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Electric Vehicle Charging Planning: A Complex Systems Perspective

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***Abstract*—In this paper, we introduce an innovative framework for the strategic planning of electric vehicle (EV) charging infrastructure within interconnected energy-transportation networks. By harnessing the small-world network model and the advanced optimization capabilities of the Non-dominated Sorting Genetic Algorithm III (NSGA-III), we address the complex challenges of station placement and network design. Our application of the small-world theory ensures that charging stations are optimally interconnected, fostering network resilience and ensuring consistent service availability. We approach the infrastructure planning as a multi-objective optimization task with NSGA-III, focusing on cost minimization and the enhancement of network resilience and connectivity. Through simulations and empirical case studies, we demonstrate the efficacy of our model, which markedly improves the reliability and operational efficiency of EV charging networks. The findings of this study significantly advance the integrated planning and operation of energy and transportation networks, offering insightful contributions to the domain of sustainable urban mobility.**

***Index Terms*—Charging infrastructure planning, complex systems theory, coupled energy-transportation networks, electric vehicle charging stations, small-world network model.**

NOMENCLATURE

Ω_n	Set of nodes in the transportation network, e.g., intersections or zones
Ω_a	Set of links in the transportation network, e.g., arcs or roads
a	A specific link in Ω_a
c_a	Traffic flow capacity of link a
t_a^0	Free travel time for link a at maximum speed without congestion
(o,d)	Origin-destination pair in the network
Ω_{od}	Set of routes connecting origin-destination pair (o,d)
q_{od}	Traffic demand for origin-destination pair (o,d)
x_a	Traffic flow on link a
f_Ω^{od}	Traffic flow on route o in Ω_{od}
f_r^{od}	Traffic flow on route r in Ω_{od} for the O-D pair (o,d)
δ_{ar}^{od}	Indicator variable, equals 1 if route r for the O-D pair (o,d) includes link a; 0 otherwise
$t_a\ (x_a)$	Travel time function for link a as a function of traffic flow x_a
BPR	Bureau of Public Roads function used to model travel time based on flow
UE	User Equilibrium, where no driver can reduce their travel time by switching routes
SO	Social Optimum, where total system travel time is minimized
NdP	Nesterov and de Palma model for handling non-convex optimization problems
T_A	Subset of links used in the traffic assignment model
π_a^*	Delay penalty at capacity for link a
λ_{od}, χ_a, and π_a	Dual variables associated with constraints in the traffic assignment model
s_a	Binary variable for the presence of an EV charging station.
y_a	Number of charging spots
R	Driving range of EVs (in km)
SOC	State of Charge of an EV; ranges between 0 (empty) to 1 (full)
ζ_o, ζ_d	SOC at the origin and destination nodes respectively
$g(y_a)$	Function defining operational capacity of charging stations based on the number of charging spots
$q_{1,a}, q_{2,a}, q_{3,a}$	Cost parameters for setting up charging stations, spots, and infrastructure developments
P_a^{sub}	Power capacity (in kVA) required for substation upgrades
n_a^c	Number of new lanes or infrastructure upgrades in the TN

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I. INTRODUCTION

THE transition to sustainable energy sources has witnessed a remarkable surge in the adoption of electric vehicles (EVs) globally [1]. This shift, driven by the dual imperatives of

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environmental sustainability and energy security [2], promises a future with reduced greenhouse gas emissions and diminished reliance on fossil fuels [3, 4]. However, the rapid proliferation of EVs introduces a pressing challenge: the establishment of a reliable, efficient, and universally accessible charging infrastructure [5, 6]. The charging infrastructure serves as the backbone of the EV ecosystem, ensuring that vehicles remain operational and users experience minimal disruptions [7, 8]. Yet, the planning and deployment of this infrastructure is a multifaceted endeavor. It necessitates a harmonious integration of the power grid, urban traffic patterns, user behaviors, and technological advancements [9, 10]. Current planning methodologies, while making strides in certain areas, often exhibit a narrow focus, primarily emphasizing individual metrics such as cost-effectiveness or charging speed [11]. Such an approach, while valuable in specific contexts, may overlook the intricate web of interdependencies that characterize the EV charging network.

For instance, while a charging station's location might be optimized for cost, it might not necessarily cater to high-demand areas or peak traffic periods, leading to potential bottlenecks and user inconveniences [12, 13]. Moreover, the current infrastructure, in many instances, does not guarantee seamless connectivity between charging stations, potentially complicating route planning for EV drivers and diminishing the overall user experience [14]. Furthermore, the resilience of these networks, especially in the face of unforeseen disruptions or station failures, has not been a focal point in many existing planning models [15, 16]. This oversight can have cascading effects, especially in densely populated urban areas where the demand for charging stations is high. Lastly, the dynamic nature of the EV market, characterized by evolving user behaviors, technological innovations, and variable energy prices, introduces a layer of uncertainty [17, 18]. Current planning models, while reliable in certain scenarios, might not be equipped to navigate these uncertainties, leading to solutions that might be sub-optimal in real-world scenarios. In essence, while the EV revolution holds immense promise, the path to its full realization is riddled with complexities. Addressing these requires a holistic, integrated, and forward-thinking approach to EV charging infrastructure planning [19, 20]. We summarize the research gaps of EV charging infrastructure planning as follows:

Limited Network Connectivity: Current EV charging infrastructure planning often overlooks the importance of a seamless user experience. Many existing networks do not offer the level of connectivity and convenience that users expect, leading to longer travel times, difficulty in locating charging stations, and potential congestion during peak periods. There's a need for a model ensuring users can easily move between charging stations, enhancing their overall experience.

Vulnerability to Disruptions: Current EV charging networks may not be equipped to handle disruptions effectively. If a charging station becomes unavailable, it can lead to significant inconveniences for users. The resilience of the charging infrastructure, especially its ability to maintain functionality during interruptions, is not adequately addressed.

Single-objective Focus: Many existing planning methods tend to focus on optimizing individual aspects, e.g., cost or charging speed. This siloed approach can lead to potential inefficiencies and vulnerabilities in the charging network. A comprehensive solution that considers multiple objectives simultaneously is lacking.

Lack of Reliable Solutions: While many planning methods aim to provide optimal solutions, they may not always account for real-world uncertainties and variations. This can lead to solutions that, while theoretically optimal, may not be reliable in practice.

The primary objective of this research is to address the identified gaps in the planning and design of EV charging infrastructure. We aim to develop a novel, comprehensive approach that integrates the principles of small-world network models and the reliability of the Non-dominated Sorting Genetic Algorithm III (NSGA-III) multi-objective optimization algorithm. Our approach is designed to tackle the fragmented nature of existing research by providing a holistic model that captures the complex interdependencies within the EV charging network [21]. By incorporating the small-world network model, we aim to enhance the connectivity and resilience of the charging infrastructure, ensuring that each charging station is within a few steps of all other stations. This study introduces a novel framework for EV charging infrastructure planning, leveraging the integration of the small-world network model with the advanced NSGA-III. Our research not only addresses the current limitations in EV charging network planning but also introduces solutions to enhance network performance significantly. The key contributions and innovations of this study are outlined as follows:

Innovative Application of the Small-World Network Model: We adopt the application of the small-world network model in EV charging infrastructure planning, fundamentally transforming the network's connectivity. This approach guarantees that charging stations are optimally interconnected, facilitating rapid and convenient access across the city. The model reduces travel and waiting times for EV users by minimizing congestion and ensuring the availability of charging options during peak times.

Scalability Through Network Design: Our study introduces a scalable model for EV charging infrastructure that maintains high efficiency and performance, even as the network expands. By incorporating the small-world network principles, we ensure that the addition of new charging stations does not compromise the network's overall functionality.

Resilience Against Disruptions: We enhance the resilience of the EV charging network by integrating redundancy into the small-world network design. This innovation ensures that the network can sustain operations despite unexpected disruptions, such as station failures. The design provides multiple alternative paths for reaching charging stations, significantly improving the network's reliability.

Multi-objective Optimization with NSGA-III: Our research advances the use of NSGA-III for multi-objective optimization in EV charging infrastructure planning. This approach allows for the simultaneous consideration of various objectives, offering a comprehensive solution to infrastructure planning challenges. We demonstrate how NSGA-III facilitates the selection of optimal solutions amidst diverse scenarios and requirements, emphasizing the adaptability of our model to real-world complexities.

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II. LITERATURE REVIEW

A. EV Charging Infrastructure Planning

As the global community shifts away from fossil fuels, the demand for EVs continues to surge, emphasizing the need for an efficient and widespread charging infrastructure. Historically, the development of EV charging infrastructure has been influenced by various factors, including technological advancements, governmental policies, and market dynamics. Ref [22] highlighted the technological challenges faced in the early stages of EV adoption, such as limited battery life and extended charging times. These challenges necessitated the establishment of charging stations at frequent intervals, especially in urban areas. Ref [23] discussed the role of governmental policies in promoting EV adoption. Incentives such as tax breaks, subsidies for charging station installations, and preferential parking have played a pivotal role in accelerating the growth of EV infrastructure. However, as [24] pointed out, the sheer volume of EVs on the road today has led to new challenges, including congestion at charging stations, inconsistent charging speeds, and the need for a more distributed network of stations to cater to the growing demand. Another significant aspect of EV charging infrastructure planning revolves around its economic viability. Ref [12] explored the economic challenges faced by charging station operators, emphasizing the need for dynamic pricing models to ensure profitability while offering competitive rates to consumers. Despite these advancements, several challenges persist. The spatial distribution of charging stations often leads to disparities, with urban areas being well-served while rural regions remain underserved. Additionally, the integration of renewable energy sources into the charging infrastructure, ensuring resilience against power outages, and accommodating the diverse charging needs of various EV models are areas that require further exploration [25].

Despite considerable advancements in the field of EV charging infrastructure planning, existing approaches exhibit notable disadvantages that limit the efficacy and scalability of the infrastructure [26]. One primary drawback is the insufficient consideration of the evolving dynamics of EV usage patterns and technological advancements. The early stages of EV adoption encountered technological challenges such as limited battery life and prolonged charging times, necessitating frequent charging stations, particularly in urban areas [27]. Although governmental policies and incentives have facilitated infrastructure growth, the rapid increase in EV adoption has introduced new challenges. These include congestion at charging stations and inconsistent charging speeds, highlighting a critical need for a more distributed and adaptive network of stations to meet growing demands. Furthermore, economic challenges persist, with the profitability of charging station operations remaining precarious. The spatial distribution of charging stations has led to disparities, underserving rural regions and potentially exacerbating urban-rural divides [28]. Moreover, the integration of renewable energy sources and ensuring resilience against power outages have not been adequately addressed, limiting the sustainability and reliability of the charging infrastructure. These issues underscore the need for a holistic approach that not only considers technological and economic factors but also aligns with the evolving landscape of EV adoption and energy transition.

B. Small-World Network Models

The concept of small-world networks has its roots in the realm of social networks, where it was observed that individuals are connected by surprisingly short chains of acquaintances, a phenomenon popularly known as "six degrees of separation". Introduced by [29], the small-world network model has since transcended its initial social context, finding applications in various scientific domains due to its unique properties of high clustering and short path lengths [30, 31]. A defining characteristic of small-world networks is their ability to maintain local interconnectedness while ensuring global reachability [32]. This balance between local clustering and global connectivity makes them particularly suitable for systems where both local interactions and broader accessibility are crucial. Ref [33] explored the application of small-world networks in power grid optimization, demonstrating their potential in enhancing grid resilience and efficiency.

In the context of transportation and urban planning, small-world network models have been instrumental in optimizing various infrastructural elements [34]. Ref [35] utilized these models to design efficient subway networks, ensuring rapid transit across vast urban landscapes with minimal transfers. The findings underscored the model's potential in reducing travel times and enhancing user experience. The relevance of small-world networks to EV charging infrastructure is particularly compelling. However, the implementation of small-world network models in real-world scenarios, particularly in the context of EV charging infrastructure, faces several challenges [36]. Firstly, the application of these models in the dynamic and complex urban environment is fraught with challenges. The inherent assumption of stable and predictable connectivity patterns does not always hold true in urban settings, where fluctuations in traffic flow, varying urban density, and unexpected disruptions can dramatically alter connectivity needs. Secondly, the scalability of small-world models in accommodating the rapid expansion of EV markets and the integration of renewable energy sources into the charging infrastructure remains a significant concern. As EV adoption increases, the demand for charging stations will rise, requiring a network model that can adapt and scale efficiently without compromising on connectivity or user experience. Lastly, there is a lack of reliable adaptive algorithms capable of addressing the dynamic and evolving demands of urban landscapes and EV user behaviors. This limitation hampers the potential of small-world network models to provide flexible and resilient charging infrastructure solutions that can meet future challenges.

C. NSGA-III Algorithm

The NSGA-III is an evolution of its predecessor, NSGA-II, and was introduced by Deb and Jain [37]. This algorithm was developed to address the challenges associated with multi-objective optimization problems, especially those with more

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than two objectives. The inception of NSGA-III was driven by the need for a more efficient and scalable approach to handle many-objective problems. NSGA-III has been widely adopted across various domains due to its versatility and reliability [38, 39]. In the realm of energy systems and EV management, Ref [39] proposed an optimal operation of a coastal hydro-electrical energy system that integrated seawater desalination to efficiently utilize coastal renewable energy and meet freshwater needs. By employing NSGA-III, the study developed virtual energy storage characteristics for desalination plants, demonstrating cost savings and ensuring a consistent desalinated water supply. Ref [40] marked a pioneering effort to incorporate flood resilience into the planning process for EV charging stations. The study introduced an integrated framework combining the NSGA-III and the technique for order of preference by similarity to ideal solution to optimize charging station locations. Through a case study in the Waikiki region, the research showcased the framework's capability to balance flood risks and charging services, offering valuable insights for EV charging station planning in the context of climate change.

One of the primary strengths of NSGA-III is its ability to maintain diversity in the solution set, ensuring a wide range of optimal solutions [41]. This is particularly beneficial for decision-makers, allowing them to choose the most appropriate solution based on varying scenarios and constraints. Additionally, the algorithm's reference-point-based approach ensures a more uniform distribution of solutions, addressing the clustering issue observed in earlier algorithms. Furthermore, NSGA-III's design inherently accounts for real-world uncertainties, making the solutions it provides not only optimal but also reliable [42].

III. Mathematical Formulation

A. Traffic Assignment Model

This section provides an overview of models and techniques used for the traffic assignment problem (TAP) within transportation networks (TN). Imagine an interconnected TN, symbolized as $[\Omega_n, \Omega_a]$. Here, Ω_n represents the collection of nodes (such as intersections or zones), while Ω_a signifies the set of links (like arcs or roads). Every link, denoted as *a* within Ω_a, possesses a traffic flow limit c_a. This limit indicates the maximum count of vehicles that can traverse link a within Ω_a in a given time frame. Additionally, each link has a designated free travel duration t_a^0, which represents the time taken to traverse link a at the maximum permissible speed without any congestion. For every origin-destination (O-D) pair, labeled (*o,d*), and connected through a set of routes Ω_{od}, there exists a traffic demand qrs. In the TN graph, links form the edges, while paths encompass all feasible routes between a starting and ending node. The traffic flows on link a in Ω_a and route *o* in Ω_{od} are represented by x_a and f_Ω^{od}, respectively. For the O-D pair (*o,d*), the traffic flow on route *r* in Ω_{od} is denoted as f_Ω^{od}. If link *a* within Ω_a is part of the route *r* in Ω_{od} for the O-D pair (*o,d*), then the traffic flow on that specific link is f_Ω^{od}. The cumulative traffic flow on that link for all O-D pairs is given by $x_a = \sum_{od} \sum_r f_r^{od} \delta_{ar}^{od}$. The indicator variable δ_{ar}^{od} equals 1 if route *r* for the O-D pair (*o,d*) includes link *a*; otherwise, δ_{ar}^{od} is 0.

Each link a in Ω_a is associated with a travel time function t_a (x_a), which determines the travel duration on link a based on x_a. Due to potential congestion, t_a (x_a) is a strictly increasing function. Several functions depict the correlation between travel time and link attributes (link traffic flow, road capacity, and free travel time). Among these, the commonly adopted BPR function serves as a notable example [43]:

$$t_a(x_a) = t_a^0 \left[1 + 0.15 \left(\frac{x_a}{c_a}\right)^4\right], \forall a \in T_A \tag{1}$$

The road capacity, denoted as c_a, is a pivotal variable when planning road expansion. This introduces a non-convex nature to equation (1). To address this non-convexity, we employ the (Nesterov and de Palma) NdP model alongside primal-dual optimality conditions. The NdP model, referenced in [44], aids in determining the utilization of the TN. We delve into two foundational principles in static traffic assignment problem (TAP): User Equilibrium (UE) and Social Optimum (SO). UE means that every driver opts for the quickest route available, i.e., no driver can independently switch to an alternative route to achieve a shorter travel time; SO indicates that the collective travel time (sum of all individual travel times) is minimized. In the SO framework, drivers must collaboratively choose their routes to ensure the TN is used most efficiently.

Under the UE framework, the travel duration, t_a, on link *a* matches its free travel time, t_a^0, when the traffic flow, x_a, is below its maximum capacity, c_a. However, when x_a reaches its peak capacity, the travel time, t_a, is equivalent to its free travel time with an added delay penalty, symbolized as π_a^* [45].

$$t_a = \begin{cases} t_a^0, & x_a < c_a \\ t_a^0 + \pi_a^*, & x_a = c_a \end{cases} \tag{2}$$

This penalty corresponds to the value of the dual variable associated with the link's capacity, as indicated in equation (7). Contrasting with the BPR function (1), the link travel time function within the NdP model exhibits convexity. The total travel time across all links is represented by $\sum_a x_a t_a$. The TAP under the SO pattern, assuming no delays (meaning t_a equals t_a^0), can be formulated as per reference [46]:

$$\min_{x_a, t_a, f_r^{od}} \sum_{a \in \Omega_a} x_a t_a = \min_{x_a, f_r^{od}} \sum_{a \in \Omega_a} x_a t_a^0 \tag{3}$$

$$\text{s.t. } \sum_k f_r^{od} = q_{od} : \lambda_{od} \tag{4}$$

$$\sum_{od} \sum_r f_r^{od} \delta_{ar}^{od} = x_a : \chi_a \tag{5}$$

$$f_r^{od} \geq 0 \tag{6}$$

$$x_a \leq c_a \ : \pi_a \tag{7}$$

The indicator variable δ_{ar}^{od} is set to 1 when the path *r* includes link *a*. If not, it is set to 0. The dual variables λ_{od}, χ_a, and π_a correspond to constraints (4), (5), and (7). The objective function (3) represents the total travel time without any delays. Constraints (4) to (6) ensure the traffic flow demand is met for every O-D pair, while constraint (7) sets the maximum capacity for each link, ensuring no congestion in the SO pattern. Ref [23] introduced the concept of using the dual variables from the link

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capacity constraint (7) as delay penalties for links operating at their maximum capacity. Every link a is associated with a dual variable π_a. By relaxing constraint (7), we can formulate the Lagrange dual problem.

$$\max_{\lambda_a \geq 0} \min_{x_a, f_r^{od}} \sum_{a \in \Omega_a} [x_a t_a^0 + \pi_a(x_a - c_a)] \quad (8)$$

Given a constant $\pi_a^0 \geq 0$ and for every pair in the O-D set, the aforementioned NdP-Lagrange dual model can be transformed into the subsequent linear problem (LP):

$$\min_{f_k^{rs}} \left\{ \sum_a \left[\sum_r f_r^{od} \delta_{ar}^{od} (t_a^0 + \pi_a^0) - \pi_a^0 c_a \right] \right\} \quad (9)$$

$$\sum_r f_r^{od} = q_{od}, f_r^{od} \geq 0 \quad (10)$$

The models represented by Equations (9)–(10) formulate a NdP-LP approach without the constraints of capacity. The objective function in (9) signifies the total travel duration, which is the sum of $t_a = t_a^0 + \pi_a^0$, for the allocation of drivers between O-D pairs. It's assumed that the optimal solution for NdP-SO is denoted by x_a, with the associated Lagrange dual multiplier of (7) being π_a. As indicated in references [6, 46], given that strong duality is applicable to linear programs, the pair (x_a^*, t_a^0) represents a traffic assignment at the Social Optimum, while (x_a^*, $t_a^0 + \pi_a^*$) indicates a traffic assignment under User Equilibrium.

In scenarios without capacity restrictions, both SO and UE yield identical traffic assignments, with the only differences being in travel time. The Lagrange multipliers, π_a^*, serve as incentives to guide self-interested drivers towards achieving the SO. Consequently, the TAP is formulated using the primal-dual optimality conditions of NdP-SO as:

$$\min \sum_a \sum_r f_r^{od} \delta_{ar}^{od} (t_a^0 + \pi_a) \quad (11)$$

$$\text{s.t.} \sum_r f_r^{od} - q_{od} = 0, \sum_r f_r^{od} \delta_{ar}^{od} - c_a \leq 0, f_r^{od} \geq 0 \quad (12)$$

$$\pi_a \geq 0, \chi_a - \pi_a = t_a^0, \lambda_{od} - \sum_a \sum_r \delta_{ar}^{od} \lambda_{od} \leq 0 \quad (13)$$

$$\sum_{od} q_{od} \lambda_{od} - \sum_a \pi_a c_a = \sum_{od} \sum_a \sum_r f_r^{od} \delta_{ar}^{od} t_a^0 \quad (14)$$

Equations (11) and (12) outline the constraints for the feasible regions of primal and dual variables, respectively. Equation (13) denotes the strong duality condition for NdP-SO. Given that NdP-SO is a linear program, its optimal solution is provided by the primal-dual optimality conditions. As such, (11)–(14) determine the traffic assignment under UE, which in turn defines π_a. The primary distinction between NdP-SO and TAP is the inclusion of an additional term in the latter's objective function, represented by $\sum_a \sum_r f_r^{od} \delta_{ar}^{od} \pi_a$. Since both f_r^{od} and π_a are determined by (11)–(14), π_a can be substituted with the optimal Lagrange multipliers π_a, rendering the TAP's objective function linear. In this study, we initially determine the values of f_r^{od} and π_a using (11)–(14), followed by the computation of the objective function. Given the values of π_a and c_a, TAP can be viewed as a linear programming model.

let's first revisit the driving range logic [47] before delving into the associated mathematical framework. Imagine a TN graph [Ω_n, Ω_a], with a singular path, k, connecting the Origin-Destination pair (1, 5), which follows the sequence: link1→link2→link3→link4. This path encompasses five TN nodes (Ω_n = 1, 2, 3, 4, 5) and four links (Ω_a = link1, link2, link3, link4), each with their respective distances d1, d2, d3, and d4. A flow demand, q15, signifies the EVs traveling between the O-D pair (1,5). These EVs, possessing a driving range θ (km), journey from the starting node 1 to the endpoint node 5 on a single charge. It's assumed that EVs embark on their TN journey at the origin node with a State of Charge (SOC) denoted as ζ_o and conclude their journey at destination node 5 with an SOC surpassing ζ_d. After charging, the EVs' SOC is presumed to be 1. The objective for network planners is to strategically position EV charging stations. The driving range logic is governed by two primary principles. The initial principle mandates that the distance separating two charging facilities must not exceed the driving range. The subsequent principle sets boundaries on the EV's SOC at the origin and destination points, with an assumption that charging stations are absent at these nodes. Specifically, the EV starts its journey at the origin node with ζ_o, ensuring it can reach the initial charging station. Likewise, the last charging station on path k must be strategically positioned to allow the EV to exit the TN with an SOC exceeding ζ_d.

$$\zeta_o - 0.5 d_1/\theta \geq 0 \quad (15)$$

$$\zeta_1 = \zeta_o - 0.5 d_1/\theta + s_1(1 - \zeta_o + 0.5 d_1/\theta) \quad (16)$$

$$\zeta_{a+1} = \zeta_a - \frac{0.5(d_a + d_{a+1})}{\theta} + s_{a+1}\left[1 - \zeta_a + \frac{0.5(d_a + d_{a+1})}{\theta}\right] \quad (17)$$

$$\zeta_a \geq 0, a = 1,2,3,4 \quad (18)$$

$$\zeta_4 - 0.5 d_4/\theta \geq \zeta_D \quad (19)$$

Given that the potential location for the EV charging station is positioned at the center of link 'a', the values 0.5da and 0.5(da + da+1) (where a = 1, 2, 3, 4) in equations (15)–(19) denote the distances between successive proposed EV charging station sites. Equation (15) guarantees that an EV starting at the origin node can access the initial proposed charging station location. In a similar vein, equation (19) ensures that an EV reaches its destination with an SOC surpassing the threshold of ζ_D. Equations (16) and (17) detail the SOC levels of an EV as it navigates through potential charging station sites. Meanwhile, equation (18) affirms that an EV can traverse all proposed charging station locations along routes connecting specific O-D pairs, maintaining an SOC that's at least zero.

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$$\min_{s_a, y_a, f_r^{od}} \left\{ \sum_a \left(q_{1,a} s_a + q_{2,a} y_a \right) + \omega \sum_a \sum_r f_r^{od} \delta_{ar}^{od} (t_a^0 + \pi_a^*) \right\} \tag{20}$$

$$\text{s.t. } \arg\min_{f_r^{od}} \left\{ \sum_a \sum_r f_r^{od} \delta_{ar}^{od} (t_a^0 + \pi_a^*) \mid (12) - (15) \right\} \tag{21}$$

$$(15) - (19) \tag{22}$$

$$y_a \leq \bar{y}_a s_a \tag{23}$$

$$\eta \sum_k f_r^{od} \delta_{ar}^{od} \leq g(y_a) \tag{24}$$

The component in (20) represents the cumulative investment costs associated with EV charging stations, encompassing both the expenses of building the stations and setting up charging points. The subsequent component in (20) quantifies the financial implications of travel time, correlating directly with the aggregate travel time of vehicles under the UE scenario. The investment costs for new EV charging stations, as outlined in Equation (20), are determined by combining the capital outlays required for physical infrastructure with the operational costs associated with integrating these facilities into the existing transportation network. The term $q_{1,a} s_a$ explicitly represents the fixed costs for constructing new charging stations, where $q_{1,a}$ indicates the unit cost of establishing a single charging station and s_a denotes the binary decision variable for the presence of a charging station at location *a*. This approach ensures that the financial planning considers both the initial expenditure on infrastructure and the long-term implications on traffic flow and vehicle operation times, which are critical for the economic viability of the project.

Equation (21) lays out the constraints for UE traffic flow, pinpointing the total time vehicles spend on the road under UE and the distribution of traffic flow within the TN. Equation (22) sets the parameters for driving range logic, considering viable EV charging station sites. Equation (23) stipulates the maximum count of charging points a station can house. Lastly, equation (24) outlines the operational capacity of each charging station, which is influenced by the number of charging points. For the sake of clarity, we've postulated a linear correlation, $g(y_a) = 3y_a + 4$. Owing to space constraints and its recognition as foundational knowledge within the power system domain, the modeling of the power distribution network (PDN) using linearized DistFlow has been omitted [48]. Given the demands in both traffic and power sectors, the coordinated planning model for this integrated traffic-electric system is detailed below:

$$\min_{s_a, y_a, n_a^c} Obj_T + Obj_P \tag{25}$$

The objective of the coordinated planning model is to optimize investment costs across both the TN and PDN. The initial component, Obj_T in equation (25), signifies the investment expenditure in the TN:

$$Obj_T = \sum_{a \in T} \left[\left(q_{1,a} s_a + q_{2,a} y_a + q_{3,a} n_a^c \right) + \omega (t_a^0 + \lambda_a) x_a \right] \tag{26}$$

In this equation, the primary component of Obj_T denotes the investment costs associated with new EV charging stations, charging spots, and lanes. The subsequent component represents the equivalent travel expenses in the UE pattern. Equation (26) details the investment costs for new EV charging infrastructure by quantifying the expenses across different components: $q_{1,a} s_a$ accounts for the construction and installation costs of each charging station at location *a*, reflecting the capital expenditure required to establish the physical infrastructure. $q_{2,a} y_a$ represents the costs for adding multiple charging spots at each station, covering the necessary electrical setup such as power connections and support facilities. $q_{3,a} n_a^c$ includes expenses related to ancillary infrastructure enhancements like lane expansions or improved access, enhancing station accessibility and user experience. Additionally, the equation incorporates $\omega (t_a^0 + \lambda_a) x_a$, which captures the operational costs linked to traffic flow, adjusted by travel time and congestion-related economic factors, illustrating the comprehensive financial planning involved in deploying and operating EV charging stations effectively within the urban transport network. This detailed breakdown facilitates a thorough understanding of the investment implications, aiding stakeholders in making well-informed decisions that align with broader urban mobility and sustainability objectives.

The next component in equation (25) represents the PDN's investment costs:

$$Obj_P = \sum_{(i,j) \in \mathbf{D_A}} q_{ij} n_{ij} + \sum_{a \in C(i)} q_{4,a} P_a^{sub} \tag{27}$$

Here, the initial term of equation (27) indicates the construction costs for the new distribution lines, while the latter term represents the capacity expansion costs for PDN substations.

IV. The Small-World Network Model Integration

The small-world network model stands as a paradigm shift in understanding and designing complex networks. This model, grounded in the principle that most nodes are not neighbors yet can be reached through a small number of steps, optimally balances between local clustering and global network dynamics [49, 50]. Its application to urban planning, particularly in the context of EV charging infrastructure, offers unparalleled advantages. These include improved network resilience, enhanced accessibility, and the facilitation of efficient resource distribution across densely interconnected yet geographically expansive urban environments.

A. Incorporation of Local Clusters into the Traffic Assignment Model

Given the TN Ω_n representing nodes (intersections or zones), we aim to define local clusters based on traffic density. For each potential cluster *c*, we can define a function *D*(*c*) that calculates the traffic density. This function can be based on the

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number of vehicles per unit area or the number of trips originating or terminating within the cluster.

$$D(c) = \frac{\sum_{a\in c} x_a}{Area(c)}$$

Where *xa* is the traffic flow on link *a* within the potential cluster *c*; *Area*(*c*) is the geographical area of the potential cluster *c*. A potential cluster *c* is classified as a local cluster if its traffic density surpasses a predefined threshold *θD*.

$$c \in C \Leftrightarrow D(c) \geq \theta_D$$

Where *C* is the set of all identified local clusters in the TN. To ensure that the nodes within a cluster are densely interconnected, we introduce a connectivity parameter $\kappa(c)$ that measures the average number of direct connections between nodes in cluster *c*.

$$\kappa(c) = \frac{2 \times \sum_{a\in c} 1}{|c| \times (|c| - 1)}$$

Where ∣ *c* ∣ is the number of nodes in cluster *c*. A high value of $\kappa(c)$ indicates that the nodes within the cluster are densely connected.

Clusters in a TN represent regions with a high density of interconnected nodes and links. These could be urban centers, commercial hubs, or residential areas. Understanding the traffic flow within these clusters is essential for efficient traffic management, infrastructure planning, and optimizing the placement of amenities such as EV charging stations. Let's define a cluster by *c* and the set of all clusters in the TN by *C*. Each cluster consists of a subset of nodes and links from the entire TN. For a specific link *a* within cluster *c*, the traffic flow can be represented as $x_{a,c}$. Given the traffic demand $q_{od,c}$ for an pair (*o*,*d*), the traffic flow on link *a* can be expressed as:

$$x_{a,c} = \sum_{od} \sum_{r} f_{r,c}^{od} \delta_{ar,c}^{od} \tag{28}$$

Due to the dense nature of clusters, congestion dynamics can differ from broader network dynamics. The travel time function for link a within cluster *c* can be represented as:

$$t_{a,c}(x_{a,c}) = t_{a,c}^0[1 + \alpha_c(x_{a,c}/c_{a,c})_c^\beta] \tag{29}$$

The UE principle ensures that all drivers within a cluster choose the quickest route available. The UE condition for traffic flow within cluster *c* can be expressed as:

$$t_{a,c}(x_{a,c}) \leq t_{a',c}(x_{a',c}) + \epsilon, \forall a, a' \in c \tag{30}$$

By understanding the traffic flow within clusters and modeling it accurately, we can make informed decisions about infrastructure development, traffic management strategies, and other essential aspects of urban planning. This detailed representation provides a foundation for further analysis and optimization in TNs.

B. Incorporation of Long-range Connections

Long-range connections play a pivotal role in TNs, especially in the context of the small-world model. These connections bridge distant clusters, ensuring efficient and rapid movement between them. They are typically characterized by major roads, highways, or expressways that bypass local traffic and provide direct routes between significant urban or commercial centers. Let's define the set of all long-range connections as $\mathcal{L}$. Each long-range connection l from the set $\mathcal{L}$ connects two distinct clusters from the set $\mathcal{C}$.

$$\mathcal{L} = \{l | l \text{ connects } c_i \text{ and } c_j, c_i, c_j \in \mathcal{C}, c_i \neq c_j\} \tag{31}$$

Given the traffic demand q_{ij} between clusters c_i and c_i, the traffic flow on the long-range connection l can be expressed as:

$$x_l = \sum_{i,j} q_{ij} \delta_{l,ij} \tag{32}$$

Long-range connections are designed to facilitate rapid movement, and thus, they have specific characteristics: higher speed limits compared to intra-cluster roads; fewer intersections or stops and priority for maintenance and upgrades due to their significance in the network. By accurately modeling and understanding the role of long-range connections, transportation planners can optimize traffic flow, reduce congestion, and ensure efficient movement between major clusters. This is especially crucial in the context of the small-world model, where long-range connections play a pivotal role in reducing the average path length in the network.

C. Optimization of EV Charging Station Placement with Small Network Model

Incorporating the Small-World Network model into the placement of EV charging stations can significantly enhance the efficiency and accessibility of these stations. By considering local clusters and long-range connections, we can ensure that EV users have optimal access to charging facilities, reducing "range anxiety" and promoting the adoption of electric vehicles. To represent the placement of EV charging stations within local clusters, we introduce a binary decision variable:

$$s_c = \begin{cases} 1 & \text{if an EV charging station is placed in cluster } c \\ 0 & \text{otherwise} \end{cases} \tag{33}$$

The traffic density within a cluster *c* can be represented as $D(c)$. This density can be derived from the total traffic flow within the cluster and can be a significant factor in determining the placement of EV charging stations.

$$D(c) = \sum_{a\in\mathcal{A}_c} x_{a,c} \tag{34}$$

The objective is to maximize the utility of the EV charging stations, which can be a function of the traffic density and other factors like proximity to commercial areas, residential zones, etc.

$$\text{Maximize} \sum_{c\in\mathcal{C}} U(c)s_c \tag{35}$$

Where *U(c)* is the utility function for placing an EV charging station in cluster. This can be a weighted sum of traffic density and other factors. The total cost of placing EV charging stations should not exceed a predefined budget *B*.

$$\sum_{c\in\mathcal{C}} \text{Cost}(c)s_c \leq B \tag{36}$$

Ensure that a certain percentage *P* of the total traffic density is covered by the EV charging stations.

$$\sum_{c\in\mathcal{C}} D(c)s_c \geq P \sum_{c\in\mathcal{C}} D(c) \tag{37}$$

The characteristics of EV charging stations in local clusters are:

Accessibility: Stations within clusters should be easily

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accessible to the majority of the traffic within the cluster.
Capacity:Due to the high traffic density, these stations should have multiple charging points to cater to the demand.
Integration with other services: Charging stations can be integrated with other services like shopping centers, cafes, etc., allowing users to utilize these services while their vehicles charge.
By optimizing the placement of EV charging stations within local clusters using the small-wolrd network model, we can ensure that the majority of the EV users have easy and quick access to charging facilities, promoting the adoption and use of electric vehicles.

D. Modification of Objective Function and Constraints

The primary goal of the TN is to minimize the total travel time for all vehicles, considering both intra-cluster (within clusters) and inter-cluster (between clusters) traffic. Additionally, we aim to optimize the placement of EV charging stations to ensure maximum utility and coverage.

The modified objective function can be represented as:

$$\text{Minimize}\left(\sum_{c\in\mathcal{C}}\sum_{a\in\mathcal{A}_c} T_{a,c}x_{a,c}+\sum_{l\in\mathcal{L}} T_{l,c1,c2}x_{l,c1,c2}\right) - \lambda\left(\sum_{c\in\mathcal{C}} U_c s_c+\sum_{l\in\mathcal{L}} U_l s_l\right) \quad (38)$$

The first part of the objective function aims to minimize the total travel time for all vehicles in the network. This includes travel within clusters (intra-cluster) and travel between clusters (inter-cluster) on long-range connections. The second part of the objective function aims to maximize the utility derived from placing EV charging stations. This utility can be a function of various factors such as traffic density, proximity to amenities, and accessibility. The weighting factor λ allows us to balance the trade-off between minimizing travel time and optimizing charging station placement. The objective function captures the essence of the small-world network model by considering both local (intra-cluster) and global (inter-cluster) traffic patterns. By optimizing this function, we can ensure efficient traffic flow while also promoting the adoption and use of electric vehicles through strategic charging station placement.

This constraint ensures that a charging station is placed in a cluster only if the traffic density within that cluster exceeds a certain threshold. This ensures that charging stations are optimally placed in areas with high traffic density, maximizing their utility.

$$s_c \leq D(c)\forall c \in \mathcal{C} \quad (39)$$

This constraint ensures that a charging station is placed on a long-range connection only if the traffic flow between the connected clusters exceeds a certain threshold. This ensures that charging stations on long-range connections cater to significant inter-cluster traffic.

$$s_l \leq F_{l,c1,c2}\forall l \in \mathcal{L} \quad (40)$$

This constraint sets an upper limit on the total number of charging stations that can be placed within clusters. This ensures a balanced distribution of charging stations and prevents over-saturation in any particular area.

$$\sum_{c\in\mathcal{C}} s_c \leq M \quad (41)$$

This constraint sets an upper limit on the total number of charging stations that can be placed on long-range connections. This ensures that the long-range connections are adequately equipped with charging stations without causing congestion.

$$\textstyle\sum_{l\in\mathcal{L}} s_l \leq N \quad (42)$$

V. NSGA-III MULTI-OBJECTIVE OPTIMIZATION

The strengths of NSGA-III lie in its superior capacity to manage numerous objectives simultaneously, without detriment to performance or solution variety. This method distinguishes itself with a reference-point selection mechanism, adept at preserving a wide spectrum of optimal solutions along the Pareto front [51]. Such a feature is indispensable in multifaceted optimization contexts requiring a delicate equilibrium among competing goals. Furthermore, the algorithm's scalability and reliability render it applicable across diverse fields, from engineering design to comprehensive resource management [39]. For the purposes of this study, we specifically use NSGA-III to tackle the complex considerations involved in designing integrated urban networks. This approach is vital in scenarios where competing factors, like cost effectiveness, system resilience, and user accessibility, come into play.

A. Criteria for Selecting NSGA-III

The selection of NSGA-III for our study was driven by specific criteria that align with the complex needs of urban infrastructure optimization. These criteria were developed through a systematic assessment of various multi-objective optimization algorithms, considering both the theoretical capabilities and practical applications relevant to our research objectives. Below, we detail the rationale behind choosing NSGA-III:

Scalability and Efficiency: Given the large-scale nature of urban infrastructure systems and the complexity of managing numerous intertwined objectives, NSGA-III's ability to efficiently handle large sets of solutions across multiple objectives was paramount. Its scalability ensures that the optimization process remains computationally feasible even as the number of objectives and decision variables grows, a common scenario in urban planning applications.

Solution Diversity: A critical aspect of our study involves exploring a wide range of feasible solutions to capture various trade-offs between competing urban planning goals. NSGA-III's reference-point based selection mechanism excels in maintaining a diverse pool of solutions, which is essential for achieving a holistic understanding of the potential impacts of different planning decisions.

Practicality in Urban Settings: NSGA-III has demonstrated applicability and success in various real-world problems, particularly in fields requiring the balancing of complex sets of objectives, such as environmental impact, cost-efficiency, and social implications. Its proven track record in sectors such as engineering and resource management underpins its suitability for addressing the multifaceted challenges of urban EV

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infrastructure planning.

Customizability: The flexibility of NSGA-III to incorporate domain-specific constraints and preferences makes it highly adaptable to the unique contexts of urban network systems. This capability is critical for tailoring the optimization process to reflect real-world conditions, regulatory requirements, and specific policy goals of urban development projects.

B. Problem Formulation

Given our TN model and the associated constraints, we can define our multi-objective optimization problem as follows:

Objective 1: Minimize the total travel time for all vehicles, considering both intra-cluster and inter-cluster traffic.

$$minZ_1 = \sum_{c\in C}\sum_{a\in A_c} T_{a,c}x_{a,c} + \sum_{l\in L} T_{l,c1,c2}x_{l,c1,c2} \tag{43}$$

The primary goal here is to ensure efficient access to EV charging stations, thereby reducing congestion and improving the user experience. By minimizing the total travel time, our model directly contributes to enhancing the network's responsiveness to emergency situations, ensuring that vehicles can be quickly charged and mobilized when necessary. This optimization also indirectly promotes the distribution of charging stations across diverse geographic areas, enhancing the network's reliability against localized failures or disruptions. Minimizing total travel time ensures that EV users can access charging stations swiftly, which is crucial during emergencies or extreme weather conditions when quick vehicle readiness is paramount. A network optimized for reduced travel times inherently supports faster evacuation and emergency response efforts, as it minimizes delays and congestion. By optimizing travel times, the network naturally evolves into a more distributed system with charging stations strategically placed to serve diverse urban areas. This distribution ensures that if one part of the network is compromised (e.g., due to a natural disaster or a localized power outage), other areas can continue to operate, thereby maintaining a level of network functionality even under adverse conditions.

Objective 2: Maximize the utility derived from placing EV charging stations.

$$maxZ_2 = \lambda(\sum_{c\in C} U_c s_c + \sum_{l\in L} U_l s_l) \tag{44}$$

This objective focuses on strategic station placement to serve not only the daily needs of EV users but also to bolster the network's support for emergency and essential services. Optimizing for utility involves situating charging stations in proximity to critical infrastructure and incorporating renewable energy sources to ensure operability during grid outages. This approach significantly boosts the network's resilience, providing an indispensable service during crises and contributing to the sustainability of urban mobility systems.

Objective 3: Minimize the total investment costs across both the TN and PDN.

$$minZ_3 = \sum_{a\in\Omega_a} (q_{1,a}s_a + q_{2,a}y_a + q_{3,a}n_a^c) \tag{45}$$

Efficient resource allocation is key to building a resilient and scalable EV charging network. By focusing on minimizing investment costs, we aim to allocate savings towards resilience-enhancing measures such as backup power solutions and infrastructure fortification. This strategic investment planning allows for the iterative enhancement of the network, ensuring its adaptability to future challenges and its sustainable expansion in line with evolving urban and technological landscapes.

C. NSGA-III Implementation

The algorithm operates by initiating with a set of potential solutions and progressively refining them through a series of evolutionary operations. Throughout its execution, NSGA-III ensures the maintenance of a diverse set of Pareto-optimal solutions, which are solutions where no objective can be improved without degrading some of the other objectives.

Initialization: Begin by generating an initial population of potential solutions. This population is typically created using random or heuristic methods, ensuring a wide exploration of the solution space.

Evaluation: For each member of the population, compute its fitness based on the predefined objectives. This step is crucial as it determines how well each solution performs in relation to the set goals.

Selection: Implement a tournament selection mechanism, where a subset of solutions is chosen, and the best among them, based on their fitness, are selected as parents. This method ensures that higher-quality solutions have a better chance of being chosen for reproduction.

Crossover: In this phase, two parent solutions are combined to produce offspring. This is achieved through various crossover techniques, such as single-point, multi-point, or uniform crossover, which help in exchanging information between parent solutions.

Mutation: To maintain diversity in the population and avoid premature convergence to sub-optimal solutions, introduce minor random alterations in the offspring. This step ensures that the algorithm explores new regions in the solution space.

Environmental Selection: After generating the offspring, it's essential to decide which solutions will proceed to the next generation. This is done by retaining the best solutions based on non-domination sorting, which ranks solutions based on the number of solutions they dominate and are dominated by. Additionally, the crowding distance metric is used to ensure diversity among the selected solutions by preferring solutions that are sparsely distributed in the objective space.

The algorithm continues to iterate through these phases until a predefined stopping criterion is met. This could be a set maximum number of generations, a convergence threshold, or any other suitable metric. At the conclusion of its run, NSGA-III provides a set of Pareto-optimal solutions, offering a trade-off between the objectives for decision-makers to choose from.

D. Solution Representation

Each solution within the population encapsulates a potential configuration of the entire TN. This encompasses not just the roadways and intersections, but crucially, the strategic positioning of EV charging stations, which are pivotal in promoting the adoption and seamless operation of electric vehicles. To achieve this, we employ a binary encoding scheme. In this representation, a solution is visualized as a binary string,

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TABLE I
LINK NUMBER CORRESPONDANCE

Link No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
From	T1	T1	T2	T1	T2	T3	T4	T5	T3	T4	T5	T6	T7	T8	T9	T7	T8	T9	T12	T11
To	T2	T3	T6	T4	T5	T4	T5	T6	T7	T8	T9	T10	T8	T9	T10	T11	T11	T12	T10	T12

where the length of the string corresponds to the total number of potential locations for EV charging stations within the network. Each bit in this string has a specific significance:

1: Indicates the presence of an EV charging station at that specific location. This suggests that, based on the current configuration, it's optimal to have a charging station at this point to cater to the needs of EV users.

0: Denotes the absence of a charging station at the corresponding location. This could be due to various reasons such as proximity to another station, low expected EV traffic, or other logistical and strategic considerations.

This binary encoding is both concise and expressive. It allows for easy manipulation during the evolutionary operations of the optimization algorithm, such as crossover and mutation. Moreover, by visualizing the solution as a string of bits, it becomes straightforward to compare different configurations, assess the density and distribution of charging stations, and make informed decisions about the most effective layouts for the TN.

E. Decoding the Binary Representation and Comprehensive Evaluation

The evaluation process is a pivotal step in our optimization algorithm, as it determines the efficacy of a given solution in the context of the TN. This involves two primary stages: decoding the binary representation and subsequently evaluating the decoded configuration using our predefined criteria. The initial step is to interpret the binary string that represents a potential configuration of the TN. Each bit in the string, as previously mentioned, signifies the presence (1) or absence (0) of an EV charging station at a specific location. By decoding this string, we obtain a clear and tangible layout of where the EV charging stations are positioned within the network. This decoded representation serves as a blueprint, detailing the strategic placement of each station.

With the decoded configuration in hand, we proceed to evaluate its performance. Leveraging the mathematical models developed in earlier sections of the paper, we assess multiple facets of the configuration:

Total Travel Time: This metric gauges the efficiency of the TN, factoring in the placement of EV charging stations. An optimal configuration would minimize the travel time for EV users, ensuring they can reach charging stations without significant detours.

Utility of EV Charging Stations: Beyond just the placement, it's essential to understand the utility of each station. This involves analyzing the frequency of use, accessibility, and overall contribution to the network's efficiency.

Investment Costs: Establishing EV charging stations involves capital. By evaluating the investment costs associated with a particular configuration, we can strike a balance between economic feasibility and network efficiency.

VI. EMPIRICAL CASE STUDIES

In our empirical case study, the chosen scale, involving a 12-node TN coupled with a 33-node PDN, serves as a comprehensive representation of urban and suburban environments. This allows us to demonstrate the model's applicability and effectiveness in optimizing EV charging infrastructure across diverse urban layouts, showcasing its potential for larger-scale urban planning and energy management initiatives. We utilize a 12-node TN highway, as referenced in [2], in conjunction with the IEEE 33-node PDN, as detailed in [37], to demonstrate the suggested planning approach. The choice of a 33-node PDN is pivotal for several reasons, each underscoring the network's critical role in our analysis of optimizing EV charging infrastructure. This network configuration is not arbitrary; rather, it is representative of a medium-scale urban PDN, offering a realistic framework within which the complexities of integrating EV charging infrastructure can be thoroughly examined. The 33-node PDN provides a sufficiently complex system that mimics real-world urban power distribution scenarios. This complexity is crucial for testing the effectiveness of our proposed EV charging infrastructure planning model, ensuring that the findings are applicable to actual urban environments. By employing a 33-node network, our study can effectively demonstrate the scalability of the proposed planning approach. It allows us to explore how the model performs as the size and complexity of the PDN increase, offering insights into the adaptability of our methodology to larger or more intricate urban networks. The integration of EV charging stations into existing PDNs presents numerous technical and operational challenges, including load balancing, maintaining power quality, and ensuring network reliability. The 33-node PDN serves as an ideal testbed for identifying and addressing these challenges, showcasing how our model navigates the intricate balance between energy supply and demand in the context of EV charging.

In the comprehensive examination of our coupled energy-transportation network, TABLE I, TABLE II, and Fig. 1 synergistically illustrate the methodology and outcomes of our optimization strategies. TABLE I methodically lists the structural links within the TN, specifying the origin and destination nodes for each link. This detailed mapping is instrumental in understanding the network's baseline connectivity and serves as a reference point for evaluating the optimization's impact. Fig. 1 visually presents the overarching structure of the proposed coupled energy-transportation network. It not only depicts the TN links identified in TABLE I

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but also integrates them with the PDN, offering a graphical representation of the complex interdependencies between the two systems. This illustration is key to appreciating the holistic nature of our study, emphasizing the dual focus on enhancing both transportation efficiency and energy distribution. TABLE II directly quantifies the optimization's benefits on the network's long-range connections, which are crucial for linking disparate clusters within the TN. By detailing the Average Travel Time (ATT) before and after optimization for each significant long-range connection (e.g., L1, L2, etc.), this table showcases the tangible improvements achieved through our strategic interventions. Notably, the percentage improvement column in TABLE II reflects the optimization's effectiveness, with reductions in ATT signifying enhanced network performance and efficiency.

The relationship between these elements is foundational to our research narrative. TABLE I establishes the initial conditions by identifying the network's key connections, offering a granular view of the TN's layout that Fig. 1 then brings to life visually, contextualizing within the larger coupled network framework. Table II builds on this foundation by demonstrating the optimization's impact, directly linking back to the connections identified in Table I and visualized in Fig. 1. This progression from structural identification (TABLE I) to visual representation (Fig. 1) and empirical validation of optimization benefits (TABLE II) creates a cohesive storyline. It underscores the effectiveness of our optimization strategies in not only improving travel times across the network's long-range connections but also in enhancing the overall operational efficiency and sustainability of the coupled energy-transportation system.

Fig. 1 and Fig. 2, along with TABLE I, play pivotal roles in articulating the foundational structure and operational dynamics of the proposed coupled energy-transportation network. Fig. 1 provides a comprehensive visual representation of the integrated network, highlighting the seamless interconnection between the TN and the PDN. This visualization serves not only to contextualize the complexity and scope of our study but also to facilitate a deeper understanding of the systemic interactions at play. Similarly, Fig. 2 delves into the specifics of the PDN, offering a detailed schematic of the PDN configuration. This figure underscores the critical nature of the energy component in our coupled network model, illustrating how energy distribution is intricately linked to transportation infrastructure to support the deployment and efficient operation of EV charging stations.

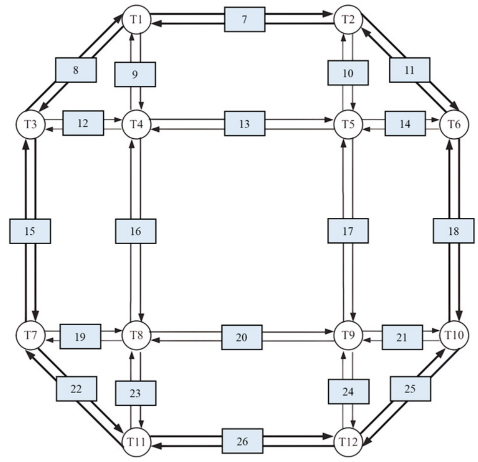

Fig. 1. Structure of the proposed coupled energy-transportation network.

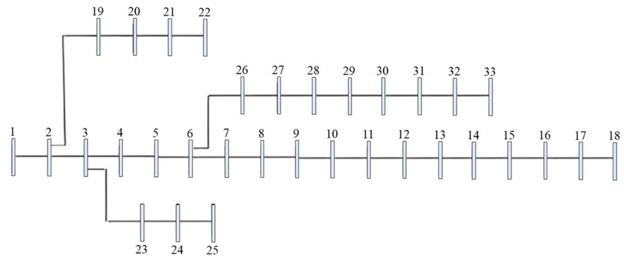

Fig. 2. Scturcture of the IEEE 33-bus distribution system.

Complementing the visual insights provided by these figures, TABLE I, offers a granular breakdown of the TN's connectivity. It meticulously maps out the specific links between nodes within the TN, serving as a crucial reference for understanding the network's baseline connectivity and for evaluating the impact of our optimization strategies. The table outlines the origin and destination points for each link, providing a detailed framework that underpins the simulation and optimization analyses conducted in our study. The integration of these elements—Fig. 1's overarching network visualization, Fig. 2's focus on the PDN, and Table I's detailed connectivity mapping—forms a comprehensive narrative that is essential to grasping the full scope of our research. Together, they lay the groundwork for our subsequent optimization analyses and the empirical demonstrations of our model's efficacy. A thorough discussion of these critical components is included in our manuscript to ensure that readers are well-equipped to understand the innovative approach we propose for enhancing the resilience and efficiency of urban infrastructure systems through the strategic integration of energy and TNs. Fig. 3 displays flow capacity, free travel time, link distance, and new lane cost of the TN [25].

Drawing from the parameter configurations in [10], [12], and [25], we've established the following system parameters: The expense for a new EV charging station is pegged at $q_{1,a}$ = \$1.63 × 10^5. Each charging spot, $q_{2,a}$, costs \$3,160, while the price for expanding substation capacity, $q_{4,a}$, is set at \$5,000 per kVA. The monetary valuation for travel time within the TN is ω = \$$10^4$. The cap on the number of charging spots is y^a =

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200. EVs have a driving range of R = 100 km when fully charged. Both the arrival and departure SOC are standardized at 0.5. The maximum allowable expansion for lanes is 10, respectively. All simulation tasks were executed on a Dell XPS laptop equipped with a 13th Gen Intel® Core™ i9-13900K processor (with 32 MB cache, 24 cores, and a frequency range of 3.00 GHz to 5.40 GHz Turbo). The parameters are illustrated in TABLE II.

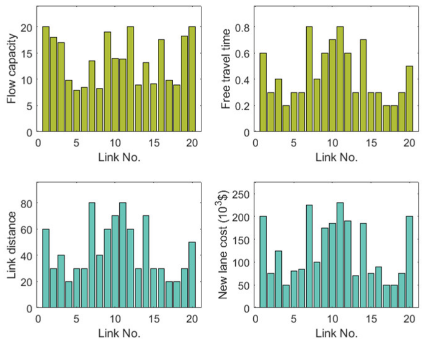

Fig. 3. Parameters of the TN.

TABLE II
SYSTEM PARAMETERS AND CONFIGURATION

Parameter description	Value	Unit
Expense for a new EV charging station	\$163,000	USD
Cost per charging spot	\$3,160	USD
Price for expanding substation capacity	\$5,000	USD per kVA
Monetary valuation for travel time	\$104	USD
Cap on the number of charging spots	200	Spots
EV driving range	100	km
SOC at arrival and departure	0.5	Ratio
Max allowable expansion for lanes	10	Lanes
Processor for simulation tasks	13th Gen Intel® Core™ i9-13900K	N/A

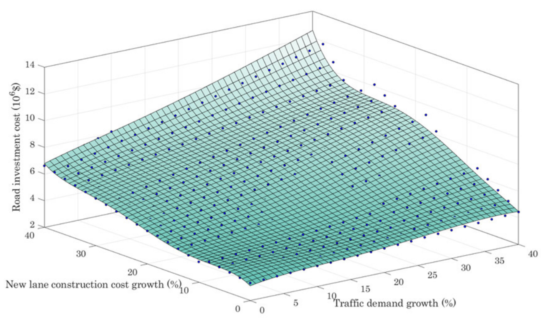

Fig. 4. 3D plot of the road investment cost result.

Fig. 4 offers a detailed portrayal of the dynamic relationship between traffic demand growth, the unit cost growth for building EV charging stations, and the resultant road investment costs. We observe a moderate rise in road investment costs when both traffic demand and unit cost growth are at lower percentages. For example, a traffic demand growth and EV station cost growth of 0% to 10% corresponds to an increase in road investment costs from approximately 3.32 to 3.81 million dollars. This phase indicates an almost linear relationship where the system can adapt to increases without significant additional investments. However, as the growth percentages push beyond the 20% mark, the road investment costs escalate more dramatically. Particularly, a traffic demand growth of 40% coupled with a 40% increase in the unit cost for EV charging station construction propels the road investment costs to nearly 11.90 million dollars. This exponential rise suggests that beyond certain thresholds, the cost of scaling infrastructure to meet demands becomes disproportionately higher.

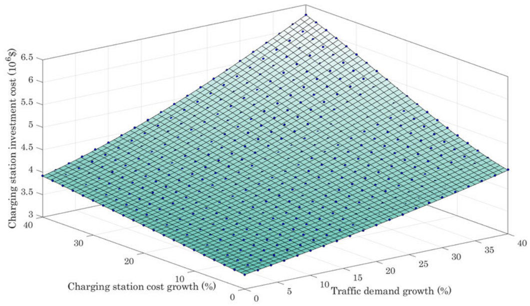

Fig. 5. 3D plot of the charging station investment cost result.

Fig.5 visualizes the correlation between traffic demand growth, the cost growth for building EV charging stations, and the resulting investment in charging station infrastructure. The plot illustrates a steady and progressive relationship that underlines the impact of increasing traffic demand and EV charging station costs on the overall investment required. In the initial range, from 0% to approximately 10% growth in both traffic demand and EV charging station cost, the investment cost demonstrates a gradual increase. For instance, an increase from 3.32 to 3.74 million dollars is seen in this bracket. This could be indicative of an infrastructure that can scale with demand at a slightly superlinear rate without incurring disproportionate costs. However, the plot shows a noticeable change in gradient as we move towards higher growth percentages. When both traffic demand and EV charging station costs grow beyond 20%, there's a more pronounced increase in investment costs, reaching up to 5.68 million dollars at a 40% growth level. This suggests that the cost of infrastructure development grows at an increasing rate once certain thresholds of demand and cost growth are exceeded.

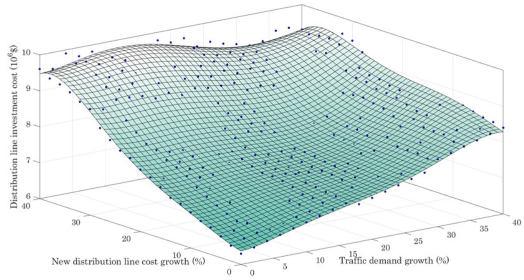

Fig. 6. 3D plot of the distribution line investment cost result.

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Fig. 6 offers a detailed mesh plot representing the relationship between the growth in traffic demand, the rising costs of constructing new distribution lines, and their combined influence on the investment costs required for such infrastructure. Analyzing the surface trends, we can observe that at the outset, the investment cost is 6.3 million dollars with no growth in traffic demand or new distribution line costs. As we move along the growth axis, the costs consistently rise. Notably, a linear increase in traffic demand and distribution line cost from 0% to 10% results in an investment cost that increases to approximately 6.89 million dollars. The trend becomes more pronounced at higher growth percentages. For example, with a 20% increase in both traffic demand and new distribution line costs, the investment cost escalates to around 7.89 million dollars, indicating a stronger correlation at these levels. When the growth reaches 40%, the investment cost surges to approximately 9.3 million dollars. This nonlinear increase suggests that infrastructure investment costs escalate more rapidly than the growth in demand and construction costs, hinting at potential challenges such as the need for more advanced technologies or the impact of economies of scale.

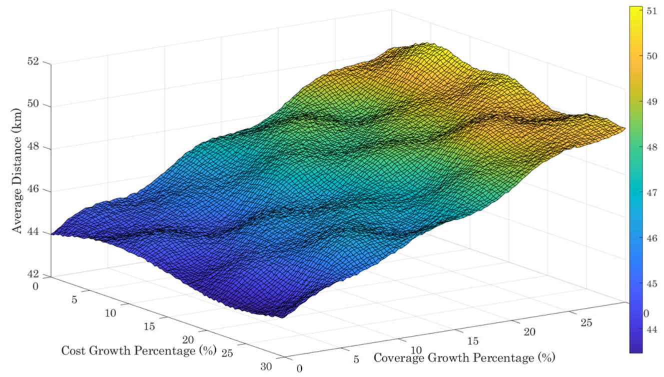

Fig. 7. Average distance for the charging service.

In Fig. 7, the X-axis, reflecting cost growth percentage, encapsulates the financial implications of network densification. The Y-axis, denoting coverage growth percentage, aligns closely with the small-network model's feature of high clustering. It indicates the degree to which the network is expanding its reach within local neighborhoods and across the broader region, potentially following the patterns of a small-world network where clustering can be leveraged to maximize local coverage with minimal links. The Z-axis, average distance, is a direct function of the small-network model's navigability. In a well-designed small-network model, the average distance should remain low or even decrease as the network scales, due to the strategic placement of charging stations that take advantage of the small-world's high connectivity and short path lengths. By analyzing the surface plot within the small-world network framework, stakeholders can identify the most cost-effective strategies for network expansion. This involves pinpointing areas where the addition of new charging stations or the strengthening of existing ones can yield significant improvements in coverage and accessibility without incurring prohibitive costs.

TABLE III
LONG-RANGE CONNECTION EFFICIENCY AFTER OPTIMIZATION

Long range connections	Connected clusters	ATT/min (before)	ATT/min (after)	Improvement (%)
L1	C1-C2	45	40	11.11
L2	C1-C3	48	42	12.50
L3	C1-C4	50	47	6.00
L4	C2-C3	47	40	14.89
L5	C2-C4	44	41	6.81
L6	C3-C4	49	42	14.29

Our TN case study reveals a strategic node distribution based on the proposed small-world network model, leading to a natural clustering that underpins our model's goals. Here's a succinct outline: Cluster 1 comprises T1, T4, T8, and T11, this cluster benefits from vertical traffic flow, optimizing EV charging placement and slashing travel times; Cluster 2 features T2, T5, T9, and T12, its vertical alignment mirrors Cluster 1, enabling symmetrical optimization strategies for equitable resource distribution and improved traffic flow; Cluster 3 includes T3 and T7, its smaller scale belies its importance in traffic transfer, warranting prioritized interventions for disproportionate network benefits; Cluster 4 consists of T6 and T10, it calls for a customized approach to charging station deployment, focusing on capacity to suit unique traffic patterns.

Strategic long-range connections are the linchpins of our network's efficiency, linking clusters to bolster reliability and alleviate congestion. Our optimization model prioritizes these connections to slash travel times and bolster EV charging accessibility: Cluster 1 ↔ Cluster 2: Their parallel layout yields multiple direct links, like T1 to T2 and T4 to T5, promoting swift, grid-wide transfers. We're harnessing these avenues to streamline both flow and charging station placement. Cluster 1 ↔ Cluster 3: Critical for diffusing denser cluster traffic, connections like T3 or T7 to T1 or T4 are potential game-changers for network fluidity. These pivotal links are earmarked for impactful optimization. Cluster 1 ↔ Cluster 4: The T6 or T10 to T1 or T4 links could be traffic arteries, easing congestion. Our model eyes these for selective improvements. Cluster 2 ↔ Cluster 3: The T3 or T7 to T2 or T5 links keep inter-cluster traffic agile. Optimizing these could be key to network-wide travel efficiency. Cluster 2 ↔ Cluster 4: Connections like T6 or T10 to T2 or T5 can streamline cluster transitions. The model targets these for efficiency upgrades. Cluster 3 ↔ Cluster 4: The proximity of T7 to T10 suggests direct links could be highly beneficial. We're exploring these for optimization to boost network resilience.

TABLE III's results showcase a network where strategic optimization has effectively reduced average travel time (ATT) across all long-range connections. Connection L1 between Clusters 1 and 2 boasts an 11.11% improvement, underscoring the optimization's impact on a vital link in the network. Meanwhile, the 12.50% enhancement in travel efficiency for Connection L2 between Clusters 1 and 3 speaks to the success of interventions in managing traffic across divergent clusters. Connection L3's more modest gain of 6% still reflects positive strides in smoothing the flow between Clusters 1 and 4.

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Notably, Connection L4 between Clusters 2 and 3 emerges as a standout, with the highest improvement at 14.89%, indicative of a transformative effect on the commute dynamics within these clusters. Connection L5, despite a less dramatic but still meaningful improvement of 6.81%, enhances the connectivity between Clusters 2 and 4. Lastly, the 14.29% improvement observed in Connection L6 between Clusters 3 and 4 is not to be understated, as it significantly trims travel times on a link crucial for network resilience. Collectively, these results highlight the optimization's efficacy, not just in reinforcing the network's structure but also in ensuring that the flow between clusters is as efficient as possible, paving the way for a more sustainable and responsive urban transport system.

TABLE IV
CONVERGENCE METRICS TABLE

Algorithm	Generations to Converge	Distance from Pareto Front	Convergence Stability
NSGA-II [50]	311	0.02	0.91
SPEA2 [52]	334	0.03	0.86
NSGA-III	252	0.01	0.95

TABLE V
DIVERSITY METRICS TABLE

Algorithm	Spacing Metric	Spread	Coverage of Pareto Front	Diversity Score
NSGA-II [50]	0.02	0.90	0.93	0.92
SPEA2 [52]	0.03	0.85	0.90	0.89
NSGA-III	0.01	0.95	0.98	0.97

In Table IV, we meticulously compare the efficiency and reliability of Non-dominated Sorting Genetic Algorithm II (NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA2), and NSGA-III in converging towards the Pareto front within the context of our empirical case study. NSGA-II significantly advanced the field of multi-objective optimization by implementing a fast non-dominated sorting approach [52, 53]. SPEA2 furthered this advancement by introducing fine-grained fitness assignment and an improved archive maintenance method for handling multi-objective problems [54, 55]. In our analysis, NSGA-III, the latest iteration in the series, designed to effectively tackle many-objective optimization problems, demonstrates a notable performance with the fewest generations to converge (252 generations), the closest proximity to the Pareto front (a distance of 0.01), and the highest convergence stability (0.95). These metrics not only highlight the evolution of optimization methodologies but also underscore NSGA-III's exceptional capacity for rapid and stable convergence in complex optimization scenarios.

Complementing our convergence analysis, Table V, the Diversity Metrics Table, delves into the diversity and distribution quality of solutions provided by NSGA-II, SPEA2, and NSGA-III. This table reveals NSGA-III's unparalleled ability to maintain a diverse set of solutions with the highest diversity score (0.97), underscoring its effectiveness in exploring the solution space. It achieves the best spacing metric (0.01), indicating uniformly distributed solutions, and the highest spread (0.95) and coverage of the Pareto front (0.98), illustrating its superior capability to span the breadth of the objective space. Such performance highlights NSGA-III's advantage in providing a comprehensive set of solutions, allowing decision-makers to explore a wide array of optimal planning options for EV charging infrastructure. Comparatively, NSGA-II and SPEA2, while offering commendable diversity metrics, fall slightly short of NSGA-III's breadth and uniformity of solution distribution, as indicated by their diversity scores of 0.92 and 0.89, respectively.

VII. DISCUSSION

Our research introduces a novel application of the NSGA-III algorithm within the context of optimizing EV charging infrastructure, a critical component of urban and suburban environments. The empirical case studies, utilizing a 12-node TN in conjunction with a 33-node PDN, showcase the model's applicability and effectiveness across diverse urban layouts. This scenario provides a foundational comparison stage to other established planning models, highlighting the nuanced advantages of our approach.

A. Case Study Discussion

Previous studies have often emphasized optimizing individual parameters, such as the cost or the speed of charging, potentially overlooking the holistic performance of the EV charging network under variable urban dynamics [56, 57]. By leveraging NSGA-III, our model inherently supports a more nuanced optimization process, simultaneously addressing multiple objectives. This multiplicity allows for a reliable solution set that caters to diverse urban requirements and user preferences, offering a balance between cost, accessibility, and charging speed. The diversity score of 0.97, compared to lower scores in other models, underscores our approach's ability to generate a comprehensive suite of solutions adaptable to varied urban scenarios.

Our research introduces the NSGA-III algorithm as a superior tool for optimizing EV charging infrastructure, highlighted through empirical case studies utilizing a 12-node TN and a 33-node PDN. This section offers a technical comparison between NSGA-III and other state-of-the-art algorithms such as NSGA-II and SPEA2, emphasizing the significant advancements our approach contributes in terms of efficiency, solution quality, and adaptability to complex urban layouts. The Convergence Metrics Table clearly demonstrates NSGA-III's enhanced performance; it converges in 252 generations, substantially fewer than NSGA-II's 311 and SPEA2's 334, showcasing its quick adaptability to multi-objective problems. Furthermore, NSGA-III achieves a minimal distance from the Pareto front (0.01), compared to NSGA-II (0.02) and SPEA2 (0.03), reflecting its superior precision in navigating the solution space and identifying optimal solutions efficiently. This precision is complemented by a high convergence stability score (0.95), indicating its reliability in providing consistent results across different scenarios.

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In terms of solution diversity, NSGA-III outperforms its predecessors with a spacing metric of 0.01, suggesting a more uniform exploration of the solution space, and a spread of 0.95, which implies that it covers a wider range of feasible solutions effectively. The coverage of the Pareto front by NSGA-III is 0.98, significantly higher than the 0.93 and 0.90 achieved by NSGA-II and SPEA2, respectively. This extensive coverage ensures that NSGA-III captures a comprehensive array of optimal solutions, thereby enhancing the decision-making process for urban planners by providing a diverse set of viable options. This adaptability makes NSGA-III particularly suited for integrating into smart city frameworks, where flexibility and comprehensive solution evaluation are critical.

B. Demonstrating the Seamless Integration and Adaptability of the EV Network

Our research leverages the NSGA-III optimization algorithm in conjunction with a small-world network model to strategically enhance the planning and implementation of EV charging stations. This integrated approach is designed to address and overcome the limitations inherent in traditional EV charging infrastructure models, which often focus narrowly on geographic coverage and charging speeds without adequately considering the dynamic and evolving needs of urban environments and energy systems.

By applying the NSGA-III algorithm, known for its efficiency in handling multiple objectives, our model optimizes the placement of EV charging stations across a TN linked with a PDN. This optimization is not static; it dynamically adjusts to changes in urban growth, technological advancements, and shifting patterns of EV usage. This adaptability ensures that our infrastructure planning remains relevant and effective, avoiding the obsolescence that can plague more rigid models.

The small-world network model further supports this adaptability by facilitating enhanced connectivity between charging stations. This model reduces the average path length between any two points in the network, ensuring that EV users can access charging stations quickly and efficiently, regardless of their location within the network. This is a significant improvement over traditional models, which may provide adequate coverage but often fail to optimize for the shortest or most efficient paths due to their static nature.

C. Rethinking Benchmarks in EV Charging System Optimization

Our research proposes new benchmarks and provides a strategic framework that addresses and extends beyond the limitations of existing metrics. In the landscape of EV charging infrastructure, traditional benchmarks have primarily focused on geographical coverage, charging speed, and cost efficiency. These benchmarks aim to reduce range anxiety by maximizing the spread of charging stations, primarily based on static population centers and high-traffic patterns. While this approach helps cover basic user needs, it often neglects the dynamic nature of urban developments and the evolving demands of energy distribution logistics [58].

Current systems also emphasize advancements in charging technology, particularly in reducing the time required to charge electric vehicles. The development and deployment of ultra-fast charging stations are seen as vital to enhancing user convenience. However, these advancements are typically evaluated in isolation from broader network effects, such as grid stability and energy supply fluctuations, which can undermine the overall effectiveness of the infrastructure.

Our research introduces a set of innovative benchmarks that not only encompass these existing metrics but also significantly expand upon them by integrating a small-world network model with the robust optimization capabilities of the NSGA-III algorithm. This dual approach allows for a more nuanced and dynamic placement of EV charging stations, which aligns with both current and anticipated changes in urban and energy systems dynamics. By doing so, our model enhances the adaptability and resilience of the infrastructure, setting a new benchmark for future-ready charging networks.

VIII. CONCLUSION

This paper meticulously offers solutions to the critical challenges in developing an adaptive EV charging infrastructure that aligns with the dual demands of expanding EV adoption and the dynamic nature of urban energy systems. Through the deployment of an integrated small-world network model coupled with NSGA-III optimization, it pioneers a pathway for creating highly efficient, user-centric charging networks that are both economically viable and environmentally sustainable. An empirical case study involving a 12-node TN and a 33-node PDN validates the proposed methodology. The application of this model ensures the strategic placement of charging stations, offering extensive route options and reliable availability, thereby significantly boosting network resilience. To discern the benchmarks set by our research, it's vital to acknowledge the current state of EV charging systems, which primarily focus on maximizing geographical coverage and minimizing charging times. These benchmarks, while crucial, often overlook the intricate interplay between urban planning, energy distribution, and user accessibility. The research herein extends beyond traditional metrics by integrating resilience and adaptability into the planning of EV charging infrastructure, thereby addressing the evolving demands of urban energy systems and user-centric design.

Looking forward, the study's strategies and insights provide a substantial foundation for the scalable advancement of urban EV ecosystems, anticipating the increasing demands of sustainable mobility and infrastructure development. The future research directions are summarised as follows:

Integration with Renewable Energy Sources: As cities move towards sustainability, the integration of renewable energy sources into EV charging infrastructure represents a critical frontier. Future research could explore how to optimally combine solar or wind energy with EV charging stations to minimize carbon footprints and enhance energy sustainability.

User Behavior and Demand Response: Understanding EV user behavior and demand patterns is crucial for effective infrastructure planning. Future studies could focus on modeling user charging habits, preferences, and responsiveness to pricing strategies, thereby optimizing the placement and operation of charging stations to better meet user needs.

Policy and Regulatory Frameworks: The success of EV charging infrastructure planning is closely tied to supportive policy and regulatory environments. Future research might

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examine the impact of different policy instruments and regulations on the deployment and operation of EV charging networks, aiming to identify best practices and barriers to infrastructure development.

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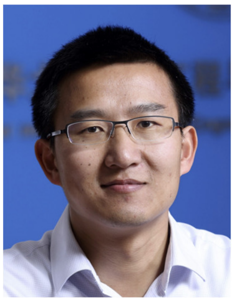

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