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Anticipatory planning for equitable and productive curbside electric vehicle charging stations

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ABSTRACT

Two challenges to planning public electric vehicle (EV) charging networks remain in U.S. cities, including uneven productivity of charging stations and inequitable charging access across user groups. The unpredictable EV market penetration over the long term further complicates the relevant infrastructure planning. However, the extant planning approaches are limited in addressing both challenges simultaneously when considering future uncertainties. Therefore, we propose a data-driven anticipatory framework to plan for EV charging station allocation near urban amenities based on charging-while-parking behavioral patterns. We focus on two user groups, i.e., multi-family and single-family residents. We compare the productivity-equity outcomes of allocation scenarios under three planning strategies and four possible ratios between both user groups. The framework addresses the incremental charging demands at different market levels for each scenario. An in-depth case study of Alachua County, FL, shows that over-emphasizing multi-family charging demands when placing EV charging stations may undermine their overall productivity. We then suggest three pathways to balance equitable access and optimized productivity for the community based on the comparison of planning scenarios. The proposed framework is generalizable to other EV-initiating communities. This study sheds light on future-oriented adaptive planning for transportation infrastructure during the energy transition.

1. Introduction

Promoting equity and inclusion is a critical social-economic goal during the national energy transition across the United States (National Academies of Sciences, Engineering, and Medicine [NASEM], 2021). Particularly, inequities among communities of different dwelling types are significant in electric vehicle (EV) market shares and spatial distributions of charging stations (Carlton & Sultana, 2022). Multi-family housing (MFH), such as apartments or condominiums, serves approximately 43.9 million residents and accounts for 31.1 % of households in the U.S. (U.S. Census Bureau, 2021). Yet, even in many EV-friendly states, MFH residents only occupy less than 15 % of the current EV market share, while single-family housing (SFH) residents take the rest (Burk et al., 2020; California Energy Commission, 2021; O'Connor et al. 2022). In addition to the fact that EVs are less affordable for MFH residents (Higueras-Castillo et al., 2021; Ju et al., 2020), the gap in EV adoptions between SFH and MFH residents is also attributed to varied access to public EV charging stations (EVCSs; Shi et al., 2021; Sierzchula et al., 2014). MFH EV users have a higher reliance on public charging since they have less access to private chargers than SFH users (Kim et al., 2022). The insufficient accessibility to public charging has discouraged prospective MFH consumers from purchasing EVs (Broadbent et al., 2021; O'Connor et al., 2022) and further exacerbate the imbalanced EV ownership across user groups, polarizing geographical EV penetrations and aggravating environmental inequity (Hardman et al., 2021; Hsu & Fingerman, 2021).

Additionally, planners or stakeholders need to leverage the effectiveness of EVCS installations, considering the cost remains high (LaMonaca & Ryan, 2022). Increasing use-productivity while minimizing the required EVCSs is crucial for both public utilities and for-profit facilities (Huang et al., 2019). However, an allocation plan focused solely on productivity often relies on current data from existing EV markets, resulting in EVCSs clustered in areas preferred by existing users. The approach inhibits the equitable distribution of charging

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accessibility in low-penetration neighborhoods. On the other hand, an indiscriminate EVCS allocation solely based on geographical equity can introduce challenges in the opposite direction. Existing research suggests that only public EVCSs in central districts are visited frequently, while those in low EV penetration areas may be underused (Bauer et al., 2021). The uneven utilization of public EVCSs places unnecessary burdens and congestion on popular stations while reducing the cost-effectiveness of less frequently used ones (Dong et al., 2019). Without strategic planning that simultaneously harmonizes both objectives, equity and use-productivity, the goals can potentially conflict with each other, which needs to be addressed (Marmaras et al., 2017; International Council on Clean Transportation, 2020).

The extant studies on planning optimal locations for EVCSs have pursued objectives beyond maximizing utility, including reducing energy loss and increasing charging coverage, among others (Erbaş et al., 2018; Guo & Zhao, 2015; Xu et al., 2023). However, existing knowledge has yet to provide equitable access to public charging across different population groups while simultaneously facilitating the productive utility of EVCSs. The EV penetrations among MFH communities are presumed to change, making the context of the future EV market and charging demands unpredictable (Khan et al., 2022). The two intertwined nature of the two planning is particularly intriguing given the uncertainties involved, which highlights the need for a proactive and dynamic allocation method in the planning process.

To address the knowledge gaps in allocating EVCSs to achieve equity and productivity amid the growing EV market, we propose a data-driven anticipatory planning framework for EVCSs, which is complemented by an in-depth case study. Our spatial allocation relies on the multi-criteria decision-making (MCDM) method to determine the suitability of candidate locations. To plan for productivity, suitability criteria are built upon the estimation of "charging while parking" behaviors (Kang et al., 2022; Guerra & Daziano, 2020; Patil et al., 2023). We focus on curbsides in urban amenity centers as key locations to enable charging activities for both nearby residents and guest visitors from other neighborhoods due to their better visibility and accessibility (Yang et al., 2014; Ge et al., 2021; He et al., 2022a). To plan for equity, we design three planning scenarios to incorporate different future-oriented strategies. Each scenario further anticipates distinct proportions of EV market share among MFH residents that reflect uncertain future changes. We then assess the performances of the three planning strategies in a case study in Alachua County, Florida, regarding the two objectives. In light of the finding—that equity and productivity have an evolving antithetical relationship—we explore potential pathways to achieve co-beneficial planning. This research intends to guide use-productive and equitable EVCS planning under the uncertain future of energy transition and transportation electrification.

2. Literature review

Existing planning approaches for sitting EVCSs have been dominated by two types of methods: simulation-optimizing methods (e.g., Shi et al., 2021) and Multi-Criteria Decision-Making (MCDM) methods (e.g., Sánchez-Lozano et al., 2013). The former focuses on optimizing EVCS allocation for various objectives, while the latter emphasizes the locational context, aligning with the purpose of our study. However, the travel-mobility behaviors of EV users have rarely been incorporated in the current MCDM-based studies, despite their effectiveness in planning for EVCSs with high productivity (Luo et al., 2018). Furthermore, to balance long-term equity with productivity, we introduce anticipatory planning as a valuable approach, specifically considering the concern for future uncertainties. In the following three subsections, we review the existing studies and discuss the specific knowledge gaps.

2.1. Existing studies on EVCS allocation planning methods

EVCSs planning objectives based on existing simulation-optimization approaches, such as the often-used Generic Algorithm (GA), were generally directed to increasing the efficiency of EVCSs from perspectives of energy, transportation, and installation costs. For example, Xi et al. (2013) used a linear integer programming-based simulation-optimization model to determine the location and size of EVCSs to optimize their utilization. Xie et al. (2018) focused on inter-city long-range EVCS allocation with a mixed integer programming model with a planning objective to maximize cost-effectiveness and address the range anxiety of EV users. Huang et al. (2019) proposed a design method to minimize the life cycle cost of EVCSs when considering the optimal locations and numbers in high-density cities. The study especially considered the building roof solar energy potentials in channeling renewable resources for the EVCSs. Xiao et al. (2020) suggested a GA-based optimal location model to cut overall charging costs, which was particularly advanced in considering vehicle queuing behaviors when charging. Pan et al. (2020) demonstrated a public EVCS model that attempts to meet the increasing demands in charging while preserving EV drivers' current travel behaviors. A GA-based location optimization strategy was used to minimize the government's costs, which included objectives of lowering construction costs, meeting drivers' charging demand, and reducing emissions. While optimization methods have been effective in allocating EVCSs based on distinct planning objectives with a macro-level perspective, they often neglect the importance of locational suitability and the local impacts of EVCSs.

Other studies used MCDM-based EVCS allocation planning approaches to supplement the former method with a focus on local features. For example, Guo and Zhao (2015) identified optimal locations for EVCS using the fuzzy TOPSIS (i.e., Technique for Order of Preference by Similarity to Ideal Solution) technique, an MCDM method. They considered various aspects of semantic features to determine the suitability of candidate locations, including the environment, economy, society, electric power system, and transportation system. However, their research regarded social-economic and human-center factors less. Erbaş et al. (2018) suggested a method that integrated GIS techniques and MCDM methods for determining the best locations for EVCSs in Ankara, Turkey. This research considered environmental, economic, and urbanity factors in determining suitable sites. Guler and Yomralioglu (2020) also adopted a GIS-based TOPSIS, which ranked the alternative EVCSs locations that were selected based on a suitability analysis of built environment attributes. To conclude, the existing MCDM-based EVCS allocation approaches rarely considered the total productivity of EVCSs, which necessitates the incorporation of charging and traveling behaviors of EV users into their analyses.

2.2. EVCS allocation based on people's travel-mobility patterns

Charging demands have been found to harmonize with residential locations and real-time mobility patterns of EV users (Liu et al., 2022; Wang et al., 2022a). Researchers have assessed the extent to which EVCSs met charging demands on separate occasions, at home or when visiting amenities. A few studies have considered spatial coverage of EVCSs by focusing on providing charging access to nearby residents. For example, Vazifeh et al. (2019) allocated EVCSs by solving a covering problem with dual objectives, to minimize the number of EVCSs and the average distance for drivers to the nearest accessible EVCS.

Additionally, many studies allocated EVCSs based on mobility behaviors such as origin-destination (O-D) travel features to maximum charging coverage for visitors or guests. Efthymiou et al. (2017) used the O-D data of conventional automobiles (non-electric vehicles) to forecast EV behaviors in the coming years. Based on the simulated behavior, the model used charging demand coverage as an optimizer to determine the optimal numbers of EVCSs. Kontou et al. (2019) used O-D data to investigate the relationship between EVCS spatial charging coverage and charging opportunity. The simulation on charging activities suggested that charging stations concentrated in a few popular places where drivers often stopped could significantly support public charging accessibility. Dong et al. (2019) used point of interest (POI) and traffic data to decide on the optimal location for EVCSs, which can maximize the extent to which they accommodated the charging demands. Huang and Kockelman (2020) investigated allocating EVCSs using O-D data that simulated the users' behaviors with transportation behavior using GA optimization. These two aspects, however, have not yet been integrated into a holistic framework, which is essential for advancing the consideration of equitable EVCS allocation.

2.3. Scenario planning for equitable EVCS allocation

Increasing studies have acknowledged that inequitable EV charging capacity allocation could exacerbate the existing uneven EV ownership among specific user groups (Guo & Kontou, 2021; Sierzchula et al., 2014). The disparities in accessing EVCSs among socioeconomic groups and communities have been examined in different cities and regions (Khan et al., 2022; Canepa et al., 2019; Hsu & Fingerman, 2021). For example, Roy and Law (2022) considered inequitable access to EVCSs as one component of a holistic spatial inequality indicator. This indicator encompassed multiple socioeconomic and built-environmental factors, allowing them to examine the overlap between projected EVCSs allocation and inequity areas. However, only a few new approaches have been proposed to address inequity issues, such as the optimization model applied by Yi et al. (2022) aimed to mitigate the spatial mismatches between charging demands and the existing allocation of EVCSs. There is a growing demand for future-oriented investigations to achieve long-term equitable strategies for the changing context of the EV market.

Anticipatory and visionary planning is often employed in climate change adaptation planning (Birchall et al., 2021; Muiderman et al., 2020). The scenario-based analysis is an effective tool for examining planning strategies in the face of future uncertainties (Muñoz-Erickson et al., 2021). To date, this methodology has only been applied in EVCS allocation methods to represent uncertainties driven by market changes or innovations. For example, Singh et al. (2022) simulated EVCS demands and allocation with scenarios representing EV market shares ranging from 1 % to 50 % and technological innovations that varied EV battery size. The research confirmed the linkages between environmental factors and EVCS demands. In an EVCS allocation study, Xie et al. (2018) also investigated potential scenarios with different EV diffusion stages. Huang et al. (2019) presented a substantial rise in the life cycle cost of EVCSs as the required coverage ratio increases. However, the application of this method to target long-term equitable goals remains untapped.

To conclude, current studies on anticipatory planning for equitable EVCS allocation encountered multiple gaps. First, existing studies have primarily focused on inequitable access to EVCSs from a geographical perspective, overlooking the disparities among different user groups. Their differences in charging demands require further emphasis on adaptive methods. Second, it has been well understood that charging demands, both for residents when nearby their homes or guests during parking, are critical for guiding human-behavior-oriented EVCS allocation (Liu et al., 2022). However, there has not been an integrated framework considering public charging accessibility and demands for both occasions. Third, despite various market-growth scenarios being studied, there has been a lack of investigation into time-series differences, which would enable an incremental vision of when and where to allocate EVCSs. The untapped potential of scenario planning methods can be leveraged to investigate the effectiveness of equitable EVCS planning strategies from a development perspective.

3. Developing an anticipatory planning framework for equitable and productive EVCS allocation

To address the knowledge gaps, we propose an anticipatory planning framework to allocate EVCSs incrementally under three different strategic scenarios. Our framework explicitly addresses productivity and equity while allowing adaptation to the changing EV market over the long term. Anticipatory planning is a scenario-based method that has been increasingly used in assessing adaptive strategies in a wide range of uncertain futures (Birchall et al., 2021; Maffei et al., 2020; Quay, 2010). The planning framework consists of two modules to allocate EVCS incrementally (see Fig. 1). Module 1 uses a Gradient-boosted Tree machine learning model (i.e., XGBoost model) to project the probability of owning EVs for each census block group (CBG) in the study area. The outcomes feed into Module 2 to select optimal locations for new EVCS using an MCDM method. Notably, since the accessibility to EVCSs alters EV adoption (Chakraborty et al., 2021), the probability of EV ownership of CBGs is re-calculated with Module 1 at different EV penetration levels, considering the EVCS allocation from the prior phase. We estimate the number of EVCSs demanded at each EV market level using Electric Vehicle Infrastructure Projection Tool (Lee et al., 2021).

To maximize the EVCS use productivity, the allocation is built upon the anticipated "charging-while-parking" activities based on the analysis of travel behaviors using "big" POI data (Fig. 2; Dong et al., 2019). Given that curbside parking activities often have a sufficiently long duration to allow EVs to charge (Wang et al., 2022b), we consider the overall charging activities as a function of the total EV visits to surrounding POIs. These charging activities occur when users park adjacent to their homes (i.e., resident charging) or when parking while visiting POIs (i.e., guest charging, Pagany et al., 2019). The use-productivity of certain EVCS represents the aggregated charging activities of both types (resident charging and guest charging). This is taken into consideration when determining the optimal site in Module 2 (Fig. 1).

To reflect the changing demands in EV charging over the coming decades across planning scenarios, we characterize the market penetration levels with constant EV adoption increments (e.g., adding 1000 EVs at each level). In addition to matching the supply with increased charging demands, this procedure is designed to avoid conflict with existing EVCSs and to ensure the cost-effectiveness of EVCS installations.

To explore pathways toward equitable access among user groups (Taylor, 2004), we develop three scenarios that reflect different equitable strategies for EVCS allocation (Fig. 1). The Non-Equity strategy is the least equity-driven one. It only pays attention to the productivity of the EVCSs during the allocation procedure, regardless of equity objectives. The Opportunity Equity strategy equally weighs the charging-while-parking behaviors among SFH and MFH EV users when allocating EVCSs. It considers every EV user ought to have an equivalent right to charge at public EVCSs. The Outcome Equity strategy aims to provide users of SFH and MFH with equitable access to collective charging opportunities that combine at-home and public charging. Most MFH users cannot access private charging, so this scenario accounts for their higher reliance on public EVCSs. The framework poses heterogeneous weights on the charging demands among SFH residents, MFH residents, and guests when deciding on suitable locations, reflecting the differences among the three strategies (Fig. 1). We then measure the equitable objective with the EVCS accessibility each scenario generates for SFH and MFH EV users. By doing so, we compare the effectiveness of the equitable strategies and further suggest win-win plans.

3.1. Module 1: downscaling EV distribution probability to census block group level

Studies have investigated EV adoption rates mostly at large spatial scales, such as countries or states (Javid & Nejat, 2017). Established methods have seldom projected EV spatial distribution at a fine spatial scale like CBG. Available data on EV ownership or registration numbers are mostly at the county level or zip-code level for many U.S. counties. However, the spatial units are too large that the demographic patterns may be less representative of those in small spatial scales. To anticipate fine-grained charging activities, we down-scale the county-wide EV ownership to the CBG level by spatially distributing total EV numbers

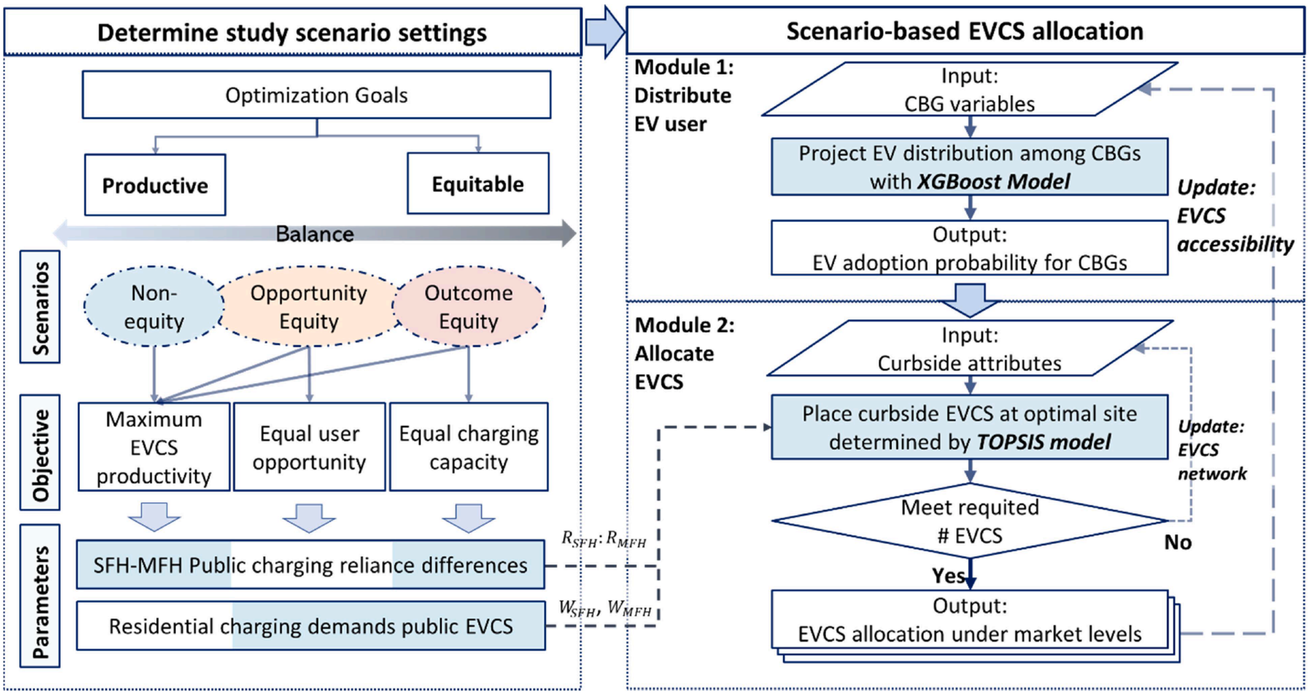

Fig. 1. An anticipatory scenario planning framework for EVCS allocation.

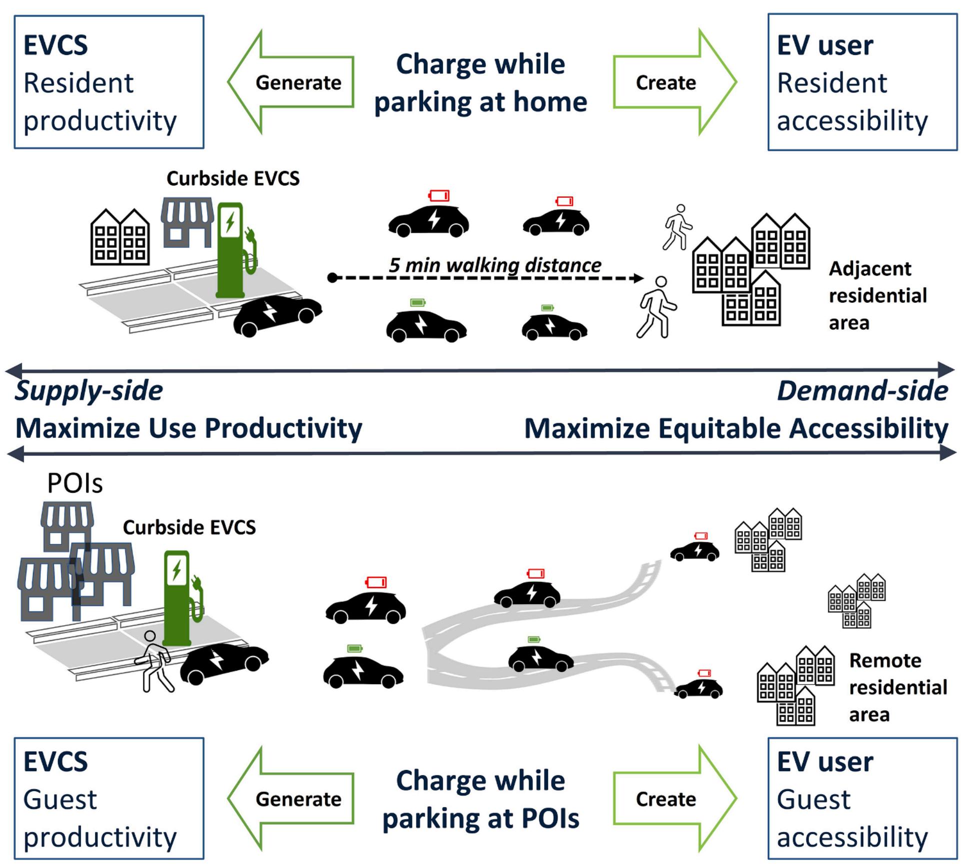

Fig. 2. Two types of charging-while-parking behaviors for different purposes.

using the XGBoost Regression Tree model (Chen & Guestrin, 2016).

The proposed model includes five attributes across environmental and consumer characteristics as explanatory variables. The EV registration rate (i.e., the number of EVs among all private vehicles) is the response variable. We first fit the XGBoost model with the county-level data. We make the following assumptions to use the fitted model to project the probability of EV adoption per CBG at each market level, including (i) environmental attributes (i.e., fuel and electronic prices) are constant across different EV market penetration levels (Zhuge et al., 2020); (ii) consumer characteristics (i.e., household and housing type, income level, vehicle availability) are distinct across CBGs but constant through market penetration levels (Chen et al., 2020); (iii) the charging accessibility of each CBG will change subject to the allocated EVCS at each market penetration level; and (iv) the correlations between explanatory variables and the response variable remain homogeneous across counties.

The model predicts the probability ($P_{EV|i}$) of owning an EV for any residents in CBG_i. For each level of the EV market, the EV counts in CBG are calculated by a function of the anticipated EV number (# *TotalEV*) using Eq. (1):

$$Number_{EV_i} = Number_{TotalEV} \times P_{EV|i} \Big/ \sum_{i=1}^{N} P_{EV|i} \tag{1}$$

N represents the total number of CBGs in the county. As it remains unclear how the compound incentives (e.g., financial subsidies, technology advancement) change the EV market share among MFH and SFH users, we introduce a parameter, *Ratio*, to quantify the extent to which the MFH EV market has changed, calculated by Eq. (2).

$$Ratio = P_{EV|SFH,i} / P_{EV|MFH,i} \tag{2}$$

$P_{EV|SFH,i}$ and $P_{EV|MFH,i}$ represent the probability of owning an EV for SFH households and MFH households in CBG_i, respectively. Four *Ratios* that produce different scenarios are employed to distinguish the share of MFH users in the EV market and mirror different EV incentives assumptions (Slowik & Lutsey, 2017), as shown in Table 1. We start from the current status (i.e., business-as-usual scenario, BAU) with a low EV penetration among MFH residents. For example, the probability of owning an EV for SHF residents ($P_{EV|SFH,i}$) in Florida's EV market is about three times of that for MFH residents, denoting as $Ratio \sim 3$. Then we include three levels of incentives (i.e., moderate, aggressive, and extreme) that lead to scenarios in which MFH residents have higher EV ownership than they do at present. The most optimistic scenario is $Ratio = 1$, which assumes that an MFH resident has the same probability of owning an EV as an SFH resident.

Finally, we calculate the probability of EV adoption of SFH ($P_{EV|SFH,i}$) and MFH ($P_{EV|MFH,i}$) consumers separately in each CBG under the four assumed MFH EV market shares using the designated *Ratios* with Eq. (3) and Eq. (4).

$$P_{EV|SFH,i} = P_{EV|i} \times SFH\% \times Ratio_{SFH} \tag{3}$$

$$P_{EV|MFH,i} = P_{EV|i} \times MFH\% \times Ratio_{MFH} \tag{4}$$

SFH% and *MFH*% represent the percentage of SFH and MFH residents among all households in the CBG, respectively. The CBG-level EV adoption probability estimation is repeated for each EV market level. The output is fed into the EVCS allocation process discussed in Session 3.2 to estimate the resident and guest charging productivities.

Table 1
Scenario assumptions for four MFH EV market structures.

EV market scenario	*Ratio* ($Ratio_{SFH}$: $Ratio_{MFH}$)	Market context description	Incentive assumption
BAU (Ratio ~3)	1.56:0.51	MFH EV market share remains the same as current	None
Ratio = 2	2:1	MFH EV market share increases by minor steps	Moderate incentive
Ratio = 1.5	1.5:1	MFH EV market share increases significantly	Aggressive incentive
Ratio = 1	1:1	The share of MFH EV boosts to the same level as SFH EV	Extreme incentive

3.2. Module 2: allocating EVCS on curbsides in urban amenity centers

3.2.1. Identify candidate curbside for locating EVCSs

Public curbsides and street spaces are highly competitive when serving multiple uses, necessitating in-depth understanding prior to planning for an extra function (Hao et al., 2023; Noland et al., 2022). To identify the candidate curbsides for placing EVCSs, we first extract the road map from public-available datasets of Open Street Map (OpenStreetMap, 2015). Then, we exclude roads unsuitable for curbside facilities (e.g., major roads, connective roads, and non-drive routes) and divide the remaining roads into segments at intersections. Locating EVCSs at centers of urban amenities (i.e., POIs), where drivers often visit and park, is typically effective in providing charging access to guests and visitors (Efthymiou et al., 2017; Kontou et al., 2019). We identify agglomerations of POIs using a density-based clustering tool and define the adjacent areas within a radius of 0.25 miles (estimated 5-min of walking distance) as the boundaries. We consider the curbsides of road segments that intersect with the adjacent areas of POI clusters as candidate locations to place EVCSs.

3.2.2. Multi-criteria-based incremental allocation with strategic scenarios

We adopt the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to determine the locations of EVCS among the candidate curbsides identified in Section 3.2.1. TOPSIS is an MCDM approach used to determine the best alternative among a set of options (Erbaş et al., 2018). It allows for the consideration of the multiple attributes in complex curbside environments and has been successfully applied in previous research on EV allocation (Guo & Zhao, 2015; Zhang et al., 2022).

The TOPSIS model takes a variety of curbside attributes as input and identifies the optimal site for the next EVCS based on these attributes. In the allocation process, we first construct an evaluation matrix with the attributes of all candidate curbsides. A weighting vector (denoted as *W*) is introduced to assign weights to the attributes in the decision matrix. The model then identifies ideal solutions based on all input criteria. The guiding principle for selecting the optimal alternative is to choose the curbside with the shortest Euclidean distance from the ideal solution and the greatest distance from the negative ideal solution. The curbside identified as the optimal solution is considered the suitable location for the new EVCS.

We construct the three strategic scenarios using two important parameters in the TOPSIS process (Table 2): the reliance parameters and a weighting matrix (i.e., *W*). The reliance parameters represent the ratio of charging activities by EV user groups relying on public EVCSs. R_{SFH} and R_{MFH} indicate the reliance parameter for SFH and MFH users, respectively. For the Outcome Equity scenario, we use the entropy weighing method that evaluates the importance of each variable according to the amount of information (Li et al., 2011), while also adopting heterogeneous reliance parameters for SFH and MFH residents. For the Opportunity Equity scenario, both weights of attributes and reliance parameters are set indifferently to value SFH residents, MFH residents, and guests' demands equally. The Productivity (Non-Equity) scenario sets the weight of both SFH (W_{SFH}) and MFH (W_{MFH}) residential charging activities as 0, so they are excluded from the optimization objectives. Table 2 shows a sample set of parameters for three scenarios.

Overall, 12 incremental EVCS allocation plans are produced,

Table 2
Scenario parameters.

Scenarios	Reliance parameter R_{SFH} : R_{MFH}	Weighting vector [W_{Visit}, W_{SFH}, W_{MFH}, W_{Net}, W_{Road}]
Productivity	0.2 : 0.6	[0.6, 0.0, 0.0, 0.2, 0.2]
Opportunity equity	0.4 : 0.4	[0.2, 0.2, 0.2, 0.2, 0.2]
Outcome equity	0.2 : 0.6	Entropy-based weighed

considering three planning strategic scenarios across four MFH EV market share scenarios, which are defined in Section 3.1 (Fig. 3).

Three dimensions of characteristics for each curbside j are considered in the TOPSIS model to determine their EVCS suitability: the anticipated productivity, the competition among other chargers, and the situations of the streets. The first dimension, the anticipated productivity of the EVCS usage (denoted as $Prod_j$), represents charging activities that potentially occur at the curbside. Both guests and residents may contribute to the collective productivity of curbside j, which is calculated by Eq. (5).

$$Prod_j = Prod_{SFH|j} + Prod_{MFH|j} + Prod_{Guest|j} \tag{5}$$

The productivity conducted by SFH residents (denoted as $Prod_{SFH|j}$), MFH residents (denoted as $Prod_{MFH|j}$), and guests (denoted as $Prod_{Guest|j}$) are calculated separately with Eq. 6, Eq. 7, and Eq. 8:

$$\begin{cases} Prod_{SFH|j} = R_{SFH}\sum_i HH_{SFH|i} \times P_{EV|SFH,i}\ i \in N_j & (6) \\ Prod_{MFH|j} = R_{MFH}\sum_i HH_{MFH|i} \times P_{EV|MFH,i}\ i \in N_j & (7) \\ Prod_{Guest|j} = Visit_j \sum_{i=1}^{N} \left(P_i \times P_{EV,i}\right)\ where\ P_i = Visit_{ij}/Visit_j,\ N = 160 & (8) \end{cases}$$

where N_j are the adjacent census blocks of curbside j; i indicates the ith CBG in the study area; $Visit_j$ represents the total visits to amenities nearby j; $Visit_{ij}$ indicates the number of visits originated from CBG i.

The second dimension reflects the competition of the EVCS network (denoted as $Network_j$), which is calculated by Eq. (9). and Eq. (10):

$$Network_j = Net_{CBG|j} + Net_{block|j} \tag{9}$$

$$Net_{block|j} = \begin{cases} 1; & when\ Block_j \in B \\ 0; & otherwise \end{cases} \tag{10}$$

where $Net_{CBG|j}$ represents the number of EVCS in the same CBG of the evaluated curbside j; $Block_j$ means the census block of the curbside j; B includes a set of blocks that are adjacent to allocated EVCS. The framework regards existing EVCSs as constraints to the placement of new ones to avoid overlaps and maximize spatial coverages of EVCS service areas. Thus, the $Network_j$ is minimized in the evaluation matrix. We plan to prevent two EVCS in the same or nearby census blocks, so curbsides that have $Net_{block|j}$ as 1 is excluded from the candidate EVCS locations.

Lastly, the framework intents to minimize the negative externality of EVCS installation to mainline traffic. The street condition is concluded in

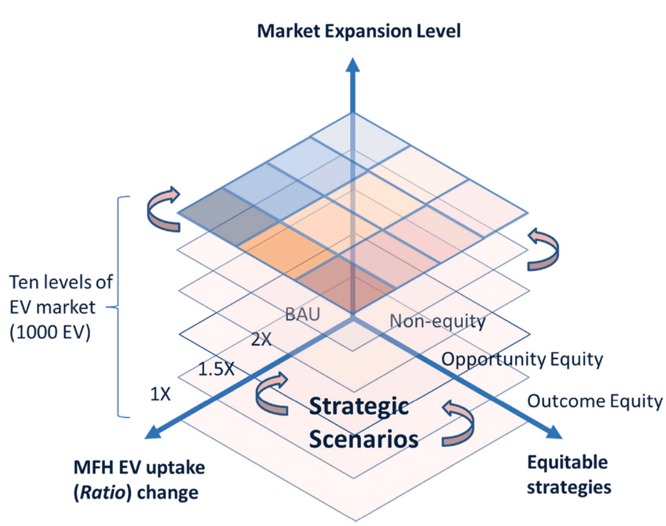

Fig. 3. Constructing Strategic Scenarios for EVCS Planning.

$Road_j$ which is calculated with Eq. (11):

$$Road_j = \frac{1}{3}\left[nor\left(\text{AADT}_j\right) + nor\left(MaxSpeed_j\right) + nor\left(Bus_j\right)\right] \tag{11}$$

where $(x) = \frac{x - min_x}{max_x - min_x}$; AADT_j is the annual average daily traffic of the road where curbside j is located; $MaxSpeed_j$ represents the maximum speed limit of the road; Bus_j is a binary variable that encodes whether there are bus stations on the road segment, with 1 indicating the existence of a bus station and 0 indicating otherwise.

The attributes of curbsides and spatial units discussed above build up the evaluation matrix for the TOPSIS model and are updated after each new EVCS is allocated. Under each level of the EV market, this process continues until the EVCS target is met.

4. Case study of Alachua county in the state of Florida, United States

4.1. Case description

The state of Florida has the second-largest EV market among all states in the U.S., owning 93,221 EVs on road by 2021 (Florida Department of Highway Safety and Motor Vehicles [FLHSMV], 2022). Given the policy incentives and market growth across the state, an increasing EV adoption rate is expected (Higueras-Castillo et al., 2021). Particularly, Alachua County is selected as our study area because its core urban area, the City of Gainesville, is the first city in the state that has pushed the zoning reform to end single-family zoning recently (Spauster, 2022). Such advances allow more land for MFH in the future. Meanwhile, the local EV market is at a beginning level: among the 257, 985 private vehicles registered in Alachua County by March 2022, only 1066 private vehicles are electric ones, which include 716 battery EVs and 350 plug-in EVs (FLHSMV, 2022). The low penetration of EVs makes the county a suitable testbed to examine the future increasing EV market and EVCS allocation for EV-initiating MFH communities. We defined the ten anticipated EV market levels of Alachua County with an increment of 1000 at each level, ranging from 1000 EVs to a maximum number of 10, 000. These thresholds of EV market levels represented a near-to-medium future when the EV market share increased to around 5 % of the total private vehicles in the area. We estimated the EV ownership probability of CBGs corresponding to different market levels.

4.2. Allocating curbside EVCS with place-specific data

To define the adjacent areas of urban amenity centers, we located 4280 amenity POIs in Alachua County from Safegraph Place data. The average monthly visits to the selected amenities were retrieved for one year during May 2021 and May 2022. With the clustering method (in Section 3.2.1), we identified 54 urban amenities centers and subsequently determined potential curbsides to allocate EVCS accordingly (Fig. 4).

We trained the XGBoost model with the explanatory variables of 67 counties in Florida from 2017 to 2021. The model was applied to CBGs in Alachua County to project their EV ownership probability. Table 3 concludes the statistics of explanatory variables. To take existing public EVCS under consideration, we extracted their geodata from the Alternative Fueling Station Locator (Alternative Fuels Data Center, 2022) and excluded those that were reported to be removed based on EVCS review websites (e.g., PlugShare). Forty-two existing EVCSs were included for our further analysis.

According to the survey in the Florida EV Roadmap report (2020), 60 % of MFH EV charging activities take place at public EVCS, while this number is as low as 20 % for SFH EVs. The reliance parameters for Outcome Equity strategy scenarios were then determined based on the current situation, where R_{SFH} = 0.2 and R_{MFH} = 0.6. Opportunity Equity strategy defined $R_{SFH} = R_{MFH} =$ 0.4 to disregard heterogeneous

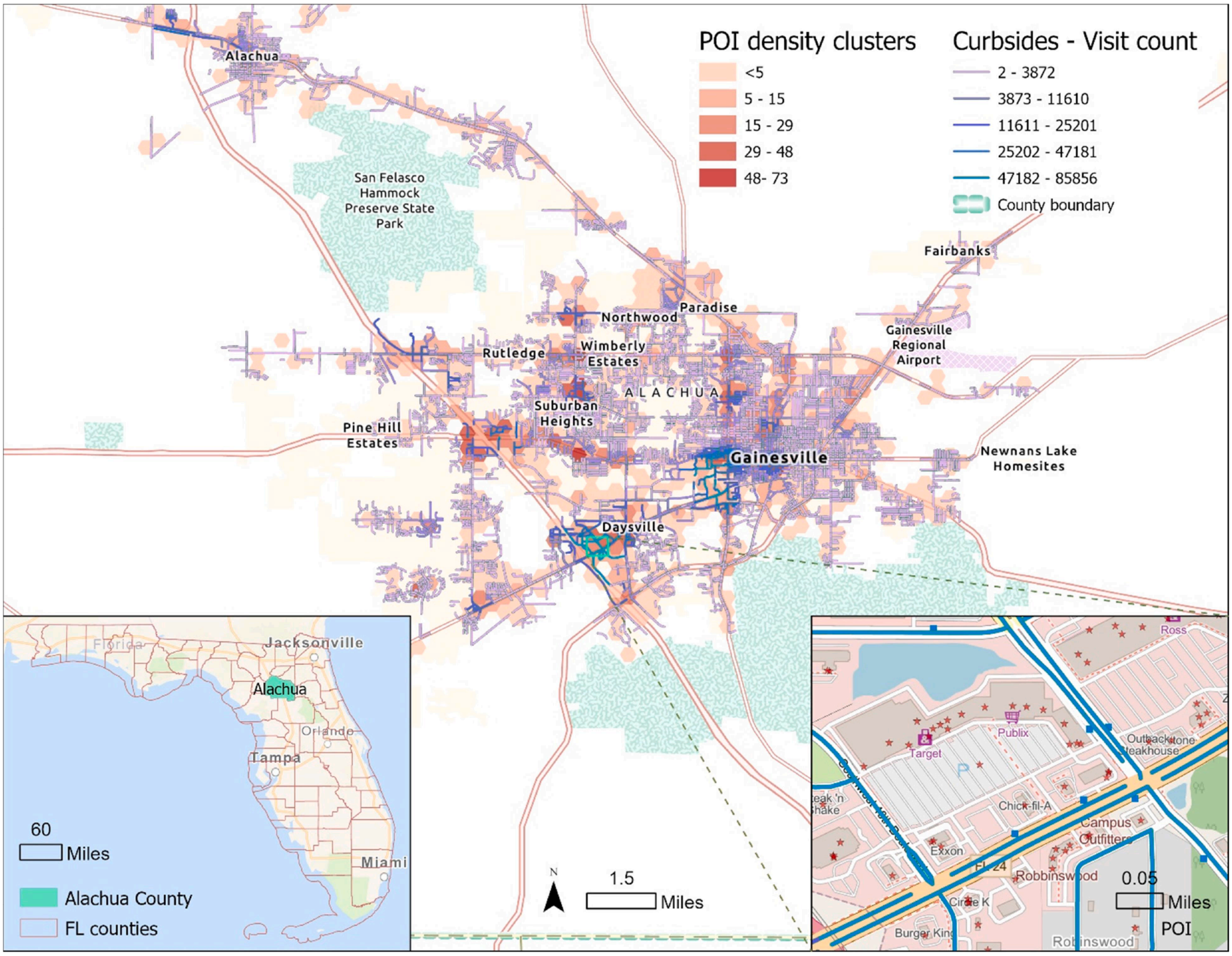

Fig. 4. Locating candidate curbsides for installing EVCS.

reliance. We finally generated EVCS allocation plans under three strategic scenarios based on rankings of candidate curbsides in the study area with the TOPSIS model according to these semantic parameters. Fig. 5 shows the results under the assumption of moderate incentive on MFH EV uptake (i.e., *Ratio* = 2).

4.3. Comparative analysis of case study results

4.3.1. Comparing the productivity of EVCS across strategic scenarios

Our case study of Alachua County demonstrates that the proposed planning framework effectively assesses different planning strategies that result in various performances across equity and productivity objectives. Fig. 6 shows the origins of productivity for the allocated EVCSs in strategic scenarios, which reveal that the three strategies serve distinct user groups as designed. In all scenarios, most of the anticipated EVCS productivity is attributed to guest charging activities. The percentage of productivity conducted during visiting activity could maintain a level above 80 % under the most productivity-targeted scenario. However, the percentage of residential charging activity would increase with the expanding installation of EVCSs under all strategies. The Productivity (Non-Equity) strategy shows the slightest improvement, from 3 % to 18 %. This indicates an insufficient supply of charging capacity for residential charging among SFH and MFH users. The Opportunity Equity scenario shows the highest support for the charging demand of SFH residents. Under the broader adoption of EVs, residential charging among SFH users is predicted to increase from less than 1 % to 25 %, while for MFH users, residential charging only reaches 13 %. In comparison, the Outcome Equity strategy successfully generates a large portion of MFH charging activity as anticipated, increasing from 9 % to 37 % of the total charging activity.

The use-productivity of the three scenarios varies in response to the distinct origins. Specifically, the Productivity (Non-Equity) scenario and Opportunity Equity scenario yield comparable total charging productivities, while the Outcome Equity plans generate significantly lower productivity (Fig. 7). For example, in the current context of the EV market (BAU scenario), Outcome Equity plans result in approximately 25 % less productivity compared to other plans. We thus cautiously conclude that the emphasis on local MFH charging activity is related to decreased overall use productivity in the current landscape of Alachua County.

However, the results also imply the two following ways to plan for equitable EVCS distribution while maximizing productivity. First, the Opportunity Equity strategy is the most efficient to achieve equitable accessibility in an expanding market in this case. This strategy increases productivity slower than the Non-Equity strategy but eventually reaches a comparable level when the EV number approaches 10,000. Second, the increase in MFH EV market share, from low ownership at present (i.e., “BAU” scenarios) to higher ownership (i.e., 1X scenario, See Fig. 7), mitigates the gaps between the Outcome Equity plans and Productivity plans. Under the Outcome Equity plans, the total productivity of EVCSs exhibits an increase when MFH residents have an equal likelihood of owning EVs as SFH residents (i.e., *Ratio* equals 1). This increase is

Table 3
XGBoost-based EV distribution projection model variables at the CBG level.

Variables ($N = 160$)	Mean	Median	Std. Dev.	Min	Max
Numbers of Households	742.388	637.5	399.272	32	2659
Housing types					
Single family households share	56.65 %	64.47 %	34.50 %	0.00 %	100.00 %
Mobile Households Share	34.95 %	17.54 %	37.06 %	0.00 %	100.00 %
Multi-family Households Share	8.40 %	0.00 %	15.50 %	0.00 %	83.96 %
Vehicle availability					
% of HH with 1 vehicle	37.01 %	35.25 %	14.52 %	7.78 %	100.00 %
% of HH with 2 or more vehicle	42.94 %	41.61 %	19.99 %	0.00 %	92.22 %
Household income					
< 50k	44.47 %	44.70 %	20.11 %	1.00 %	100.00 %
50–100k	23.24 %	21.37 %	12.65 %	0.00 %	66.93 %
> 100k	18.43 %	13.88 %	17.06 %	0.00 %	71.33 %
EVCS accessibility					
Numbers of EVCS	1.73	0.00	3.60	0	19
EVCS per single-family household	0.049	0.000	0.319	0.000	3.800
EVCS per multi-family household	0.013	0.000	0.064	0.000	0.704
Share of SFH access to EVCS	35.63 %	0.00 %	48.04 %	0 %	100 %
Share of MFH access to EVCS	35.00 %	0.00 %	47.85 %	0 %	100 %

approximately 1.43 times greater than what is observed under the Non-Equity strategy.

4.3.2. Comparing equitable access to EVCS across three planning strategies

We measure EVCSs accessibility for each CBG from residential- and guest-charging perspectives. The prior indicates spatial proximity to EVCSs from SFH and MFH residents, while the latter accounts for chances to access EVCSs during guests' visits to amenities. In our case, residential accessibility is calculated by the share of households that have been covered by EVCS service areas (i.e., within 5-min walking distance). Guest charging accessibility is calculated by the percentage chances of visits that originated from each CBG to amenity centers adjacent to EVCSs. Access to EVCSs during parking for different purposes as residents or guests is equally important. They supplement EVCSs service coverage of each other and contribute optimal charging accessibility to the entire community and all groups of EV users. Fig. 8 maps the spatial distribution of EVCSs accessibility from both lenses under the three scenarios. The three strategies alter the geographical distribution of residential charging access more visibly than guest charging access.

We aggregated resident charging accessibility and guest charging accessibility of public EVCS plans to compare the performance of different strategic scenarios (Fig. 9). The Outcome Equity scenario demonstrates the most extensive residential charging access for MFH residents, exceeding 70 % coverage with the wide EV adoption. On the contrary, the Productivity strategy generates around half of the resident charging access as the Outcome Equity strategy does. Under all strategic scenarios, SFH EV users have less access to EVCSs adjacent to their homes, with the Opportunity Equity strategy offering the best charging coverage reaching over 20 %. One reason for such divergent residential charging accessibility between SFH and MFH is the local land use pattern (Orsi, 2021). The higher-density residential communities tend to locate in the areas adjacent to amenity centers, while SFH clusters are often remote from them (Dong, 2020). The guest charging accessibility only varies by different strategies with no confirmed distinctions between user groups, except for the Outcome Equity scenario. This scenario provides higher guest charging access for MFH residents than SFH residents, yet the coverage percentage is the lowest among the three scenarios.

4.3.3. Place-specific EVCS planning strategies for productive and equity

The case study demonstrates that our proposed planning framework effectively ensures use-productive and equitable EVCSs allocation. Suggested plans under all scenarios contribute to significant improvements in public EVCSs productivity and charging accessibility for MFH residents. This is even true under the Non-Equity strategy, which only aims at maximum productivity. However, the comparison of strategic scenario planning outcomes further suggests a deviation between MFH access to EVCSs and overall productivity, which amplifies with the EV market penetration levels. To be specific, if planners take the high reliance of MFH residents on public EVCSs under consideration (i.e., Outcome Equity strategy), the allocated plan will not achieve maximum productivity of EVCSs.

The research findings suggest three local adaptive pathways toward a more productive and equitable future of charging capacity distribution. First, local planners should choose the most suitable allocation strategy to balance the two goals. In our case study, the county can start with the Opportunity Equity strategy since it prioritizes existing EV owners who utilize charging stations the most, as opposed to the Outcome Equity strategy. Allocation plans in this scenario ensure EVCSs serve both SFH and MFH residents, allowing for a co-benefit of productivity and equity. Meanwhile, the adaptive pathways extend beyond the strategic EVCS allocation, as the deviation between the two objectives stems from the contexts of the local EV market and land use (Orsi, 2021). We suggest facilitating the MFH EV market through subsidies or incentives for innovations to make EV purchases as affordable for prospective MFH users as for SFH users. Equity-aimed strategies can be more productive in a context with increased EV penetration among MFH residents. In addition, the final adaptive pathway suggests reforming local land use patterns and advocating mixed-used developments. Allocated EVCSs partially fail to serve MFH residential charging while simultaneously ensuring the frequency of guest visits due to some MFH communities being located far from urban amenities. Thus, mixed land use that bands MFH use with amenity centers may also mitigate the deviation and promote co-beneficial plans.

5. Discussion

5.1. Findings and implications

The existing EVCS planning approaches have not fully addressed the issues of equity and use-productivity, especially through a future-oriented lens. We proposed an anticipatory planning framework for curbside EVCS allocation in urban amenity centers to address inequitable charging accessibility and uneven utilization. Our case study of Alachua County, FL, further suggests incremental and adaptive planning for when and where to place curbside EVCSs across three equitable strategies. The comparison among different strategic scenarios divulges the trade-off between equity and productivity objectives that amplify as the EV market expands. Equity-aimed strategies are effective in diminishing charging accessibility gaps between user groups and planning for increasing charging demand from MFH EV users. However, local planners should balance the two objectives when MFH EV penetration is low.

This EVCS allocation framework contributes to methodologies of adaptive planning in the face of disruptive technologies. We utilize anticipatory planning methods, such as scenario-based analysis, to explore plausible future contexts of the EV market and allocation strategies. Anticipatory planning techniques allow for the investigation of adaptive pathways to address the challenges of uncertainty (Birchall et al., 2021). However, applications of such methods in infrastructure planning for emerging urban technologies are rare (Borozan et al.,

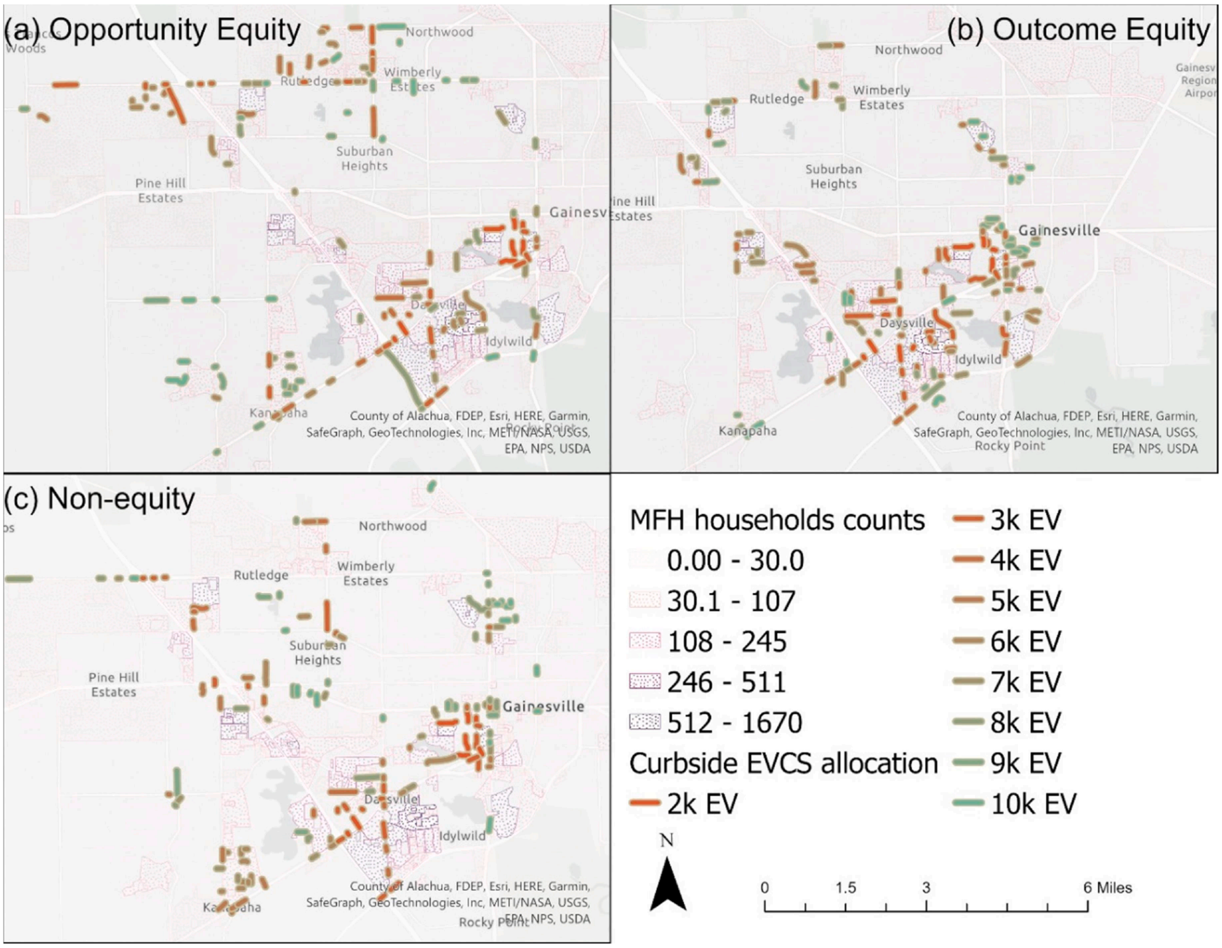

Fig. 5. EVCS allocation on curbsides of amenity centers across three strategic scenarios.

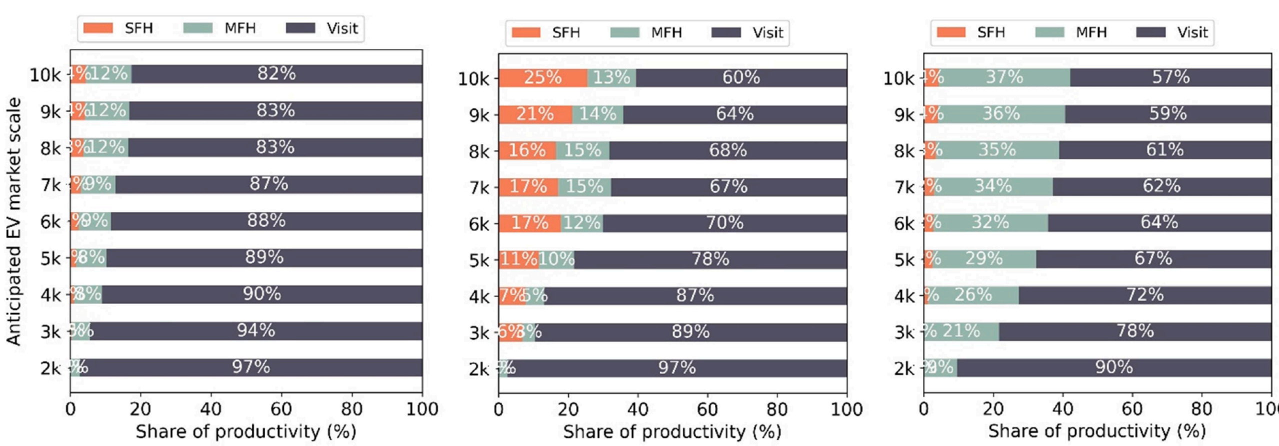

Fig. 6. Productivity origins from different user groups (a) Non-Equity scenario; (b) Opportunity Equity scenario; and (c) Outcome Equity scenario.

2022).

Static EVCS planning, which only considers existing charging demands, may fall short in meeting the unanticipated demands that arise in the evolving EV market, particularly among historically underrepresented user groups (Kang et al., 2022). In contrast, our strategic scenarios anticipate uncertainties and propose adaptive EVCS allocation plans to accommodate the expanding EV market among MFH occupants (Burk et al., 2020).

Our research is innovative in optimizing equitable charging access for MFH residents by considering their reliance on public EV charging. Despite the growing attention given to MFH EV adoption and charging capacity (Ge et al., 2021), there is a lack of solid investigations into their specific behaviors and demands in the unpredictable EV market. We address this gap by establishing the allocation framework on the holistic understanding of human-centered parameters that capture the charging and travel behaviors of MFH users. The heterogeneous public charging reliance among user groups is further used to construct three strategic scenarios that shed light on the pathways toward the equitable goal.

In addition, the allocation framework considers the charging activities of both residents and guests when locating optimal sites for EVCSs

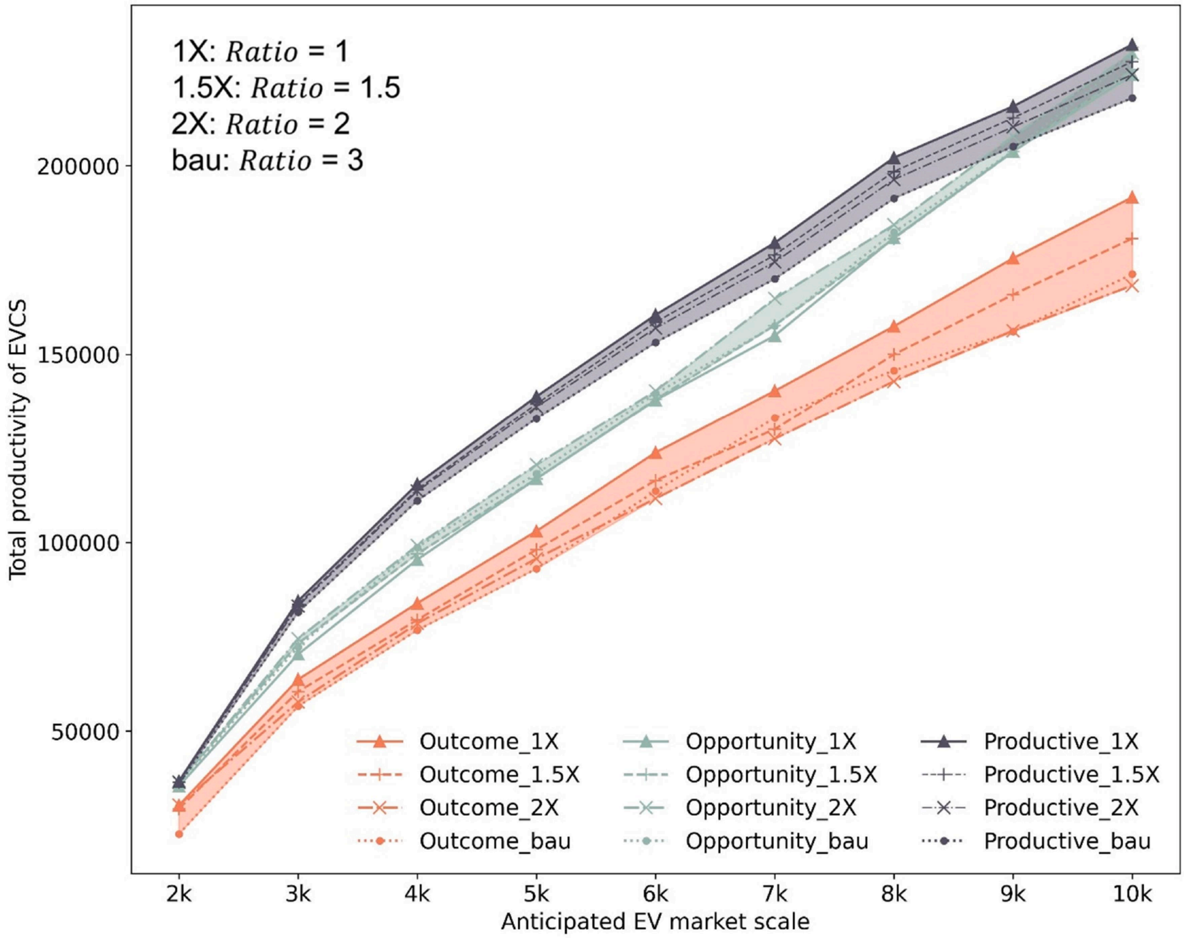

Fig. 7. Overall EVCS productivity of 12 plans under the three scenarios.

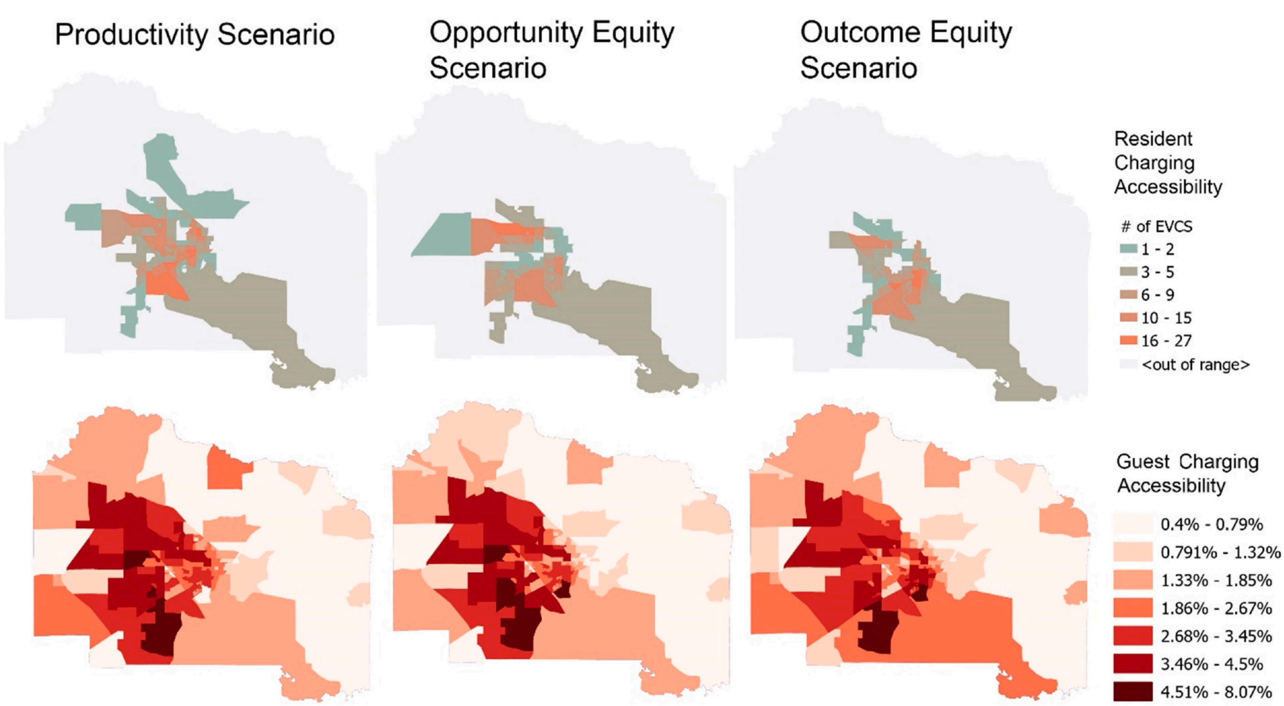

Fig. 8. Mapping EVCSs accessibility of residential charging and guest charging at the CBG level across scenarios.

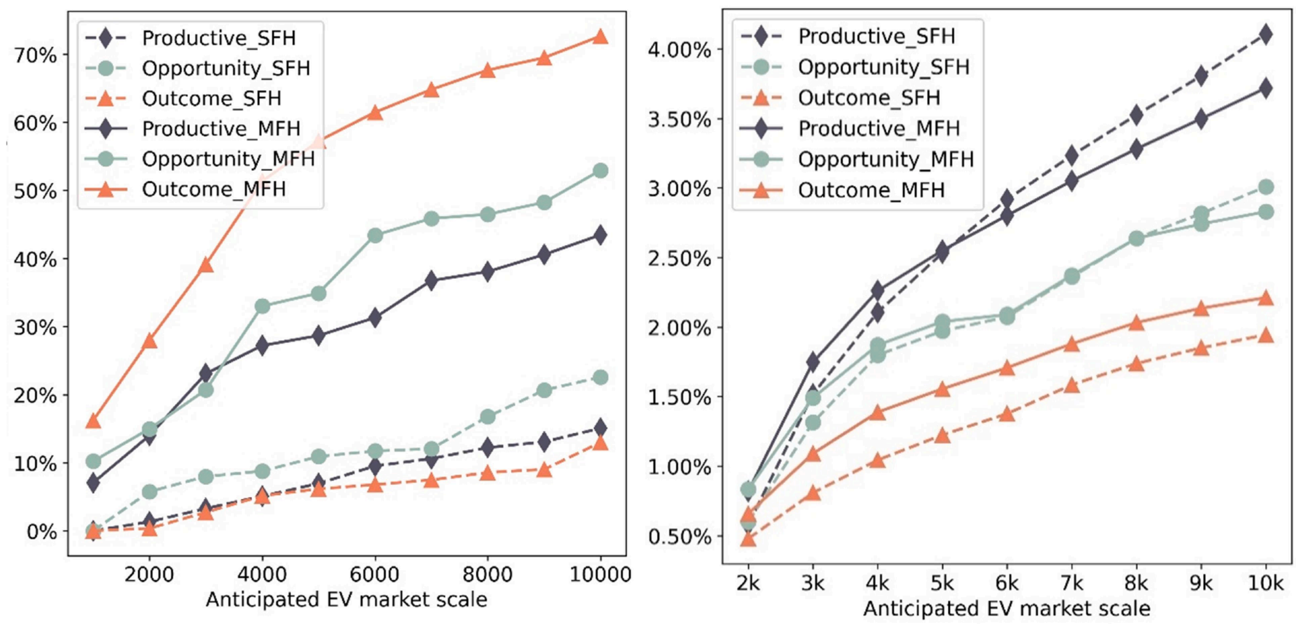

Fig. 9. Aggregated EVCSs accessibility for (a) residents; (b) guests and visitors.

and evaluating charging accessibility. Existing studies have focused either on stop-based charging opportunities (Dong et al., 2019; Kontou et al., 2019) or home charging, which the latter skewed to the demands of SFH residents. Our research eliminates potential bias and guarantees an equitable prerequisite for infrastructure planning. The designed method effectively captures the emerging MFH EV charging demands since it is sensitive to EV adoption changes across spatial areas.

Our study is among the first to apply a few cutting-edge strategies to pursue productive EVCS allocation while catering to various user groups. First, we focus on curbsides in urban amenity centers to take advantage of the high visibility, ubiquity, and accessibility of curbside spaces to increase EVCS usage (Yang et al., 2014). Existing studies on blocks or road segments still focused on off-street charging (Yu et al., 2022). This research explores the potential of allocation plans to boost the productivity of both charging stations and curb spaces, which fills the knowledge gaps in curbside EVCSs to keep up with the increasingly diversified uses of curbsides (Diehl et al., 2021). Second, our incremental procedure is novel as it reflects the EV adoption raises caused by better charging accessibility across the allocation process. While other EVCS allocation studies only acknowledge charging accessibility as a critical predictor of EV adoption (Globisch et al., 2019; Hsu & Fingerman, 2021), our framework reflects this relationship with the design of a recurrent procedure. This ensures the productivity of every additional EVCS dynamically and possibly facilitates EV uptake, especially among MFH users.

5.2. Limitations and future work

Undeniably, our study has limitations in three aspects, which in turn open up future research opportunities. The first aspect pertains to the scope of our study. While our study focused on curbsides, we have not discussed how other curb uses (e.g., pick-up and drop-offs, and short-term parking) would be affected by EV charging (Noland et al., 2022; Wang et al., 2022a). Future studies may need to coordinate EVCSs with other curb uses to achieve sustainability and safety goals. Our method also did not consider contextual factors, such as transportation and energy system, in the analysis of curbside EVCS suitability. Future research should couple the road networks to fully consider traffic flow and integrate power systems to pre-assess the energy capacity, especially in low-income MFH communities.

Second, we lacked fine-scaled EV adoption data to predict the future EV market for each CBG. We have strategically downscaled county-level data to form a dataset at the CBG level, which is deemed sufficient for our specific case study. Further application of our method can take advantage of available CBG-level EV data collected by surveys and sensors.

Additionally, our TOPSIS method disregarded residents' characteristics that may alter their attitudes toward EV adoption and their demands for public charging (Canepa et al., 2019; Guerra & Daziano, 2020), such as the presence of dedicated parking spaces for MFH residents. This may bias the prediction of EV distribution among neighborhoods. Instead, we estimated the EV adoption of CBGs based on their demographic patterns, such as income and the number of vehicles (He et al., 2022b). Future studies may acquire detailed profiles of neighborhoods to deepen the understanding of the MFH charging dilemma.

Furthermore, our study has not accounted for the intricacies of more complex EVCS market scenarios. We assumed EVCSs as public facilities that provide essential services. However, in practice, there are various types of EVCSs that differ in their business models and services, leading to a complicated equity problem. For instance, some EVCSs may seek profit, while others may provide exclusive services for EVs of specific brands. Future studies could explore the impact of such differences on social equity if the required data becomes available. Nonetheless, our proposed method can still be applied to specific charging networks by isolating EVCSs of certain types from the larger group, as equity and productivity remain common goals.

Lastly, we primarily focused on stationary EVCSs, which have been prevalent in most U.S. cities. As innovative EV charging technologies emerge (e.g., rapid, mobile, and wireless charging), future-oriented planning can be more proactive and adaptive to new scenarios arising from these innovations. However, our incremental planning paradigm provides the flexibility for integrating diversified charging options.

6. Conclusion

This study proposed an anticipatory EVCS planning framework to optimize objectives of use-productivity and equity when allocating EVCSs on urban curbsides. In the case study, we compared three equitable strategies with scenario analysis, including Productivity (Non-Equity), Opportunity Equity, and Outcome Equity strategies. We have observed an evolving relationship between the two objectives. As the local EV market expands, there is a projected increase in the conflict between equitable charging access and overall productivity. To address this, we suggest that the strategic allocation of EVCSs should be accompanied by EV market incentives or mixed-used urban MFH development planning. The novel anticipatory planning framework can be generalizable to other EV-initiating cities or isolated EV charging networks. It is also adaptable to EVCS allocation in built environments other than curbside areas. The framework provides a valuable reference for local planners to balance the two objectives through practical scenario-based planning. In light of the uncertain EV market, particularly with the potential increase of MFH EV users, EVCS planning requires additional future-oriented strategies. The anticipatory planning approach empowers local communities to proactively plan for and adapt to uncertain challenges brought by the energy transition, all while ensuring that social equity goals are met. In the long run, the profitability of the anticipatory EVCS plans could incentive public EVCS investments and accelerate transportation electrification.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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