Received 13 January 2026, accepted 18 February 2026, date of publication 25 February 2026, date of current version 12 March 2026.

Digital Object Identifier 10.1109/ACCESS.2026.3668018

APPLIED RESEARCH

Behavior Modeling and Performance Assessment of E-Scooter Rental Mobility Systems in Discrete Event Simulation Framework

TAHA BENARBIA[1,2], HUSSEIN AHMAD AHMAD[2], ANTOINE KAZADI KAYISU[3], JEAN CHAMBERLAIN CHEDJOU[2], DANIEL JIAN SUN[4], AND KYANDOGHERE KYAMAKYA[2,3]

[1]Industrial Engineering Department, Institute of Maintenance and Industrial Security, University of Oran 2 Mohamed Ben Ahmed, Oran 31000, Algeria
[2]Institute for Smart Systems Technologies, Universität Klagenfurt, 9020 Klagenfurt am Wörthersee, Austria
[3]Faculté Polytechnique, Université de Kinshasa, Kinshasa, Democratic Republic of the Congo
[4]School of Future Transportation, Chang'an University, Xi'an 710021, China

Corresponding author: Kyandoghere Kyamakya (kyandoghere.kyamakya@aau.at)

ABSTRACT Recently, E-Scooter (ES) rental systems have played a significant role in urban mobility, particularly by improving first- and last-mile connectivity. However, they face a critical challenge in ensuring an adequate supply of E-scooters in most areas to meet growing demand. This paper presents a comprehensive study on the modelling of e-scooter rental systems using Stochastic Petri Nets (SPN) and discrete-event simulation, highlighting their potential in capturing the dynamics of such systems. Furthermore, a repositioning strategy is proposed for maintaining the balance and availability of supply across different locations based on SPN modelling. Attesting the reliability of the model requires the incorporation of a performance evaluation algorithm and the analysis of key performance metrics, such as average wait time and the rental rate of scooters. Additionally, the model is used to assess the impact of several decision parameters, such as battery range and fleet size, on the overall behavior/dynamics of an ES rental system. The results indicate that the proposed repositioning strategy significantly reduces the number of unserved users and decreases imbalances within the network. This work provides important insights into system implementations (at both strategic and operational levels), while highlighting the effectiveness of SPN in assessing the performance of these dynamic and stochastic systems.

INDEX TERMS E-scooter mobility, stochastic petri nets, discrete event systems, shared mobility repositioning, E-scooter network behavior, last-mile connectivity.

I. INTRODUCTION

In recent years, E-Scooter rental systems have emerged as a highly attractive and convenient solution for urban transportation. These systems allow users to rent electric scooters for short distance trips using mobile applications, enabling seamless mobility within urban environments. The simplicity of use, combined with affordability and on demand availability, has contributed significantly to their widespread adoption. ES sharing platforms offer a flexible and fast alternative for covering short urban distances, especially those not conveniently served by public transportation. The rising demand for efficient first- and last-mile connectivity solutions in modern cities has made ES rental services an integral component of contemporary urban mobility systems.

The growth of shared ES services can be traced back to the pioneering efforts of companies such as Bird, which is widely regarded as the originator of the electric scooter sharing model. Bird introduced its first fleet of e-scooters in Santa Monica, California, in 2017 [1], [2]. Following this initial success, the company rapidly expanded its operations to other major cities around the world, effectively establishing a new global trend in micromobility. By 2018, numerous other companies had followed suit, launching their own services and contributing to the rapid proliferation of rental ES networks. Prominent names in the industry today

The associate editor coordinating the review of this manuscript and approving it for publication was Minh C. Ta.

include Voi, Tier, Neuron Mobility, Spin, and Lime [3]. These operators manage fleets that are typically distributed across various areas of a city, allowing users to pick up and drop off scooters at different locations. This dockless model enhances user flexibility and operational reach, making it especially effective for bridging gaps between transit hubs and final destinations.

The popularity of shared ES systems is also driven by their potential to reduce environmental impact and reduce urban traffic congestion. These systems offer a low-emission transportation alternative, supporting broader efforts toward sustainable and climate-friendly urban mobility. According to recent Fraunhofer ISI research, shared e-scooters in Paris have been estimated to reduce emissions per passenger kilometer by about 20.7 g CO2 when replacing higher-emission transport modes [4]. In addition, they can help reduce traffic congestion in areas with overburdened road infrastructure and decrease the number of short car trips, which are among the least fuel-efficient. The social and environmental appeal of these services has translated into growing user adoption worldwide. For example, according to IAA Mobility's report citing the Statista Mobility Market Outlook, the number of e-scooter users in Germany rose to 9.9 million in 2022 [2]. Furthermore, studies indicate that a considerable rate of e-scooter trips either begin or end at public transport stations, further reinforcing their role in complementing multimodal transportation networks [3].

Shared e-scooter systems, while technically and operationally complex, also play a crucial role in the broader transition toward sustainable urban mobility. The CalmMobility paradigm [5] highlights the importance of predictability, integration, and user centered design as guiding principles for the evolution of future mobility systems. In this context, the present study focuses on the modeling and performance evaluation of shared e-scooter networks using a stochastic framework that captures demand dynamics, charging, and repositioning processes. The proposed SPN-based model supports a balance between supply and demand by evaluating system performance and enabling more adaptive repositioning strategies. This approach contributes to more reliable and efficient operations, aligning with the CalmMobility vision of sustainable, predictable, and user-centered micromobility within urban environments.

Despite their many advantages, shared ES rental systems are naturally complex, dynamic, and stochastic. Their operations are influenced by highly variable and un-predictable user behavior, including random trip initiation times, diverse route choices, and varying trip durations. Moreover, factors such as differing charging levels, battery constraints, and localized demand spikes introduce additional layers of variability. These uncertainties pose substantial challenges in accurately predicting the flow and distribution of scooters across the urban network. In large-scale systems, this often leads to significant imbalances, where some areas experience persistent shortages of available scooters (supply deficits), while others accumulate unused scooters (supply surpluses). Such imbalances reduce service reliability, discourage users, and lead to inefficient use of operational resources. A major challenge in managing these imbalances lies in the limited battery range of e-scooters and the need for regular charging or battery swapping. Maintaining a balanced and functional fleet requires not only forecasting demand patterns but also dynamically redistributing scooters across the network based on real-time and anticipated conditions. Repositioning operations are typically performed using dedicated vans or staff who collect e-scooters from surplus areas and redistribute them to areas facing shortages (as shown in Figure 1). These operations must consider logistical constraints such as van capacity, road conditions, charging station locations, and scooter battery levels. Consequently, designing effective repositioning strategies requires robust and flexible modeling techniques that can represent the system's stochastic behavior while supporting performance evaluation under different scenarios.

To address these challenges, this paper proposes a stochastic modeling framework for shared ES rental systems based on SPN and Discrete Event Simulation (DES). The work presented in this paper is an extension of the research originally reported in [6] and [7]. This paper initially identifies several technical key research challenges related to e-scooter rental mobility systems in literature and academia. While previous research in this field has primarily focused on optimization, fleet sizing, or energy-related issues, few studies have examined the complexity of repositioning within a stochastic and dynamic context. Accordingly, this paper seeks to answer the following research question: How can a stochastic modeling and simulation framework based on SPN and DES be developed to evaluate and enhance the operational performance of shared e-scooter systems under dynamic demand and spatial variability? To address this question, the proposed approach integrates SPN-based modeling, simulation-based performance assessment, and repositioning strategy analysis within a unified decision- support framework. To the best of our knowledge, few studies have applied SPN to shared micromobility systems, and none have specifically combined SPN and DES to model e-scooter repositioning and performance dynamics in both static and dynamic scenarios. The proposed SPN model captures the key components of the system, including user behavior, scooter availability, battery charging dynamics, and van-based redistribution mechanisms. It allows the evaluation of key performance metrics such as average scooter availability, frequency of unserved demand, time spent in deficit or surplus situations, and fleet utilization efficiency.

By integrating operational parameters such as fleet size, van capacity, charging thresholds, and area-specific demand patterns, the model provides a valuable decision-support tool for both strategic planning and day-to-day operations. The simulation results, based on real-world-inspired data, demonstrate that the proposed repositioning strategy effectively reduces the number of unserved users and improves the balance of scooter distribution across the network. This makes the model highly applicable for cities and operators seeking to optimize shared micromobility services in a dynamic urban environment.

The main contributions of this paper are summarized as follows:

- ✓ Novel SPN-based modeling framework: We propose, for the first time, the use of Stochastic Petri Nets to explicitly model and analyze the stochastic behavior of shared e-scooter rental systems, including user demand, charging dynamics, and repositioning processes.
- ✓ Repositioning strategy under stochastic demand: We design and implement a repositioning mechanism based on decision thresholds that dynamically redistributes scooters across network areas, thereby mitigating surplus/deficit supply imbalances.
- ✓ Integrated performance evaluation: We implement a discrete-event simulation framework that enables the quantitative assessment of multiple key performance indicators, including surplus and deficit supply times and unserved demand rate.
- ✓ Case study with real-world-inspired data: We validate the proposed model using data from a real shared e-scooter system (Neuron, Rockhampton), demonstrating its applicability in both strategic planning (fleet sizing and charging infrastructure dimensioning) and operational management (real-time rebalancing).
- ✓ Decision-support potential: The proposed SPN model provides operators and city planners with a scalable decision-support tool to evaluate "what-if" scenarios, test repositioning policies, and support the development of sustainable and user-centric micromobility systems.

The remainder of the paper is structured as follows. Section II reviews the existing literature on shared e-scooter systems, focusing on modeling techniques, repositioning strategies, fleet management, and charging logistics. Section III presents the Petri nets formalism, while Section IV introduces the problem formulation using SPN tool, including assumptions, parameters, and structural components. Section V details the simulation experiments, analyzes the system's behavior under different operational scenarios, and evaluates key performance indicators. Finally, Section VI concludes the paper by summarizing the main findings and proposing future research directions, including integration with optimization methods and expansion to multi-modal mobility systems.

II. STATE OF ART IN E-SCOOTER SHARED MOBILITY

This literature review identifies key operational research issues in shared rental mobility systems including: (1) modelling and simulation; (2) repositioning and vehicle routing for ES redistribution; (3) fleet optimization; (4) energy management and recharging station placement. For each issue, the review investigates the proposed solutions and highlights gaps in the current approaches.

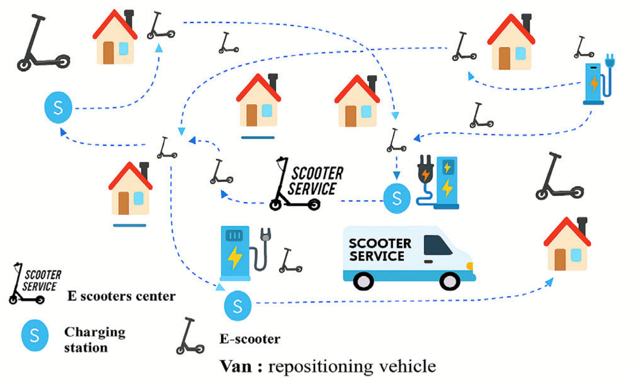


FIGURE 1. Illustration of E-scooter unbalanced network.

A. MODELLING AND SIMULATION

Modeling and simulation in ES systems are crucial for understanding usage patterns, optimizing operations, and predicting system behavior. In this regard, Tzouras et al. [8] proposed a comprehensive study assessing the suitability of various agent-based models for e-scooter systems used to simulate user behavior. These models were qualitatively evaluated based on criteria such as shared mobility mode representation, open-source adaptability, and large-scale simulation capability. The authors highlighted that the stochastic behavior of e-scooter users introduces new challenges, requiring hybrid simulation models to address these issues effectively. With the objective to investigate, the dynamics of e-scooter rental mobility Diallo et al. [9] have employed an agent-based modelling approach with application on ES system in Lyon, France. The study has indicated that changing factors such as fleet sizes, distribution strategies, can significantly affect the system performance. However, the model still requires empirical validation with real data to improve the integration and sustainability of such shared mobility services in urban areas. The multi-modal routing optimization problem has been addressed by Shah et al. [10], by developing an open-source platform designed to optimize user-centric shared e-mobility services by integrating user behaviour models, energy consumption model, and demand forecasting modules. Nevertheless, the study considered a limited number of optimization objectives, which restricts the evaluation of scalability with respect to map size. With the objective of optimizing the design and operation of e-scooter systems, Fathabad et al. [11] have proposed a data-driven approach using comprehensive data analysis and optimization algorithms. Their approach involved analyzing historical trip data to develop predictive models for scooter demand and optimal deployment locations. For demand forecasting of e-scooter rental network, Kim et al. [12] proposed a model integrating social network analysis to identify community structures and applying deep learning algorithms to predict usage patterns. However, the model requires further testing across different urban areas to validate its scalability. Furthermore, Bai and Jiao [13] used geospatial analysis tools within a Geographic Information System (GIS) framework to simulate user interactions with e-scooter systems, providing insights into usage patterns and demand variations. However, their approach lacks the ability to adequately handle stochastic elements present in real-world scenarios.

B. REPOSITIONING AND VEHICLE ROUTING FOR ES REDISTRIBUTION

Concerning repositioning: Ensuring the optimal distribution of e-scooters to meet dynamic demand across different areas is a significant challenge. Several heuristic and optimization based approaches have been proposed to address this issue. In this context, Turan and Wakolbinger [14] have developed a strategic framework to optimize the repositioning by using optimization algorithms combined with real data of e-scooters in Vienna to determine the most efficient roads and schedules for repositioning e-scooters. They have reduced collection costs and increased the availability of e-scooters in high-demand areas. However, their proposed solution fails to consider scalability to other cities, which may affect the model's performance and reliability. Predicting demand meaning estimating where and when scooters will be needed can be highly useful for the deployment and repositioning of e-scooter fleets. In this context, Saum et al. [15] developed an approach based on machine learning algorithms to predict e-scooter demand across different locations. To train the machine learning models, they integrated real-time analytics with historical e-scooter traffic data. The optimization model also considers several constraints, including battery range, operating costs, and charging station capacity. However, scalability issues may arise due to the integrated framework's complexity and the accuracy of demand predictions, particularly for large urban areas with large scooter networks. By using deep reinforcement learning framework (DRL) Losapio et al. [16] have addressed the issue of e-scooter rebalancing to optimize the repositioning of e-scooters in shared mobility systems and predict future demand patterns. The methodology involves training a DRL agent using a simulated environment. This environment includes several factors such as user demand, battery range, and travel times. However, the computational complexity of the DRL algorithm might pose challenges in scaling the solution to larger urban areas with large networks. On the other hand, the vehicle routing problem for relocation also occupies an important place in the literature, where the routing of repositioning e-scooters using trucks or vans involves solving complex routing problems. In this context, Lee et al. [17] have tackled the issue of vehicle and staff routing in free-floating electric scooter sharing systems. They formulated the problem as a vehicle routing problem with pickup and delivery using a mixed-integer programming model. They proposed a clustered iterative construction heuristic approach (CICA), based on approximations of operational costs and a minimum spanning tree. Likewise, Masoud et al. [18] addressed the challenge of e-scooter repositioning in urban environments as a vehicle routing problem. Their approach focuse on developing heuristic methods to optimize the assignment of e-scooters to pickup and drop-off locations, aiming to minimize operational costs and enhance service efficiency.

C. FLEET OPTIMIZATION

Regarding fleet optimization and dimensioning: Studies have typically used historical data and demand forecasting methods but often did not consider the randomness of user behavior. Several studies have focused on the optimization of fleets in e-scooter sharing systems to enhance efficiency and meet variable demand. Giordano and Chow [19] developed an optimization framework for ES systems that considers elastic demand when designing service regions and allocating fleet sizes. Maximizing operational efficiency and user satisfaction through the optimal spatial distribution of e-scooters is the objective of the model. In addition, the model seeks to maximize coverage and minimize operating costs while balancing supply and demand. In contrast, the model depends too heavily on assumptions regarding demand elasticity, which might not fully replicate the randomness of user behavior in different urban situations. Ciociola et al. [20] developed a demand model by preprocessing open data using spatiotemporal disaggregation techniques, applying kernel density estimation for spatial demand and Poisson processes for customer arrivals. The simulation takes into account parameters including user preferences, fleet size, allocation policies, and scooter characteristics. Results highlight the need for a large e-scooter fleet to meet diverse demand and the significant cost of frequent battery swaps. Manout et al. [21] have addressed the optimization of shared mobility services for e-scooters through the use of an agent-based transport simulation framework. They have analyzed the effects of different pricing methods and fleet sizes on the performance of the service. Based on real data from electric scooter rental systems in the city of Lyon-France, they simulated user behavior and operational dynamics. Shah et al. [22] also analyzed the impact of fleet size on the effectiveness of e-scooter mobility systems. They employed a mixed-methods approach, combining data analysis and simulation to evaluate e-scooter demand and supply. The results showed that larger fleets enhance service reliability, which in turn improves user satisfaction and strengthens the competitiveness of e-scooter systems within the broader transportation landscape. However, managing larger fleets can pose significant logistical challenges and lead to a substantial increase in operational costs.

D. ENERGY MANAGEMENT AND RECHARGING STATION PLACEMENT

Regarding energy, battery swapping and recharging stations placement: Efficient management of battery charging level and the strategic placement of recharging stations are crucial for maintaining service reliability. In this context, Colovic et al., [23] have addressed the critical issue of infrastructure planning for shared ES systems. They have developed a multi-objective optimization model to strategically design parking spaces for e-kick scooters that take in consideration some factors such as accessibility, user convenience, and urban space use. The approach integrates several urban planning objectives to balance the needs of different stakeholders, including users, operators, and local authorities. The central part of infrastructure and operational planning for dockless electric micromobility systems have been addressed by Liu and Ouyang [24]. They have developed a queuing network model to determine the optimal locations for charging stations and to optimize service operations, considering factors such as battery range, user demand, and operational cost. However, they assumed trucks collect only fully discharged e-scooters and distribute fully charged ones randomly. This can conduct to inefficient use of resource of that might conduct to unused e-scooters occupying valuable space. Furthermore, Yan et al., [25] have addressed the issue of infrastructure location to determine the optimal locations for battery swapping stations. They have proposed a mathematical model based on mixed-integer linear programming approach that considers several factors, including user demand, operational costs, and spatial distribution of scooters. However, the study is based on static demand patterns and needs accurate data on user behavior and battery performance. Similarly, mixed integer linear programming framework has been employed by Lee et al. [17] to simultaneously optimize the location of battery swapping stations, the rebalancing of scooters, and the routing of staff. However, they have assumed no limit on the number of batteries staff trucks can carry, ignoring constraints on vehicle load capacity and battery logistics, which affects feasibility and cost-effectiveness. Additionally, assuming staff do not return fails to consider the potential needs for recharging and maintenance, which might affect overall efficiency.

This review of the most recent and relevant research papers has raised crucial research questions and highlighted the significance of e-scooter mobility for first- and last-mile connectivity. However, Overall, existing studies tend to focus on specific operational aspects such as demand prediction, fleet sizing, or vehicle routing, often using optimization or data-driven techniques. In addition, the most models proposed do not consider the stochastic behavior of e-scooter users as those users can behave both as pedestrians and as vehicle operators. For example, users may ride on sidewalks or streets, might impact the traffic flow and repositioning process. This randomness makes the modelling and demand prediction very challenging. It is crucial to recognize that the performance of e-scooter mobility is highly constrained by factors such as battery range, random user behavior, and weather conditions. These factors are crucial challenges must be considered when modelling such systems. The proposed approach complements these studies by providing a stochastic modeling and simulation framework capable of evaluating time-based performance metrics under different operational scenarios. To provide a clearer synthesis of the literature and facilitate comparison between existing studies, Table 1 summarizes the main objectives and modeling approaches adopted in prior works on shared e-scooter mobility systems.

III. STOCHASTIC PETRI NETS FORMALISM

Stochastic Petri nets and Generalized Stochastic Petri Nets (GSPN) are two commonly used extensions of the classical Petri net formalism [6]. In this study, we adopt the GSPN framework with exponential transition firing times and Poisson arrival processes. GSPNs are powerful modeling tools for the representation, simulation, and performance evaluation of stochastic and complex systems. In addition, several factors justify the use of SPN/GSPN for modeling e-scooter (ES) systems:

- ✓ Analytical and simulation capabilities: SPN belong to a special class of graph based models grounded in algebra and formal analysis methods, enabling both qualitative (how the system behaves logically regardless of time or probabilities.) and quantitative (timing, rates, and probabilities in the SPN model to measure system performance) evaluations within the same framework.
- ✓ Flexibility in applications: Petri nets can be applied not only to modeling and performance evaluation but also to addressing specialized problems such as resource optimization, control and supervision, fault diagnosis, and system safety.
- ✓ Discrete event nature: The studied ES system is naturally a Discrete Event System (DES), making SPN a natural modeling choice.
- ✓ Parallelism and resource sharing: The system reveals parallel processes (e.g., multiple stations operating simultaneously) and shared resources (e.g., a user cannot rent an e-scooter from two stations at the same time).

The proposed SPN formalism also allows incorporating the stochastic nature of user interactions with the ES system, such as random arrival times for renting or returning scooters, variable charging durations, travel times, and ride durations. This makes it possible to estimate important performance indicators, including the average customer waiting time at each station and the average sojourn time of e-scooters in an area or charging station.

Time can be integrated into a Petri net model in several ways, for example, by associating it with places, transitions, or arcs. In T-timed Petri nets, each transition is as-signed a time interval or firing delay [26], representing the time that must elapse before the transition can fire once it becomes enabled. Additionally, a Petri net with inhibitor arcs is defined as a directed bipartite graph consisting of two types of nodes: places (representing conditions or resources) and transitions (representing events).

To clarify the applicability of SPN to shared e-scooter systems, places in the proposed model represent key system states such as available e-scooters in a service area, scooters under charging, or scooters in use by customers. Stochastic transitions represent events such as rental requests, charging

TABLE 1. Summary of state-of-the-art studies on shared E-Scooter systems.

Reference	Main Objective	Modeling / Methodological Approach
Tzouras et al. [8]	Analyze operational behavior of e scooter shared mobility systems and mixed traffic systems	Agent Based Modeling
Diallo et al. [9]	Evaluate the impact of introducing bike and e scooter mobility on existing travel modes.	Agent based simulation
Shah et al. [10]	Propose an open-source, agent-based platform for shared electric mobility	Multi-modal route optimization
Fathabad et al. [11]	Optimize operating cost	Analytical and optimization method
Kim et al. [12]	Demand prediction for the use of ES system	Machine learning
Bai and Jiao [13]	Evaluate the spatiotemporal patterns of e-scooter	Spatial analysis
Turan and Wakolbinger [14]	Optimize the relocation of ES	Modelling based on vehicle routing problem
Saum et al. [15]	Predict e-scooter demand to optimize repositioning	Machine learning algorithms
Losapio et al. [16]	Repositioning optimization	Deep reinforcement learning framework
Lee et al. [17]	Repositioning and battery swapping	Mixed integer programming model and clustered iterative construction heuristic approach
Likewise, Masoud et al. [18]	E-scooters repositioning optimization	heuristic methods to optimize the assignment of e-scooters
Giordano et al. [19]	E scooter fleet optimization	Heuristics optimization
Ciociola et al. [20]	Behavior modelling and fleet optimization	Spatiotemporal disaggregation technique
Manout et al. [21]	Study fleet size impact	Agent-based transport simulation framework
Shah et al. [22]	Analyze the impact of fleet size	Mixed-methods approach, combining data analysis and Simulation
Colovic et al., 23]	Infrastructure planning for shared ES systems	Optimization under uncertainty
Liu et al., [24]	Optimization of charging stations locations	Queuing network theory
Yan et al., [25]	Optimize the locations for battery swapping stations.	Mixed-integer linear programming approach
This work	Stochastic modelling and performance evaluation with repositioning analysis	Stochastic Petri Nets (SPN) and Discrete Event Simulation (DES)

completion, or repositioning actions. The firing of a transition updates the system marking by moving tokens between places, allowing the dynamic and stochastic behavior of the e-scooter network to be naturally captured.

This representation provides an intuitive and flexible way to model complex interactions between demand, fleet availability, and operational decisions, which is particularly suitable for performance evaluation of shared e-scooter mobility systems.

IV. MODEL FORMULATION

The modelling and analysis of shared mobility systems in the literature mainly follow three directions: Analytical models provide optimization solutions for specific operational issues, they employ mathematical and optimization techniques to address issues like fleet sizing, rebalancing, and routing [27], [28]. Agent-based models simulate the interactions of individual agents (e.g., users, vehicles) within the shared mobility system [29]. Machine learning can enhance analytical models by providing data-driven insights and improving the accuracy of user behavior predictions in shared mobility systems [30]. Given the stochastic nature of ES shared rental systems as discrete event systems, we have employed SPN formalism and discrete event simulation to model their behavior. Petri Nets have significantly contributed to the modelling, simulation and analysis of transportation, railway and logistic systems [31]. In addition, there are some studies have used SPN for the modelling and performance evaluation of shared mobility systems, highlighting their importance in these contexts [6], [7].

The proposed decision framework based on SPN and DES shown in the Figure 2 not only supports operational optimization but also offers practical implications for urban governance and sustainability. By integrating SPN graphical modeling with discrete event simulation, the platform allows both operators and city planners to test ''what-if'' scenarios before implementing new regulations or infrastructure investments. For instance, city authorities can simulate the impact of different parking restrictions or charging-station locations on service accessibility and public space use. Similarly, the model's outputs such as the percentage of time stations remain empty, the average number of unserved users can help in the deployment of efficient fleet distribution strategies, ensuring that low demand, or peripheral areas are not systematically underserved. In this way, the model becomes a decision-support tool that links micro level operational data with macro level policy objectives, promoting fairer, more predictable and energy efficient e-scooter networks in line with sustainable urban mobility goals.

Many operating concepts for shared ES rental systems can be found in the literature. We employed one such concept with simplifying assumptions. The system consists of multiple essential components: battery-powered e-scooters equipped with GPS and IoT devices for tracking, a mobile application

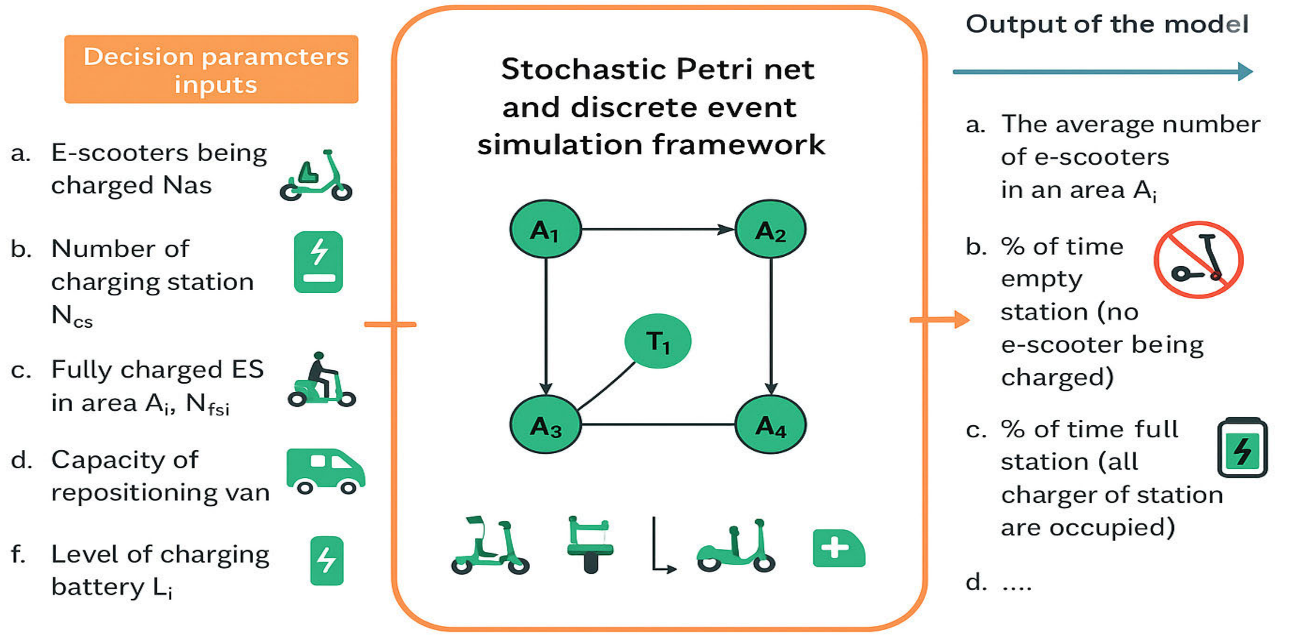


FIGURE 2. Comprehensive illustration of the proposed decision-support framework.

that allows users to unlock and pay the ride, charging infrastructure for recharging or swapping e-scooters' batteries, and an operations center that control ES fleet, maintenance, and user support. Users normally register via the mobile app, locate the closest scooter, then unlock it using a QR code, ride to their destination, and park the scooter in designated areas or any legal spot within the service area. It is assumed in this paper, that an e-scooter can be rented only when it is fully charged or when its battery level (L) is equal to or greater than the defined availability threshold (s), which is set to 50% in this model. Throughout the day, the operations team ensures the availability of e-scooters in deficit areas by redistributing them from surplus areas, using vans with limited capacity and taking into account the battery range of the e-scooters. Based on this operational description, a SPN model with variable weights has been developed to represent the stochastic nature of the e-scooter mobility network. For simplicity, the basic model is designed for a network consisting of two areas and two charging stations (see Figure 3). Naturally, by employing a DES approach, the proposed model can be extended to larger networks with multiple areas, more fleet, and several charging stations.

We assume that each area contains one charging station, and that user demand follows a Poisson process. In addition, the developed model takes into account the system's stochastic nature by incorporating stochastic transitions associated to an exponential probability distribution law.

The network is defined as unbalanced when an unequal distribution of e-scooters occurs during the day, resulting in some areas experiencing a deficit of supply (few or no e-scooters available), while others have a surplus of e-scooters. In terms of *SPN*, the total number of ES in area *Ai* (*Ntsi*) is represented by the sum of the markings of the places *Pchi* (e-scooters being charged *Nasi*), *Pavi* (available e-scooters with at least a 50% charging level, *Nhsi*), *Pwi* (E-scooters parked in area *Ai* waiting for a ride, recharging/swapping batteries, or repositioning, *Nwsi*), *Pcdi* (fully charged ES in area *Ai*, *Nfsi*) and *Puci* (e-scooters in use, *Nusi*). The following equation is used to formulate this mechanism:

$$Ntsi = Nasi + Nhsi + Nfsi + Nusi + Nwsi \tag{1}$$

In terms of SPN, the total number of e-scooters is represented by the sum of marking of places *Pchi*, *Pavi*, *Pcdi* and *Puci*, as illustrated below:

$$Ntsi = M(Pchi) + M(Pavi) + M(Pcdi) + M(Puci) + M(Pwi) \tag{2}$$

It is important to note that when $Ntsi = 0$, it indicates that no e-scooters are available in area *Ai*. Unlike, when $Ntsi = Max$, it means that a large part of the network's fleet is located in this area. Here, *Max* represents the maximum number of e-scooters that can be located in a given area, estimated based on its size and demand intensity. The e-scooters available for users are those that are either fully charged or have a battery level of at least 50%, as formulated in the following equation:

$$Naesi = Nhsi + Nfsi \tag{3}$$

In terms of SPN, the available number of ES is represented by the marking of places *Pavi* and *Pcdi* in the model, as illustrated below:

$$Naesi = M(Pavi) + M(Pcdi) \tag{4}$$

TABLE 2. Meaning of some parameters of the model.

Parameters	Meaning
Li	Charging battery level of e scooter
Si	Repositioning threshold of area
Ncs	Number of charging stations
Ntsi	Total number of e scooters in Area *Ai*
Ei	Threshold of congestion of e scooter in area *Ai*
Pi	Threshold of deficit supply of e scooters in area *Ai*
Ci	Capacity of charging station in area *Ai*
CTi	Capacity of repositioning vehicle
Nvsi	Number of e-scooters to be redistributed
Si	Availability threshold of e-scooter battery
Bi	Average firing delay of deterministic transition
NT	Number of balancing vans
u	Average firing rate of stochastic transition

The repositioning mechanism is performed by vans that relocate e-scooters from surplus areas to deficit areas. The repositioning process is initiated only when the network becomes unbalanced. In this study, we propose a repositioning strategy based on three decision thresholds, denoted as *Pi*, *Si*, and *Ei.* The parameter *Pi* is used to detect a deficit condition in an area when the number of e-scooters *Ntsi*<*Pi*. Conversely, *Ei* identifies a surplus condition when *Ntsi*>*Ei*. The parameter *Si* represents the desired number of e-scooters in an area, serving as the balancing threshold. In the term of SPN model, surplus supply is detected through transition *TEi* and place *PE*i. Once congestion is detected, a token is deposited in place *PEi*. When the area returns naturally to a balanced state, this token is removed by the firing of transition *TREi.* Similarly, deficit conditions are identified using transition *TPi* and place *Pdi*; once balance is restored, the corresponding token is removed by firing transition *TRPi* (as shown in the detection module of critical situations in Figure 3). Further details on these parameters are provided in Table 2.

Figure 3 shows five modules of the suggested model: (A) the charging and the fleet of ES, which represents the availability of scooters whether they are plugged in, parked, or in use; (B) the dynamic of e scooters inter areas module; (C) the repositioning module, (D) the demand module and (E) the maintenance module. For readability, places and transitions are denoted using a generic index *i* (e.g., *Pavi, Trci*) to represent any service area *Ai*. In the *SPN* graph, this index is designated numerically (e.g., *Pav1, Trc1* for Area *A1*).

A. CHARGING AND E-SCOOTERS FLEET MODULE IN AREA

The fleet module incorporates e-scooters being charged, fully charged, with 50% battery range, parked e-scooters, and those currently in use in area *Ai*. This module takes into account some decision variables such as the charging battery level *L* and availability threshold *s*, indicating that E-Scooter with battery charging levels over a minimum threshold are available to be used by costumers.

In terms of SPN, this module is represented by a set of places, *Pavi, Pci, Pchi, Pcdi,* and *Puci*, as well as a set of stochastic transitions associated with exponential distribution, *Tsi, Tchi, Trci, Trchi*, and *Tdri*. The marking of the place *Pchi* represents the number of e-scooters that have just arrived and plugged in charging station (charging level $L \leq 50\%$), the marking of the place *Pavi* indicates the numbers of e-scooters with charging levels greater or equal than $L \geq 50\%$ (available for using), while place *Pcdi* indicates the fully charged e-scooters. In addition, the place *Puci* represents the E-scooter currently being used in the area, while place *Pwi* represents the e-scooters that are currently parked in the area (*Ai*) and that have enough charge to make another trip. Otherwise, they rebalanced by the repositioning system, swapping their battery or plugged into charging stations.

B. DYNAMIC OF E SCOOTERS INTER AREAS MODULE

The dynamic inter-area module of the e-scooter (ES) network consists of a set of places and transitions associated with exponential probability distribution. The ES network defined as set of area *Ai* and each area contains one or more charging stations. Once user rents E-scooter from area *Ai (M(Puci*), the following rides can happen: the user ride to make a short trip (means staying in original departure area) modelled by the transition *Tsii* with the firing probability (Random switch *Rsii*) and the place *Piti*; or ride for a long trip (go to another area *Aj*), modelled by the transition *Tsij*, $i \neq j$, with firing probability (*Rsij*) and place *Pitj.* A token (e-scooter + user) is marked in place *Puci*, which serves as a shared resource for transitions *Tsii* and *Tsij* ($j = 1, 2 \ldots N$). The firing of transition *Tsii* or *Tsij* represents the user's decision to choose his destination. The firing of transition *Titi* or *Titj* (representing travel time), whose firing delay is stochastic. When the user reach destination *Aj*, can park the scooter at legal spot or at charging station within the service area (incentive of service), this is modelled by the place *Pwi*. To address conflicts associated with the place *Puci* modelling the decision regarding short ride or long ride, a priority management policy is designed. It is important to note that fully charged e-scooters are prioritized for rental over E-scooters with a charge level of $L \geq s$. To represent this behavior in the in model, inhibitor arcs are employed; the model indicates that the firing of transition *Trchi* has priority than firing of transition *Trcsi.*

C. REPOSITIONING MODULE

The repositioning module represents the process of relocating scooters from oversupplied to undersupplied areas to maintain service balance across the network. This module is represented by a set of places, *PTi*, *Pai, Pfci*, and *Psi*, and transitions *Tadi, Troi*, *Tali*, and *Tei* (as illustrated in Table 3). The decision parameter *Nvsi* denotes the number of E-scooter that must be moved from the congested area to other deficit supply areas. When the network becomes unbalanced, the van move to the surplus supply area *Ai* (with high number of e-scooters) and relocate *Nvsi* scooters to a deficit supply area *Aj* (with few or no scooters), considering each scooter battery

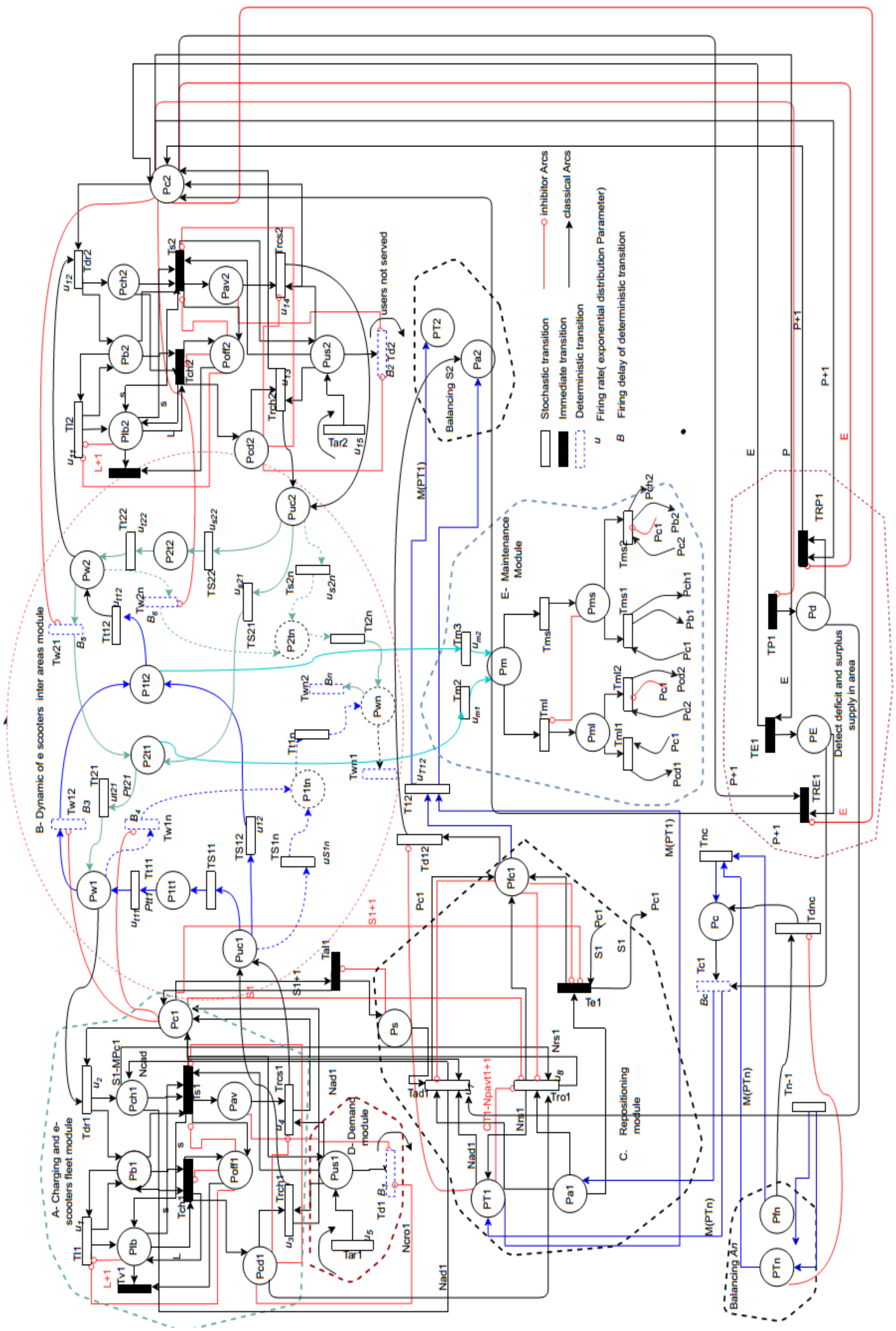


FIGURE 3. Graphical stochastic Petri net model of ES rental mobility system.

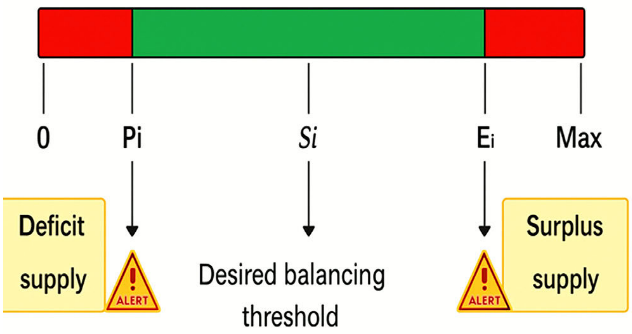


FIGURE 4. **Repositioning policy proposed.**

TABLE 3. **Meaning of some places and transitions of the model.**

Parameters	Meaning
PTi	Represents the repositioning van with capacity CT
Pai	Test the van arrival in the station/area
Pfci	Represents the end of balancing operation
PC	Represents the monitoring center, where the marking corresponds to the number of available vans.
Tadi	Represents the addition of e-scooters to area
Troi	Represents the removal of e-scooters from a service area
Teci	Represents a no-action condition when the number of e-scooters remains equal to the predefined threshold
Tdij	Represents the movement of an empty van when *(M(PTi)=0)*
Tij	Represents the stochastic transition corresponding to van movements between areas for repositioning purposes.
Tnc	Represents the van movement to the control center, it is a stochastic transition
TPi	Used to detect a deficit supply situation in an area
TEi	Used to detect a surplus supply condition in an area
TRPi	Used to remove a deficit situation when the area is naturally rebalanced through users' movements.

range in the repositioning. Figure 4 illustrates graphically the suggested policy, where the red color indicates that an area is in a critical state, and requires balancing, either by adding e-scooter in a deficit situation or moving e-scooter in a surplus situation. While the green indicates that the area is in the frame of balancing. Moreover, the following equation represents number of ES to be redistributed to deficit supply areas.

$$Nvsi = M(Pchi) + M(Pavi) + M(Pcdi) + M(Pwi)\text{-}Si \quad (5)$$

where Si denotes the repositioning threshold, which represents the target balancing level for area Ai. The number of e-scooters to be added to a deficit area in order to reach the desired supply threshold is given by equation (6).

$$Nadi = Si - [M(Pchi) + M(Pavi) + M(Pcdi) + M(Pwi)] \quad (6)$$

Figure 5 presents the flowchart of the repositioning policy proposed in this study. The objective of this policy is to detect unbalanced situations in the e-scooter network and to initiate relocation operations when surplus and deficit supply situations are identified.

The process starts by counting the total number of e-scooters in each service area Ai, denoted by $Ntsi$, which is computed as the sum of the markings of the corresponding SPN places representing available, charging, in-use, and waiting scooters. This step allows the system to continuously monitor the distribution of the fleet.

An area is considered balanced if the number of e-scooters between the predefined lower and upper thresholds Pi and Ei. If this condition is satisfied, no critical situation is detected, and no repositioning action is needed. Otherwise, the algorithm searches for surplus supply areas where $Ntsii \geq Ei$.

For each identified surplus area, the number of e-scooters to be relocated $Nvsi$ is computed based on the desired balancing threshold Si. The availability of capacity in the repositioning vans ($Npavti$ is the available places in the van to receive e-scooters) is then checked to ensure that the relocation operation is feasible (as shown in equation 7)

$$Npavti = CTi - M(PTi) \quad (7)$$

where CT represents the capacity of the repositioning van and $M(PTi)$ denotes the current e-scooters holding in the van.

If sufficient capacity is available, a repositioning decision is launched, and the van transfers e-scooters from surplus areas toward deficit areas. Finally, the algorithm identifies deficit supply areas where $Ntsi \leq Pj$, and the repositioning van delivers the relocated e-scooters accordingly the real number of e scooter existed in the area at the time of arrival. This flowchart therefore formalizes the decision-making logic governing the initiation, execution, and termination of the repositioning process, which is consequently implemented within the SPN and DES framework for simulation and performance evaluation.

Furthermore, when the system detects an imbalance across the network, repositioning vans are dispatched to restore balance according to the proposed policy. Upon arriving at a service area, a van may perform one of the following actions, depending on its capacity and the current number of e-scooters in the area, which may differ at the time of arrival.

1- E-scooter pick-up from the area: This event occurs when transition *Tcroi* fires. It is enabled when the number of e-scooters in the area exceeds a predefined threshold and sufficient empty capacity is available in the van.
2- E-scooter addition to the area: This event occurs when transition *Tcadi* fires. It is enabled when the number of e-scooters in the area is below the predefined threshold. Firing this transition adds *Ncadi* tokens to the area.
3- No-action condition: This event is represented by the firing of transition *Tei,* indicating that no redistribution action is required in the current area. The van then proceeds to the next area in the redistribution sequence.

D. DEMAND MODULE

The demand module represents the arrival and fulfillment of user requests within each service area Ai. User demand is

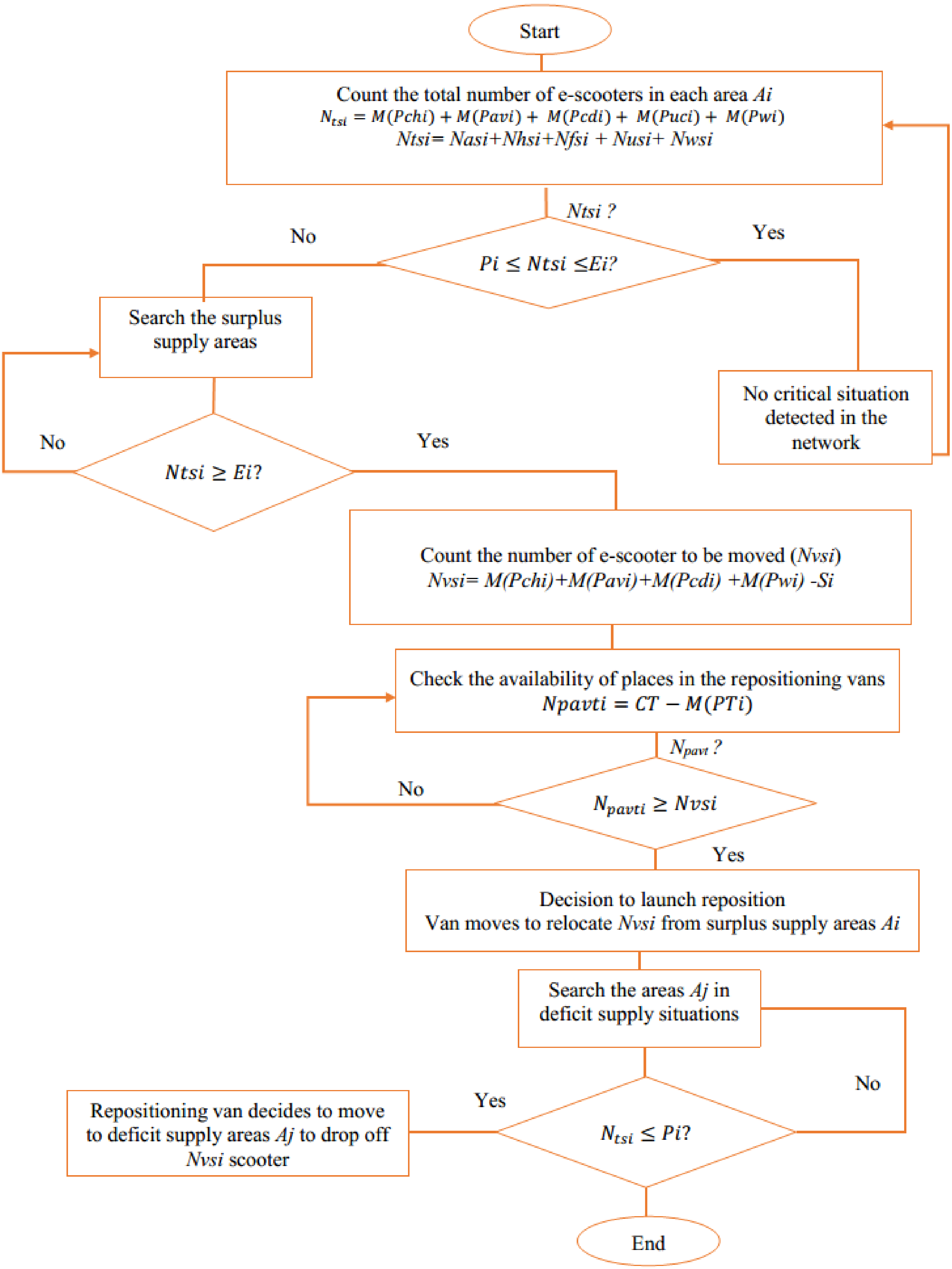


FIGURE 5. Flowchart of the repositioning policy proposed.

TABLE 4. Some performance metrics of scenario (1).

Area *Ai* / Performance metrics	A1	A2	A3	A4	A5	A6	A7	A8	A9
Average firing of *Trcsi* (average rent of available e-scooters)	0.035	0.041	0.064	0.028	0.071	0.052	0.035	0.071	0.061
% of time deficit supply	3.8%	2.4%	0.25%	16%	3.37%	7.30%	13.70%	12.12%	2.23%
% of time surplus supply	15.2%	13.2%	12.2%	0.23%	12.4%	11.2%	5.4%	6.81%	16.4%

represented by the stochastic transition *Tari*, which fires when a customer requests an e-scooter and deposits a token in place *Pusi*, which is fired when a customer requests an e-scooter. The availability of scooters in a given area is determined by the markings of places *Pavi and Pcdi*. When a scooter is available, it is assigned to the requesting user through the firing of transitions *Trci and Tusei*, moving the token to place *Puci*, which indicates that the scooter is currently in use. Unlick, if no scooter is available at the time of request, a token is removed from place *Pusi*, and the firing of transition *Trdi* allows the evaluation of user satisfaction and service accessibility across the network.

E. MAINTENANCE MODULE

The maintenance module represents the maintenance center and the reparation process within the SPN model. E-scooters that require maintenance are collected from area *Ai* and transported to the center, a process modeled by the stochastic transition *Tmi*. Once an e-scooter arrives at the maintenance center (place Pm in the model), two types of maintenance procedures are considered.

The first is short maintenance, designed to fix minor issues, represented by transition *Tms* and place *Pms*. The second is long maintenance, used to address major damages or complex repairs, represented by transition *Tml* and place *Pml*. After maintenance is completed, the e-scooter is either transferred to a charging station depending on charger availability or returned directly to an operational area *Aj* for reuse. These transfer processes are represented by transitions *Tml1* and *Tms1*, respectively.

V. SIMULATION AND DISCUSSION MODEL FORMULATION

Discrete event simulation based on SPN are a graphical and mathematical modeling framework used for analysis of discrete event systems. They constitute a powerful graphical tool for representing and analyzing situations of synchronization, parallelism, concurrency, distribution, stochastic process, and sequential mechanisms [32], [33]. These tools can replicate the stochastic and dynamic nature of complex systems, allowing for simulation and evaluation of several operational strategies and scenarios. The SPN model, developed on the MATLAB platform (As shown in Figure 7 and Algorithm 1), simulates the e-scooter network, where each cycle representing an event and updating the network marking. The simulation increases the time according to the fired transition type and delay. All transitions in the SPN adopt single-server semantics, in line with the sequential firing mechanism of the discrete-event simulation framework. The simulator takes as inputs: system characteristics, simulation time, average travel time between areas, average demand per area, and relocation strategy parameters. Using an extending algorithm, the model can be extended according to the number of areas. Then, the discrete event simulation algorithm simulates the model, following the evolution of the marking over time. Finally, the performance metrics assessment algorithm evaluates and provides all relevant performance metrics.

Several performance metrics can be evaluated from the developed SPN model, we can cite some of them as formulated in the below equations:

1. The average number of e-scooters in an area

$$M(P_i)_{avr} = \lim_{tsim\to\infty} \sum M\,(Pi)\,\pi_i \tag{8}$$

2. % of time empty station (no e-scooter being charged)

$$M(P_i)_{deficit} = \lim_{tsim\to\infty} \left(100 \sum \left(\tau_{k+1} - \tau_k\right)_{M(P_i)\leq Pi}/t_{sim}\right) \tag{9}$$

3.% of time full station (all chargers of station are occupied)

$$M(P_i)_{congest} = \lim_{tsim\to\infty} \left(100 \sum \left(\tau_{k+1} - \tau_k\right)_{M(P_i)\geq Ei}/t_{sim}\right) \tag{10}$$

where, π denotes the probability that the system is in a specific state, *lim* means long horizon of simulation, τ indicates the duration of each cycle, and *tsim* is the total simulation time.

We have simulated our model by collecting data from Neuron e-scooter rental system of the city of Rockhampton in Australia [34]. Our study focused on nine specific areas within the city and involved a fleet of 100 e-scooters (As shown in Figure 6). Collecting some data using Google

Algorithm 1 Simulation Algorithm

Initialization
Step 1: Generate PN model for N areas
Read data $M_0, N, s, P, E, S, C, CT, \mu_i, \beta_i$
for $i = 1$ to N (number of areas) **do**
  Calculate places N_P and transitions N_T:
  $N_P = N^2 + 14N + 4$
  $N_T = N^2 + 19N + 3$
Build global transition and place vectors
end for
Output
for $i = 1$ to N_T and $j = 1$ to N_P **do**
  Construct extending **Pres**, **Post**, & **inhibit** Matrices
end for
Step 2: Process simulation
Read all generated Matrices of model and data
while $Time < t_{sim}$ **do**
  1. Calculate incidence Matrix W_{inc} = **Pres – Post**
  2. Calculate R_s (Random Switch) for priority
  3. Build enabled vector V_{en} from initial marking:
  if transition T_j is enabled **then**
   $V_{en}(T_j) = 1$
  else
   $V_{en}(T_j) = 0$
  end if
  if $V_{\text{en}}(j) \neq \emptyset$ **then**
   if $V_{\text{en}}(j) \cap T_i \neq \emptyset$ (T_i **immediate** vector) **then**
    Exclude all **timed transitions** in $V_{en}(j)$.
    Keep only **immediate transitions**.
    Select immediate transition $T_c \in V_{en}(j)$ to fire, according to priorities (R_s).
   end if
   if $V_{en}(j) \cap T_i = \emptyset$ **then**
    for $i = 1$ to $T_j \in V_{en}(j)$ **do**
     Update firing delay (FD) of timed transition
    end for
    if T_j is **timed** and was enabled **then**
     $FD = FD_0 - FD(T_c)$
    end if
    if T_j is **stochastic** and was not enabled **then**
     Generate random firing delay:
     $FD = (-1/\mu) \cdot \ln(1 - P(t))$
    end if
    if T_j is **deterministic** and was not enabled **then**
     $FD_i(T_j) = \beta_i$
    end if
   end if
  else
   Go to End of simulation
  end if
  4. Determine firing transition with highest priority
  5. Construct firing vector ϕ_f, where:
  if transition T_i fires then
   $\phi_f(T_j) = 1$ else $\phi_f(T_j) = 0$
  end if
  6. Execute the firing
  7. Update marking $M_{n+1} = M_n + W_{\text{inc}} \cdot \phi_f$
  8. Send new marking to output file
  9. Memorize firing delay and marking
  10. Time = Time + delay of fired transition
end while
Step 3: Calculate performance metrics
End of simulation

Maps (2023), we have estimated the distances approximately and average travel times for e-scooters between different areas. Furthermore, several decision parameters are considered in the model, such as *Nest*, the total number of e-scooters in the network; *Nv*, the number of repositioning vans; *Nts*, the number of charging stations; *Csi*, the capacity of each charging station; *si*, the minimum battery threshold required for a scooter to leave an area or a charging station; *Li*, the battery charge level; *Cti*, the capacity of the repositioning van; Nasi, the number of e-scooters being charged; and *Nhsi*, the number of available e-scooters with a charge level $L \geq 50\%$.

Despite the relatively small scale of the system, the results can be generalized to other e-scooter systems. In our analysis, we investigated two distinct scenarios to evaluate the impact of repositioning services on the e-scooter system's performance, both using a battery-charging threshold of 50%. In the first scenario, we have analyzed the system's behavior without any repositioning service. Here, e-scooters were left to operate only based on their initial placement and usage patterns. Therefore, testing the system's ability to meet demand and manage e-scooter availability without external repositioning. In the second scenario, we integrated a repositioning service using vans to move e-scooters from areas of high supply to areas of lower supply. By implementing this strategy, we evaluated how effectively repositioning could mitigate the limitations observed in the first scenario, enhance the system's satisfaction to the stochastic demand.

A. ANALYSIS OF SCENARIOS 1 (CASE STUDY 1)

In this scenario, we test the behavior of the system without the availability of the relocation system and the e-scooter is available as long as its charging level great or equal than the fixed threshold ($s = 50\%$, $L \geq 50\%$). In term of SPN model, this scenario is achieved by taking the initial marking of place $M(PTi) = 0$ (Number of vans equal zero).

Several performance metrics are formulated to analyze the system's behavior under these conditions, including the percentage of time spent in deficit or surplus supply, and the average number of unserved users across all service areas.

Figure 8 illustrates the distribution of e-scooters across different areas over time. We can observe the surplus and deficit supply areas throughout the system's operation. This imbalance arises naturally due to the lack of a repositioning service. These graphs highlight the critical need for dynamic repositioning strategies to maintain balanced supply levels across different areas.

Although the simulated network includes 16 areas, only a representative subset (A1–A9) is reported in Table 4 for clarity, as the remaining areas show similar surplus/deficit dynamics. Based on these results, the efficiency of the system is evaluated by analyzing key performance metrics that characterize its operational behavior. These metrics include: During the total simulation time, area *A1* experiences a surplus supply of e-scooters for 15.2% of the time. That is mean, an average of 121.6 minutes (800*15.2/100) the area *A1* remain in surplus over a typical service day of 800 minutes. However, *A1* is in a deficit supply situation for 3.8% of the time, which means it spends an average 30.4 minutes in deficit within the same period.

Alternatively, we can estimate the average firing rate of *Trcs1*, which represents the average rental frequency of

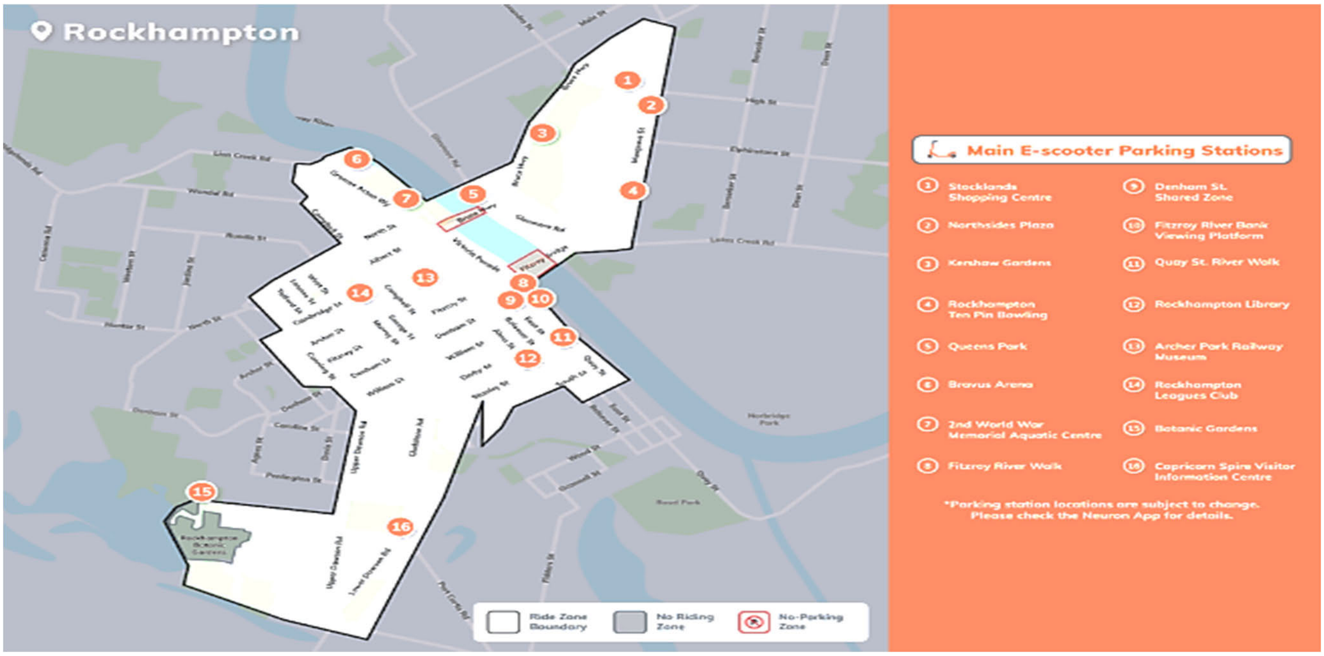


FIGURE 6. Main e-scooter parking stations/areas of Rockhampton. [32].

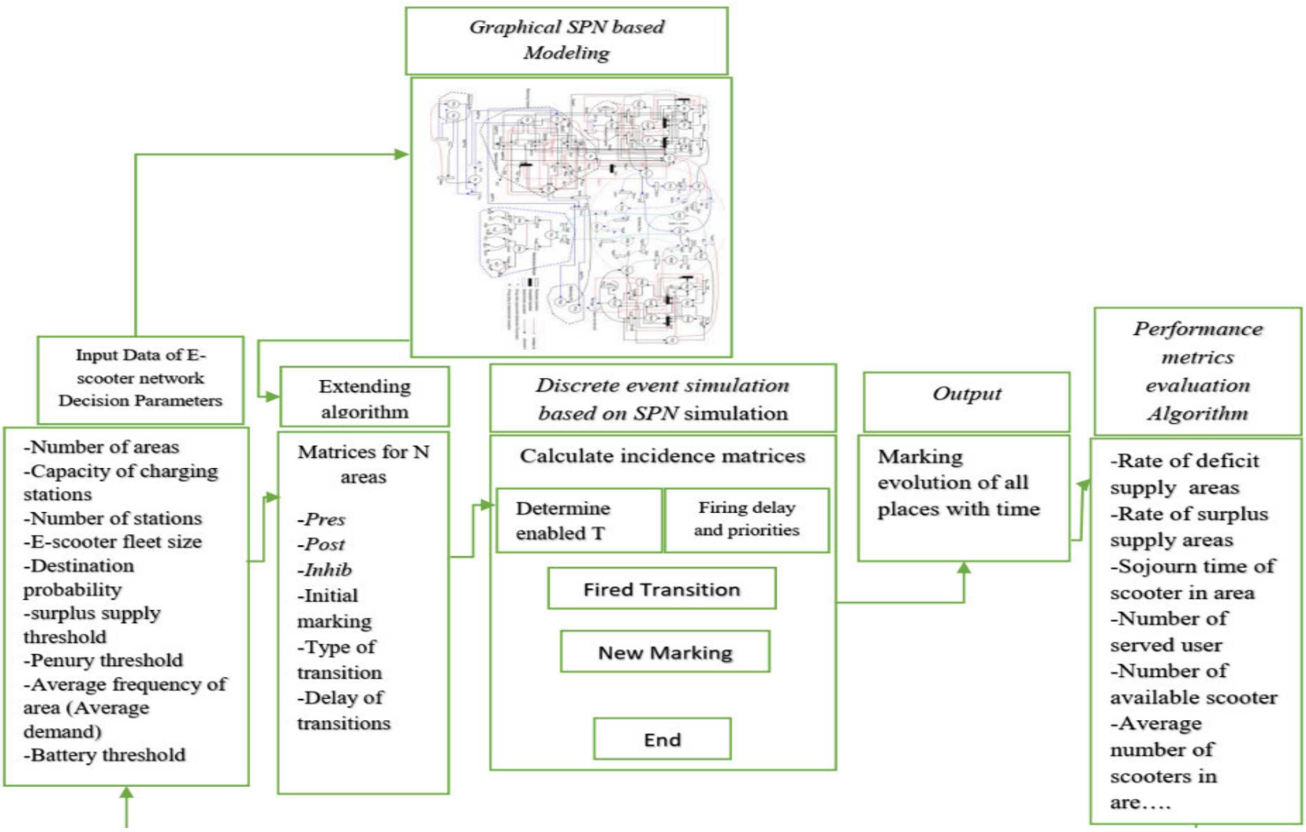


FIGURE 7. Simulation framework.

available e-scooters. According to Table 3, the average firing rate of *Trcs1* is 0.035 per minute. This indicates that an available electric scooter is rented every 28.63 minutes on average (calculated as 1/0.035 = 28.63 minutes).

TABLE 5. Some performance metrics of scenario (2).

Area *Ai* / Performance Metrics	A1	A2	A3	A4	A5	A6	A7	A8	A9
Average firing of *Trcsi* (average rent of available e-scooters)	0.062	0.054	0.072	0.037	0.089	0.073	0.069	0.083	0.073
% of time deficit supply	1.15%	1.12%	0.12%	10%	2.16%	3.66%	4.1%	5.23%	1.68%
% of time surplus supply	6.2%	7.5%	3.42%	0.25%	6.86%	5.46%	3.55%	4.76%	11.3%

The average rental frequency indicates the high demand for e-scooters in that area. A higher firing rate would indicate a higher demand and vice versa. This value helps in understanding how often e-scooters are being used. Knowing the rental frequency assists in fleet management decisions. For example, if the rate is too low, it might suggest that there are more e-scooters than needed in that area.

These metrics collectively offer a comprehensive assessment of system performance, providing valuable insights for fleet management decisions such as fleet sizing, demand forecasting, and the potential benefit of implementing repositioning strategies. They also help identify zones requiring better dimensioning, scheduling, or relocation policies to enhance both operational efficiency and user satisfaction. Future work will focus on extending these analyses by incorporating optimization mechanisms to determine the best repositioning moments and parameters, further improving the balance and sustainability of the e-scooter network.

B. ANALYSIS OF SCENARIO 2 (CASE STUDY 2)

In this second scenario, a rebalancing service using a single van with limited capacity is introduced to address the imbalances identified in the first scenario, where no such service was implemented. This rebalancing mechanism dynamically redistributes e-scooters from surplus areas to deficit areas. The objective of this scenario is to improve overall system efficiency and enhance user satisfaction by reducing both e-scooter shortages and surpluses. The graphs presented in Figure 9 illustrate the evolution of scooter flows, including both incoming and outgoing movements across the different areas of the network. A detailed analysis of these graphs demonstrates a significant improvement in system balance compared to the previous scenario.

Based on the results presented in Table 5 the efficiency of the proposed repositioning strategy can be evaluated by analyzing several key performance metrics that reflect the overall behavior of the system. These metrics include: During the total simulation time, it is important to note that area *A1* is in a surplus supply of e-scooters situation on 6.2% of the time. That is mean, an average of 49.6 minutes (800*6.2/100) area *A1* remain in surplus over a service of 800 minutes. Furthermore, *A1* remains in deficit supply situation for 1.15% of the time, which means it spends 9.2 minutes on average in deficit within the same period. In addition, it is important to see that the firing rate of transition *Trcsi* is greater than that of scenario (a), indicating an increase in the average rental rate cross all areas (e.g. 1/0.062 = 16.12 of area *A1* indicates an average of one available e scooter rented every 16.12 mn). Thanks to the rebalancing strategy integrated into the model, critical situations (surplus of deficit supply) are significantly decreased. We record a very low average rate of saturation and deficit in most areas.

The simulation results clearly demonstrate the potential of the SPN framework to capture and analyze the dynamic behavior of shared e-scooter systems under varying operational conditions. By representing discrete events such as scooter pick-ups, drop-offs, charging, and relocation, the SPN model accurately reproduces complex, stochastic interactions between demand fluctuations, battery limitations, and network imbalances.

In addition to the previously discussed performance indicators, the proposed SPN–DES framework can also be used to quantify additional performance indicators, such as average e-scooter availability. In particular, scooter availability is defined as the average number of e-scooters that are immediately accessible to users in a given area during the simulation horizon. This metric is computed from the average marking of places *Pavi* and *Pcdi,* which respectively represent the number of available and charged e-scooters. Using DES, the marking of these places is tracked over the entire simulation horizon, and the average number of available e-scooters is computed according to equations (4) and (5). This metric reflects the ability of the system to provide scooters to users over time and allows a direct assessment of service quality under different operational scenarios, including imbalance conditions and repositioning strategies. Consequently, the availability of e-scooters in each area is obtained as the mean number of available e-scooters during the observation period, providing a reliable measure of service accessibility for users.

More generally, the proposed SPN–DES framework is sufficiently generic and flexible to support the evaluation of several performance metrics related to shared e-scooter systems. While the model structure allows the computation of numerous indicators, including availability, utilization rates,

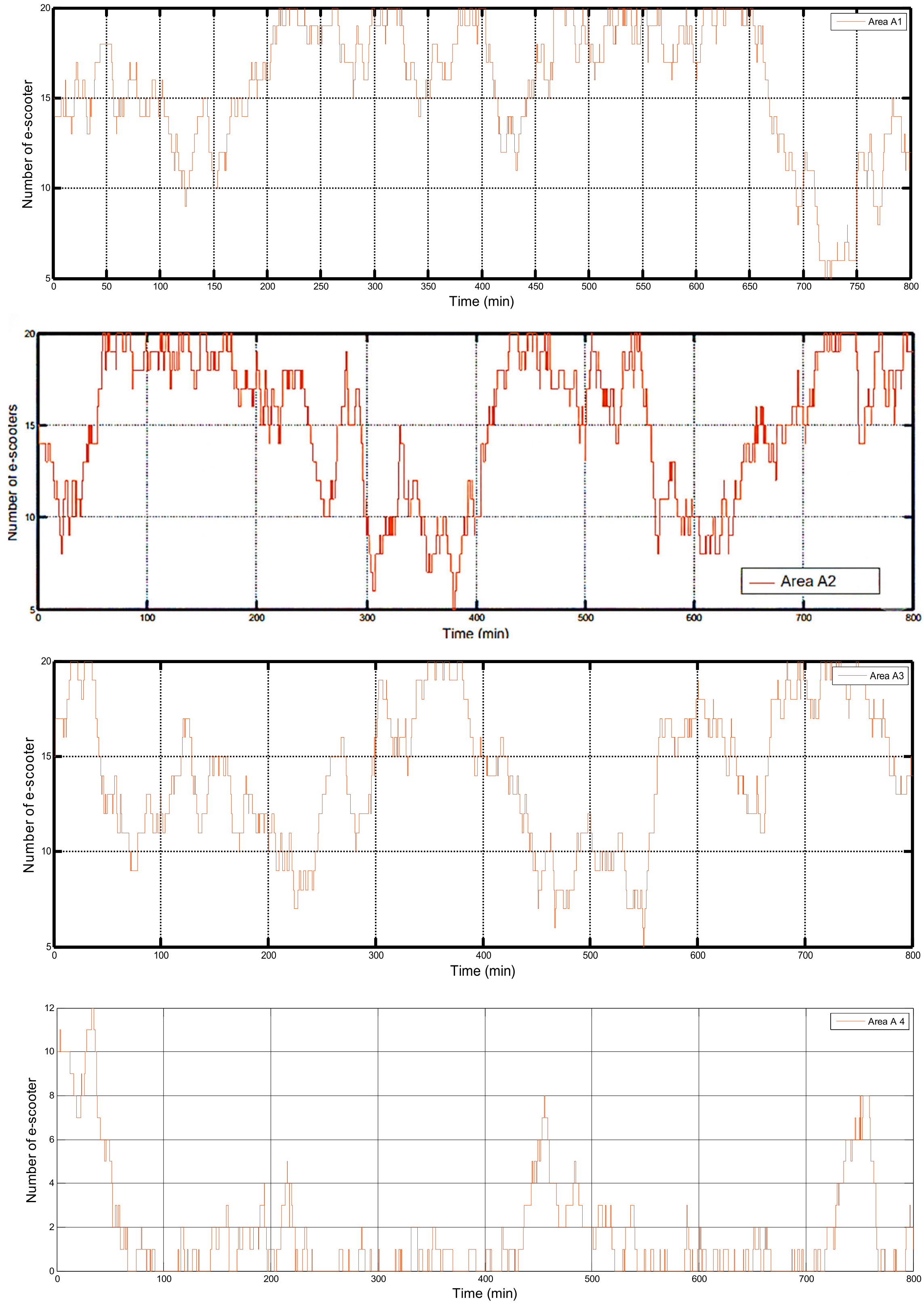


FIGURE 8. **Behavior of e-scooter mobility in each area without repositioning.**

waiting times, charging occupancy, and repositioning efficiency, only a selected subset of key metrics is explicitly analyzed in this paper. This choice is motivated by the need to maintain clarity and readability, as a comprehensive

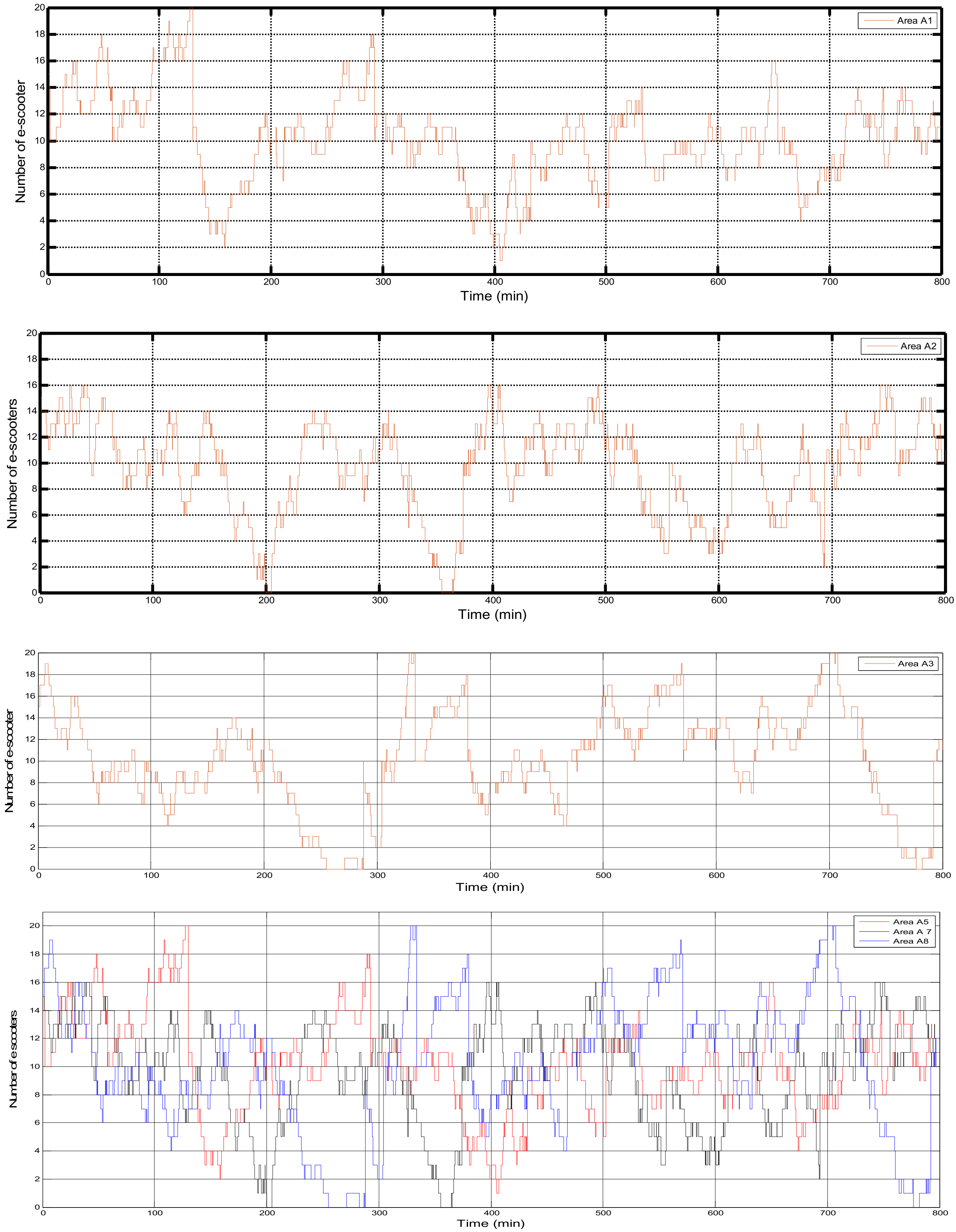


FIGURE 9. **E-Scooter mobility patterns of each areas with repositioning and a 50% Battery Charge Threshold.**

quantitative analysis of all possible metrics would significantly increase the complexity of the manuscript. Nevertheless, the proposed framework can be readily extended to evaluate additional performance measures by

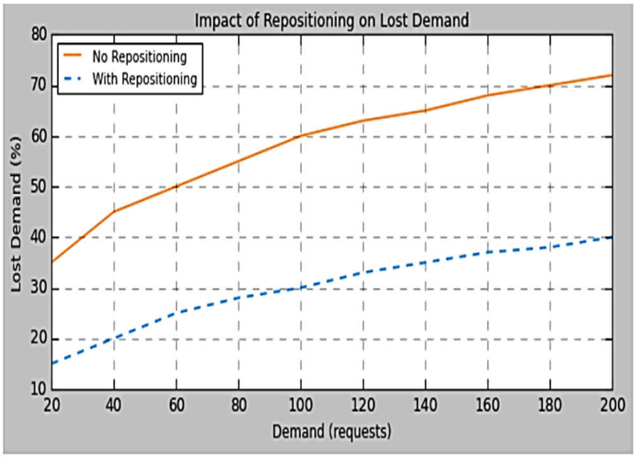


FIGURE 10. **Impact repositioning on lost demand.**

monitoring the corresponding place markings and transition firing statistics during simulation.

The analysis of the evaluated performance metrics across the different scenarios highlights the effectiveness of the proposed redistribution strategy incorporated into the model. In the first scenario (case study 1), where no repositioning mechanism is applied, the network experiences frequent and prolonged periods of imbalance, characterized by a high percentage of time in both deficit and surplus supply across different areas. In contrast, the second scenario (case study 2), which incorporates the proposed redistribution policy, shows a clear reduction in the percentage of time that areas remain in deficit supply, as well as a decrease in surplus supply durations. This improvement indicates that e-scooters are better distributed across the network, reducing prolonged shortages and oversupply situations. These results demonstrate that the proposed repositioning strategy significantly enhances system balance and operational efficiency by dynamically correcting the imbalances in scooter availability.

On the other hand, redistributing e-scooters among areas significantly reduces lost demand, as shown in Figure 10. The lost demand grows with increasing requests when repositioning is unavailable, reflecting situations where some areas experience persistent deficits while others are oversupplied. Introducing repositioning significantly reduces lost demand across all demand levels, especially under high-load conditions, by dynamically reallocating scooters from surplus to deficit areas. This finding highlights repositioning as an effective operational lever for improving service availability and user satisfaction, and it validates SPN combined with discrete event simulation as a powerful analytical tool for evaluating and optimizing shared micro mobility networks.

Although the SPN and DES framework presented here is theoretically capable of simulating very large e-scooter networks, practical challenges arise at scale. Capturing realistic behavior for thousands of scooters across dozens of areas requires high-resolution demand, travel, and charging data, which are often proprietary or unavailable for research use. However, Stochastic Petri Nets suffer from state space explosion: for a large city network, the model could easily reach more than 352,000 places and 220,000 transitions, producing an enormous marking space that computationally becomes prohibitive to analyze directly. These challenges make discrete event simulation an unavoidable and practical approach for generating large model and evaluating system behavior at such scales, as DES can approximate the dynamics without explicitly counting every state. Furthermore, DES allows the system behavior to be evaluated through sampled trajectories over time, avoiding the explicit construction of the global reachability graph. In addition, the modular structure of the proposed model enables scalable extensions by replicating area-level submodels without increasing structural complexity. Additional strategies such as model aggregation, and scenario-based simulation can further improve scalability. Therefore, while the Rockhampton case study with 100 scooters serves as a clear and computationally efficient proof of concept, the framework is designed to be extensible to larger systems once suitable data and computational resources are available. In addition, this framework evaluates performance but does not yet implement adaptive feedback or optimization-based repositioning in real time. Future work could combine SPN outputs with reinforcement learning or heuristic optimization to improve responsiveness.

Comprehensively, the present study focuses on behavior modeling and performance assessment rather than on benchmarking specific repositioning algorithms. Our objective was to evaluate the dynamic properties and operational thresholds of shared e-scooter systems using an SPN and DES framework, rather than to compare every possible heuristic or reinforcement learning strategy reported in the literature. Nevertheless, we recognize that repositioning policies strongly influence network performance. As future work, we plan to integrate optimization-based methods with the SPN framework to automatically tune decision parameters and benchmark these strategies with heuristic and machine learning based approaches to further enhance operational efficiency.

Additionally, the results of this study might also be interpreted through the lens of sustainable urban mobility transitions, particularly the CalmMobility perspective. The ability of the proposed SPN and DES framework to predict imbalance and improve service reliability aligns with CalmMobility principles such as predictability and user-centric operation. In instance, the repositioning strategy developed in this work can help reduce uncertainty for users by maintaining stable scooter availability throughout the network, which enhances perceived service reliability and comfort two central dimensions of CalmMobility.

Beyond enhancing operational performance, the proposed SPN and DES framework also has the potential to support broader climate and public health objectives. By improving fleet distribution and reducing unnecessary van based repositioning trips, the model contributes to lowering greenhouse gas emissions and energy consumption associated with e-scooter operations. For instance, maintaining a balanced fleet across service areas minimizes the number of collection and relocation trips by service vehicles, thereby directly reducing CO2 emissions. This routing and repositioning vehicle problem, which significantly influences both operational efficiency and environmental impact, will be explored in future research. In particular, it will be formulated as an optimization problem by combining the SPN model with metaheuristic algorithms or recurrent neural networks. The objective will be to determine the optimal decision parameters (*Pi, Ei, Si*) and the best timing for initiating repositioning mechanism, ultimately minimizing unnecessary trips and enhancing both system performance and sustainability.

VI. CONCLUSION

Shared e-scooter rental systems have recently contributed significantly to the urban mobility landscape; however, their complex and stochastic nature makes their modelling, optimization, and repositioning highly challenging. This study initially investigated key research issues and gaps in shared e-scooter mobility, noting that most existing models did not consider the crucial stochastic behavior of e-scooter users (who can act as both pedestrians and vehicle operators). Such behavior can affect traffic flow, complicate demand prediction, and make the modelling and simulation of such systems particularly challenging.

This paper has mainly proposed a SPN framework to address repositioning and performance evaluation. This model considers several decision parameters and can simulate various configurations, including dynamic modes with and without repositioning, as well as static modes for low-usage periods. Performance metrics such as the average number of available scooters and the duration of supply deficits can be evaluated. A repositioning strategy was proposed and simulated, involving the repositioning of scooters from surplus areas to deficit areas.

Additionally, this paper highlights the potential of Petri nets models for evaluating the performance of such stochastic systems, predicting critical situations, and analyzing control strategies. To the best of our knowledge, this study is the first to use Stochastic Petri Nets to model shared e-scooter mobility systems. Furthermore, the developed SPN model can be used at both strategic and operational levels. At the strategic level, it helps in system design and dimensioning by simulating different scenarios to determine optimal configurations. At the operational level, the model can help to dynamically relocate e-scooters, ensuring a balanced supply and demand across different areas.

The key outcomes can be summarized as follows:

- ✓ SPN formalism provides a flexible and mathematically rigorous tool for representing the stochastic and dynamic nature of shared micromobility systems.
- ✓ The proposed repositioning strategy effectively mitigates system imbalances, reducing deficit and surplus conditions across network areas.
- ✓ Performance metrics such as average availability, rental frequency, and deficit duration provide actionable insights for operators and city authorities.
- ✓ Even in relatively small-scale case studies, the results indicate strong potential for generalization to larger urban environments.

In addition, the SPN formalism demonstrates significant potential for modeling, analysis, and simulation of shared e-scooter systems under diverse operational conditions. Owing to its flexibility, the SPN model can reproduce system behavior across various scenarios, ranging from nighttime operation with low demand to dynamic or event-driven situations, such as peak hours or special events (e.g., festivals) that cause sudden demand fluctuations. This capability enables researchers and operators to analyze performance, identify potential limitations, and test different operational strategies without requiring real-world experimentation. Consequently, SPN serves as a powerful decision-support tool for evaluating system robustness and adaptability in both regular and exceptional operating contexts.

This work opens several avenues for future research. Key optimization challenges in designing e-scooter mobility services include determining the optimal fleet size and parking station locations. Future research will involve combining the developed model with Mixed-Integer Programming to handle/address fleet optimization and vehicle routing problems. Furthermore, future extensions will incorporate multi-modal transport interactions to evaluate the role of e-scooters within integrated mobility-as-a-service ecosystems. We also plan to extend the proposed model to incorporate/include additional operational events, such as scenarios in which a subset of charging stations is temporarily taken offline during the day due to maintenance activities or other operational constraints.

REFERENCES

[1] S. Dibaj, D. Lopatnikov, and M. Mladenović, "E-scooter multi-riding: Analyzing riding practices in Helsinki, Finland," in *Proc. 103th Transp. Res. Board Annu. Meeting*, Jan. 2024.

[2] IAA Mobility. (Aug. 2023). *The E-Scooter Trend—A Popular Mobility Alternative*. IAA Mobility Newsroom. Accessed: Sep. 19, 2025. [Online]. Available: https://www.iaa-mobility.com/en/newsroom/news/smart-infrastructure/trend-t-scooter

[3] D. Wang, "Joint optimization of relocation and routing strategies for E-scooter sharing system," M.S. thesis, Politecnico di Torino, Turin, Italy, 2023. [Online]. Available: https://webthesis.biblio.polito.it/27105/

[4] L. Gebhardt, S. Ehrenberger, C. Wolf, and R. Cyganski, "Can shared E-scooters reduce CO_2 emissions by substituting car trips in Germany?" *Transp. Res. D, Transp. Environ.*, vol. 109, Aug. 2022, Art. no. 103328, doi: 10.1016/j.trd.2022.103328.

[5] K. Turoń, "Sustainable urban mobility transitions—From policy uncertainty to the CalmMobility paradigm," *Smart Cities*, vol. 8, no. 5, p. 164, Oct. 2025, doi: 10.3390/smartcities8050164.

[6] T. Benarbia, K. W. Axhausen, and B. Farooq, "Modeling, relocation, and real-time inventory control of one-way electric cars sharing systems in a stochastic Petri nets framework," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 5, pp. 2846–2861, May 2021, doi: 10.1109/TITS.2020.2976568.

[7] T. Benarbia, K. Kyamakya, F. Al Machot, and W. V. Kambale, "Modeling and simulation of shared electric automated and connected mobility systems with autonomous repositioning: Performance evaluation and deployment," *Sustainability*, vol. 15, no. 1, p. 881, Jan. 2023, doi: 10.3390/su15010881.

[8] P. G. Tzouras, L. Mitropoulos, E. Stavropoulou, E. Antoniou, K. Koliou, C. Karolemeas, A. Karaloulis, K. Mitropoulos, M. Tarousi, E. I. Vlahogianni, and K. Kepaptsoglou, "Agent-based models for simulating e-scooter sharing services: A review and a qualitative assessment," *Int. J. Transp. Sci. Technol.*, vol. 12, no. 1, pp. 71–85, Mar. 2023, doi: 10.1016/j.ijtst.2022.02.001.

[9] A. O. Diallo, T. Gloriot, and O. Manout, "Agent-based simulation of shared bikes and E-scooters: The case of Lyon," *Proc. Comput. Sci.*, vol. 220, pp. 364–371, Jan. 2023, doi: 10.1016/j.procs.2023.03.047.

[10] M. H. Shah, Y. Ding, S. Zhu, Y. Gu, and M. Liu, "Optimal design and implementation of an open-source emulation platform for user-centric shared e-mobility services," in *Machine Learning, Optimization, and Data Science*, G. Nicosia, V. Ojha, S. Giesselbach, M. P. Pardalos, and R. Umeton, Eds., Cham, Switzerland: Springer, 2025, pp. 43–57.

[11] A. M. Fathabad, X. Li, J. Cheng, and Y.-J. Wu, "Data-driven optimization for E-scooter system design," Dept. Syst. Ind. Eng., Univ. Arizona, Tucson, AZ, USA, Tech. Rep. NITC-RR-1382, 2022.

[12] S. Kim, S. Choo, G. Lee, and S. Kim, "Predicting demand for shared E-scooter using community structure and deep learning method," *Sustainability*, vol. 14, no. 5, p. 2564, Feb. 2022, doi: 10.3390/su14052564. .

[13] S. Bai and J. Jiao, "Dockless E-scooter usage patterns and urban built environments: A comparison study of Austin, TX, and Minneapolis, MN," *Travel Behav. Soc.*, vol. 20, pp. 264–272, Jul. 2020, doi: 10.1016/j.tbs.2020.04.005.

[14] B. Turan and T. Wakolbinger, "The electric scooter collection problem: A case study in the city of Vienna," *Sustainability*, vol. 15, no. 13, p. 10058, Jun. 2023, doi: 10.3390/su151310058.

[15] N. Saum, S. Sugiura, and M. Piantanakulchai, "Optimizing shared E-scooter operations under demand uncertainty: A framework integrating machine learning and optimization techniques," *IEEE Access*, vol. 12, pp. 26957–26977, 2024, doi: 10.1109/ACCESS.2024.3365947.

[16] G. Losapio, F. Minutoli, V. Mascardi, and A. Ferrando, "Smart balancing of E-scooter sharing systems via deep reinforcement learning: A preliminary study," *Intelligenza Artificiale*, vol. 16, no. 1, pp. 49–67, Jul. 2022, doi: 10.3233/ia-210126.

[17] G. Lee, J. S. Lee, and K. S. Park, "Battery swapping, vehicle rebalancing, and staff routing for electric scooter sharing systems," *Transp. Res. E, Logistics Transp. Rev.*, vol. 186, Jun. 2024, Art. no. 103540, doi: 10.1016/j.tre.2024.103540.

[18] M. Masoud, M. Elhenawy, M. H. Almannaa, S. Q. Liu, S. Glaser, and A. Rakotonirainy, "Heuristic approaches to solve E-scooter assignment problem," *IEEE Access*, vol. 7, pp. 175093–175105, 2019, doi: 10.1109/ACCESS.2019.2957303.

[19] M. Giordano and J. Y. J. Chow, "An E-scooter service region and fleet allocation design problem with elastic demand," *Transp. Res. D, Transp. Environ.*, vol. 130, May 2024, Art. no. 104153, doi: 10.1016/j.trd.2024.104153.

[20] A. Ciociola, M. Cocca, D. Giordano, L. Vassio, and M. Mellia, "E-scooter sharing: Leveraging open data for system design," in *Proc. IEEE/ACM 24th Int. Symp. Distrib. Simulation Real Time Appl. (DS-RT)*, Sep. 2020, pp. 1–8.

[21] O. Manout, A. O. Diallo, and T. Gloriot, "Implications of pricing and fleet size strategies on shared bikes and E-scooters: A case study from Lyon, France," *Transportation*, Nov. 2024, doi: 10.1007/s11116-024-10559-5.

[22] N. R. Shah, A. Ziedan, C. Brakewood, and C. R. Cherry, "Shared E-scooter service providers with large fleet size have a competitive advantage: Findings from e-scooter demand and supply analysis of Nashville, Tennessee," *Transp. Res. A, Policy Pract.*, vol. 178, Dec. 2023, Art. no. 103878, doi: 10.1016/j.tra.2023.103878.

[23] A. Colovic, L. P. Prencipe, N. Giuffrida, and M. Ottomanelli, "A multi-objective model to design shared e-kick scooters parking spaces in large urban areas," *J. Transp. Geography*, vol. 116, Apr. 2024, Art. no. 103823, doi: 10.1016/j.jtrangeo.2024.103823.

[24] Y. Liu and Y. Ouyang, "Planning charging stations for mixed docked and dockless operations of shared electric micromobility systems," *Transp. Res. C, Emerg. Technol.*, vol. 171, Feb. 2025, Art. no. 104989, doi: 10.1016/j.trc.2024.104989.

[25] S. Yan, C.-K. Lin, and Z.-Q. Kuo, "Optimally locating electric scooter battery swapping stations and battery deployment," *Eng. Optim.*, vol. 53, no. 5, pp. 754–769, May 2021, doi: 10.1080/0305215x.2020.1751148.

[26] A. Giua, "Petri nets as discrete event models for supervisory control," M.S. thesis, Dept. Elect., Comput., Syst. Eng., Rensselaer Polytechnic Inst., Troy, NY, USA, 1992.

[27] S. Çelik and Ş. Ok, "Electric vehicle charging stations: Model, algorithm, simulation, location, and capacity planning," *Heliyon*, vol. 10, no. 7, Apr. 2024, Art. no. e29153, doi: 10.1016/j.heliyon.2024.e29153.

[28] S. Carrese, F. D'Andreagiovanni, T. Giacchetti, A. Nardin, and L. Zamberlan, "A beautiful fleet: Optimal repositioning in E-scooter sharing systems for urban decorum," *Transp. Res. Proc.*, vol. 52, pp. 581–588, Jan. 2021, doi: 10.1016/j.trpro.2021.01.069.

[29] S. Narayanan, J. M. Salanova Grau, R. Frederix, A. Tympakianaki, A. D. Masegosa, and C. Antoniou, "Modeling of shared mobility services—An approach in between aggregate four-step and disaggregate agent-based approaches for strategic transport planning," *J. Intell. Transp. Syst.*, vol. 29, no. 4, pp. 435–452, Jul. 2025, doi: 10.1080/15472450.2023.2246374.

[30] P. Zhao, A. Li, P. Pilesjö, and A. Mansourian, "A machine learning based approach for predicting usage efficiency of shared E-scooters using vehicle availability data," *AGILE: GIScience Ser.*, vol. 3, pp. 1–10, Jun. 2022, doi: 10.5194/agile-giss-3-20-2022.

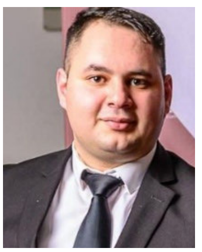
[31] Y. Ji, D. Ou, L. Zhang, C. Tang, and V. Phichitthanaset, "Railway emergency plan modeling based on Petri net," *Smart Resilient Transp.*, vol. 3, no. 3, pp. 235–248, Dec. 2021, doi: 10.1108/srt-01-2021-0001.

[32] J. O. Moody and P. J. Antsaklis, "Petri net supervisors for DES with uncontrollable and unobservable transitions," *IEEE Trans. Autom. Control*, vol. 45, no. 3, pp. 462–476, Mar. 2000, doi: 10.1109/9.847725.

[33] T. Murata, "Petri nets: Properties, analysis and applications," *Proc. IEEE*, vol. 77, no. 4, pp. 541–580, Apr. 1989, doi: 10.1109/5.24143.

[34] *Neuron's E-Scooters to Arrive in Rockhampton With a Range of Cutting-Edge Safety Features!*, Neuron Mobility, Australia, 2022.

TAHA BENARBIA received the Ph.D. degree in electrical engineering from the University of Cergy–Pontoise (UCP), France, in 2013. He is currently an Associate Professor with the Institute of Maintenance and Industrial Security, University of Oran 2 Mohamed Ben Ahmed, Oran. In 2017, he joined the Institute for Transport Planning and Systems IVT, ETH Zürich, Switzerland, as a Postdoctoral Researcher. His main research interests include shared mobility systems, connected and automated vehicles, drone delivery systems modeling, stochastic and discrete event systems optimization, performance evaluation of dynamic systems, and machine learning for perception and decision support. He serves as a reviewer for several international journals, including IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, IEEE TRANSACTIONS ON AUTOMATIC CONTROL, and *Sustainability* journal.



HUSSEIN AHMAD AHMAD received the B.Sc. degree in mathematics from Lebanese University, Lebanon, and the M.Sc. degree in applied mathematics from the University of Debrecen, Hungary. He is currently pursuing the Ph.D. degree in information and communications engineering with the Doctoral Programme in Technical Sciences, University of Klagenfurt, Austria. He is a Ph.D. Researcher with the University of Klagenfurt, with a specializing in machine learning, data analytics, and time series forecasting. His research focuses on trustworthy and efficient spatio-temporal forecasting, with applications in machine learning, explainable AI, and predictive modeling.

ANTOINE KAZADI KAYISU is currently a Lecturer and a Researcher with the Faculté Polytechnique, Université de Kinshasa, Democratic Republic of the Congo, where he focuses on transport systems, infrastructure resilience, and smart mobility solutions. His academic work bridges road safety, system dynamics, data-driven modeling, and intelligent systems applied to African urban contexts. He has collaborated on international research projects with the University of Klagenfurt, Austria, and other partners, particularly in the fields of micromobility, road safety, and sustainable transport innovation. His contributions include co-authored peer-reviewed publications on stochastic modeling, simulation, and performance assessment of shared mobility systems, with a strong emphasis on adapting advanced methods to the realities of rapidly urbanizing African cities. Beyond research, he is actively engaged in capacity building and curriculum development to strengthen transport engineering education in DR Congo.

JEAN CHAMBERLAIN CHEDJOU received the B.S. degree in physics and the M.S. and Ph.D. degrees in electronics from the University of Yaoundé I, Yaoundé, Cameroon, in 1990, 1992, and 1999, respectively, the second Ph.D. degree in electrical engineering and information technology from Leibniz University Hannover, Hanover, Germany, in 2004, and the Habilitation degree from the Institute for Smart Systems Technologies, Alpen-Adria University of Klagenfurt, Klagenfurt, Austria, in 2013.

From 1992 to 1995, he was a part-time Assistant Lecturer with the Department of Physics, University of Yaoundé I. He was an Assistant Lecturer, from 1996 to 1999, and a Senior Lecturer with the Laboratory of Electronics, University of Dschang, Cameroon, from 1999 to 2003 and from 2006 to2007, respectively. He was a Deutscher Akademischer Austauschdienst (DAAD) Scholar, in 2003, and a Research Fellow with the Institute of Communications Engineering, Leibniz University Hannover, from 2003 to 2004. He also held positions as a Junior Researcher with the Abdus Salam International Centre for Theoretical Physics, Trieste, Italy, in 2004, and from 2005 to 2006, and as a Research Fellow with the Agence Universitaire de la Francophonie (AUF), from 2005 to 2006. Since 2014, he has been an Associate Professor with the Alpen-Adria University of Klagenfurt. He has authored or co-authored 15 books and more than 200 peer-reviewed articles/papers. He serves as a reviewer for numerous international journals, including IEEE Transactions on Circuits and Systems, IEEE Transactions on Neural Networks and Learning Systems, IEEE Transactions on Communications, IEEE Access, *Neurocomputing*, *Nonlinear Dynamics*, *Sensors*, *International Journal of Bifurcation and Chaos*, *Journal of Applied Physics*, and *AEU–International Journal of Electronics and Communications*. His research interests include electronic circuit engineering, CMOS technology and analog computing, cellular neural networks and their applications in intelligent transportation systems (ITS), chaos theory, synchronization, and nonlinear dynamics in engineering, and ITS.

DANIEL JIAN SUN was born in Greenwich Village, New York, NY, USA, in 1977. He received the B.S. and M.S. degrees in aerospace engineering from the University of Virginia, Charlottesville, in 2001, and the Ph.D. degree in mechanical engineering from Drexel University, Philadelphia, PA, USA, in 2008. From 2001 to 2004, he was a Research Assistant with the Princeton Plasma Physics Laboratory. Since 2009, he has been an Assistant Professor with the Mechanical Engineering Department, Texas A&M University, College Station. He is the author of three books, more than 150 articles, and more than 70 inventions. His research interests include high pressure and high-density nonthermal plasma discharge processes and applications, microscale plasma discharges, discharges in liquids, spectroscopic diagnostics, plasma propulsion, and innovation plasma applications. He was a recipient of the International Association of Geomagnetism and Aeronomy Young Scientist Award for Excellence, in 2008, and the IEEE Electromagnetic Compatibility Society Best Symposium Paper Award, in 2011. He is currently an Associate Editor of the journal *Earth, Moon, and Planets*, and holds two patents.

KYANDOGHERE KYAMAKYA is currently a Professor and a Senior Researcher in intelligent systems and AI-enabled engineering. He is affiliated with the Institute of Smart Systems Technologies, Alpen-Adria-Universität Klagenfurt, Austria, and is also engaged in academic activities with AAU. His work spans cyber-physical systems, smart sensing, intelligent transportation systems, robotics, and data-driven modeling, with a strong focus on trustworthy AI for real-world deployment. His research interests include machine learning for perception and decision support, hybrid neuro-symbolic approaches that combine data-driven learning with rule-based reasoning, and efficient architectures for edge and embedded intelligence. He has contributed to the development of explainable and resource-aware AI pipelines, including methods for anomaly detection in system and network logs, smart-grid state estimation, and advanced pattern recognition for medical imaging. In recent projects, he has explored interpretable AI frameworks integrating cellular neural network variants, reservoir computing, and constraint-based reasoning (e.g., Answer Set Programming), aiming to improve transparency and reliability in safety-critical contexts. He supervises thesis and doctoral research across interdisciplinary themes at the intersection of electrical engineering, computer science, and applied AI, and regularly serves as reviewer and evaluator for academic works and research proposals.