81E+04
solution14	361	2.05E+04

demonstrates that dynamic decision variables, like dual relocation thresholds and charge levels, positively impact the EV sharing system's efficiency.

In the NEDD scenario, the lowest unserved demands in NSGA-II without station-specific allocation were 105 in Table 5, is the lowest value, compared to 99 in Table 7, with the station-specific approach. The tailored relocation thresholds and charge levels improved both cost efficiency and system performance.

Comparing NSGA-II with uniform decision variables against station-specific ones clearly shows that the station-specific approach yields more efficient results in terms of both operational costs and unserved demands. However, in some cases—such as Solutions 5 and 8 in the NEDD scenario—the uniform approach performed better than Solutions 10 and 13 with the station-specific approach. This may be due to the

TABLE 7. Best Solutions for NEDD-NSGA-II With Specific-Station Approach

Solutions	Unserved Demands	Operational Cost
solution1	99	2.45E+04
solution2	768	1.67E+04
solution3	624	1.82E+04
solution4	346	2.08E+04
solution5	450	2.00E+04
solution6	480	1.95E+04
solution7	138	2.29E+04
solution8	716	1.76E+04
solution9	565	1.86E+04
solution10	298	2.13E+04
solution11	669	1.80E+04
solution12	123	2.43E+04
solution13	761	1.70E+04
solution14	436	2.02E+04

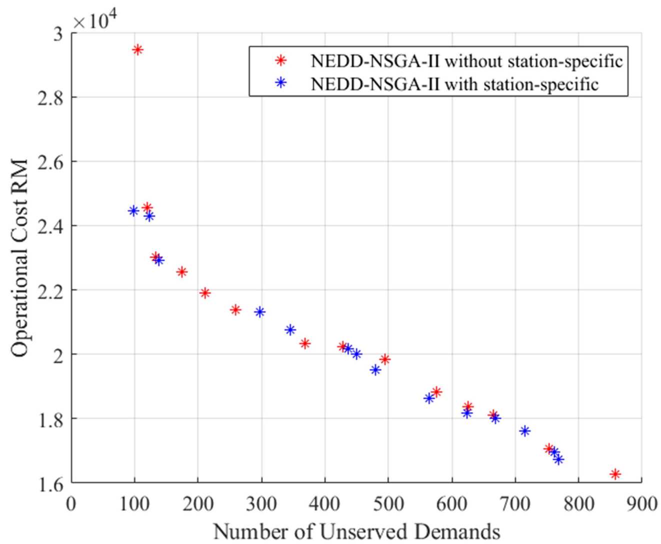

FIGURE 9. Pareto front solutions for NEDD scenario for NSGA-II with & without specific-station approach.

added complexity and potential overfitting caused by increasing dimensionality, Fig. 9.

The station-specific optimization approach significantly reduced operational costs compared to the default NSGA-II approach, for instance, in NEDD scenario, this reduction can be explained by the dynamic allocation of resources at the station level, where each station's unique demand patterns are taken into consideration. By using station-specific thresholds for relocation and customized charge levels, the system can ensure that vehicles are efficiently deployed exactly where they are needed, minimizing unnecessary relocations. This results in reduced energy consumption, lower relocation costs, and better utilization of resources, which collectively drive down operational expenses. Additionally, the station-specific approach enables localized optimization, allowing for quicker responses to changes in demand, which enhances overall efficiency and decreases operational costs significantly in the NEDD scenario.

Overall, the station-specific approach significantly improves operational costs and slightly enhances user satisfaction in EV sharing systems, though simpler solutions may sometimes perform equally well due to reduced complexity.

V. LIMITATION AND FUTURE WORK

This study applied standard probability density functions (PDFs) for creating demand through the generation that might not be able to fully represent peculiarities in a university campus. Future work could involve on-campus data collection to develop specific PDFs which are representative of this real world. The resolution method regarding the EV sharing system was significantly improved by the NSGA-II algorithm. However, this has only been done in simulations. Implementing the system on the UPM campus would provide valuable insights into its practical applicability.

The simulation model relies on several assumptions, such as high morning demand near university gates in the NEDD scenario. Such assumptions may consider typical weekday activities. Variations that may occur during weekends, holidays, or summer months may not be considered. Future scope of work may consider seasonal changes and weekend usage to establish a more comprehensive model for greater scenario coverage.

This is beyond refinements in model assumptions and involves the implementation of strategies developed at other university campuses. The NEDD scenario combined with dual threshold relocation, station-specific optimization, and adaptive charging can be customized according to different campus layouts and mobility needs. The dual threshold relocation will help in effective redistribution of the vehicles, and adaptive charging would consider partially charged vehicles to assist surge demand. These strategies are going to improve system responsiveness, optimize resource allocation, and increase user satisfaction. Testing these strategies in real-world conditions will provide valuable insights into their scalability and broader practical benefits.

Finally, this model could be extended to other small-scale environments-such as large companies with daytime peak demands similar to those of universities to test how well these models apply on scales larger than university campuses.

VI. CONCLUSION

This study optimized an Electric Vehicle (EV) sharing system for a university campus using the NSGA-II algorithm to reduce unserved demands and operational costs. By comparing (EDD represents large-scale, NEDD represents small-scale) scenarios, we found that focusing on high-demand areas in the NEDD approach significantly reduced unserved demands and improved service quality, though with higher operational costs.

The station-specific optimization approach further enhanced the system by adjusting vehicle relocation thresholds and charge levels based on each station's needs, leading to better cost efficiency and demand fulfillment. While the station-specific approach was more effective overall, simpler strategies performed adequately in certain cases, balancing complexity and outcomes.

This research offers a valuable framework for improving EV sharing systems in campus environments, emphasizing dynamic resource allocation and tailored optimization to enhance efficiency and user satisfaction.

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