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Infrastructure enabled and electrified automation: Charging facility planning for cleaner smart mobility

Bahar Azin [a], Xianfeng (Terry) Yang [a,*], Nikola Marković [a], Mingxi Liu [b]

[a] Department of Civil and Environmental Engineering, University of Utah, Salt Lake City, UT, USA
[b] Department of Electrical and Computer Engineering, University of Utah, Salt Lake City, UT, USA

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ABSTRACT

Due to higher energy efficiency and lower emissions, electric vehicles (EVs) have become attractive transportation means in developing cleaner mobility systems. Moreover, many future automated vehicles (AV) can be electrified. Hence, existing market will experience a drastic growth in automated electric vehicles (AEVs). For infrastructure enabled automation (IEA), charging facility planning is required to accommodate the increasing AEV charging demand. The planning process must also account for their impact on the power grid. This study presents an integrated demand coverage optimization model over a coupled power-transportation (CPT) network. This model aims to pinpoint candidate locations of AEV charging stations that would serve the most charging demand in the transportation network, considering the upcoming technologies in AEV also will affect the charging behavior that can influence the charging system. Besides, power grid limitations at each charging station are considered for the minimal power cost of the network. The developed model is applied to Utah state road network to determine the optimal charging station locations.

1. Introduction

The growth of energy consumption and corresponding environmental pollution of the transportation system has drawn more attention to promoting more efficient and greener vehicles. The introduction of electric vehicles (EVs) created an alternative transportation option that is energy efficient and produces fewer emissions than traditional gasoline and diesel vehicles. A combination of EVs with a low carbon power grid can promote the sustainability of this transportation mode (Onn et al., 2018). Besides, automated vehicles (AV) have shown significant improvement in reducing pollution due its driving mechanism and efficiency (Yang et al., 2020; Huang et al., 2018). Utilizing AV in ride sharing in a connected environment is shown to improve air quality and lower environmental impacts (Rojas-Rueda et al., 2019). Meanwhile, today's consumers are demonstrating increased interest in more environmentally conscious brands and products that support sustainability. Therefore, it is expected that the market penetration of EVs will dramatically grow in the upcoming years for its environment-friendly and efficient features (Bastida-Molina et al., 2020). Importance of EV market share becomes even more significant as these vehicles are predicted to be used in automated electric vehicles (AEV) in near future considering its environmental benefits (Zhuge and Wang, 2021). In addition, as AEV functioning system is based on automation, there is a higher chance that future AEVs be electrical due to their compatibility.

Range anxiety often plays as a key factor in affecting users' willingness to buy AEVs. Hence, the current charging network needs to be expanded and more charging facilities will be required to cope with the increasing demand. With the boom of AEVs, the charging infrastructure available for EVs need to expand to accommodate the surplus charging demand. On the first hand,

* Corresponding author.
E-mail address: x.yang@utah.edu (X.(T. Yang).

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the AEV charging demand might be different from EV demand due to automation attributes. Driving assisting features of the AEV results in more vehicle miles traveled (VMT), which brings up the necessity of more charging facilities due to the higher demand. Also, ride-sharing and automation require more fast-charging stations to maximize the service time and decrease the time spent for recharging. On the other hand, AEVs charging demand mainly entails vehicle behavior's study rather than drivers in human-driven EVs, which relaxes drivers' behavior constraints in charging allocation. Being in a connected environment, vehicles will have access to charging facilities' real-time data that assist in optimal charging timing and location choice, reducing the cost. One of the significant differences between AEV and EV charging demand studies is that the range anxiety is omitted in AEV which makes charging schedule more flexible. This flexibility is even higher in fully autonomous vehicles as users can assign their vehicles to be recharged without waiting at charging stations.

However, it shall be noted that the placement of additional AEV charging facilities can greatly impact the power distribution grid by bringing more electricity load to the power network (Liu et al., 2019a). When the market share of both EV and AEV increase significantly, an adapted charging facility planning for the infrastructure enabled automation (IEA) is necessary (Zhuge and Wang, 2021). The growth in AEV demand need a corresponding planning and policy to meet the transport demand and a study for its impacts on land use. Moreover, the newly deployed charging stations shall be subject to the power demand pattern. Hence, charging station sizing and allocation should be planned over the coupled power-transportation (CPT) networks, which have not been well studied in the literature yet.

More specifically, the spatial distribution of AEV charging stations should be optimized to balance the AEV charging demand, reduce congestions, optimize the power flow, and avoid over-capacity usage. As the transportation demand pattern is not stationary, AEV users can charge if there is a station in their travel routes and within an acceptable range of the intended routes. However, the limited range of AEVs can prevent users from longer trips (Chen et al., 2016; Loeb et al., 2018). Development of infrastructure with sufficient chargers on the other hand can improve the drivers' charging rate which will battle the limited range of AEVs (Zhang et al., 2021). Also, since the transportation pattern is a time-varying variable, it will affect AEV charging demands depending on traffic flow. As such, charging facilities should be placed in locations to maximize traffic flow exposure especially around major roadways (Huang and Kockelman, 2020). Charging waiting time will vary depending on the power level the station can provide and the arrival rate of vehicles. Also, charging behavior is another factor that must be considered in planning for charging infrastructure as it will impact the capacity of network and demand distribution. As a result, special consideration needs to be placed on chargers' assignment to minimize wait time while not overloading the power network during peak hours. Studies have proven optimizing the charging time by time-of-use electric price could reduce energy cost and CO_2 emission (Rupp et al., 2020). On the other hand, fitting the available infrastructure to cope with automation is another key measurement that need to be considered in planning charging framework.

Charging AEVs can impact the power distribution network by draining power network, causing severe power fluctuations, and in some cases, by exceeding power load past maximum system capacity due to high usage (Srithapon et al., 2020). The maximum power load that can be fed to each station is dependent on the link, transformer's capacity, and distribution network. The power feeders' arrangement and the number of branches will affect the power load variation in each feeder in the system and will normalize the power load during peak hours. Hence, the planning of a charging network that concerns the charging demand would be arranged to minimize the power load cost and decrease the system's risks by normalizing power load. Such an optimization problem could be formulated as a time-varying problem taking into account the AEVs' charging demand and power load varying throughout the day. Studies in literature mainly focus either on land use and transport demand coverage or power network design, however, an integrated planning is needed to consider both sides of charging infrastructure and emphasized on the IEA, which this study tries to fill this gap. More specifically, the model is with a multi-criteria framework that optimizes the number of encountered traffic flow and power cost while considering the voltage drop of feeders and transportation constraints of the AEVs. The output will be the recommended allocation of charging stations within a power network system and the level of covered demand for the daily charging pattern. To optimize this problem in this study, NSGA-II, an evolutionary algorithm (EA), is employed. NSGA-II is an elitist genetic algorithm for multi-objective problems that use the crowding distance to find the non-dominated set of solutions (Blank and Deb, 2020). The case study used for the model testing is the layover of the state of Utah's traffic and power distribution networks to find the optimal locations of charging stations while considering all aforementioned limitations and constraints. The results show the planning of charging stations that would result in the maximum AEV charging network coverage with minimum power cost in the network.

2. Literature review

In the literature, EV charging facilities can be located for residential or public use, each with unique features. Fast charging, lower cost, and more driven mileage are beneficial aspects of public facilities. Despite the high price of public fast chargers, they significantly promote customers' tendency toward EVs acquirement. Still, the lack of adequate charging stations is a significant consumer barrier for an EV purchase (Engel et al., 2018). Recently governments have been pushing legislation to speed up infrastructure expansions for charging facilities in urban areas in order to accommodate increased demand and better study and plan system management (Schott et al., 2015). The principal components impacting the charging system management design are electrical providers, urban network and site hosts, and customers' social behavior. The impact of EV owners on the system has led to the incentive programs that are being developed for vehicle charging sessions. Nevertheless, extensive groundwork is needed for the charging system management to adapt to both providers and consumers.

Table 1
Literature in integrated charging network allocation.

Study	Objectives		Output	Method
	TN	PN		
Ucer et al. (2019)	×	✓	Number of ports in each stations, charging capacity and queuing analysis and	Simulation
Alhazmi et al. (2017)	✓	×	Number of charging stations and covered demand, power load distribution	Branch and bound optimization
Wei et al. (2018)	✓	✓	Individual EV routing (UE) and power distribution and cost	Best-response optimization
Liu et al. (2019a)	✓	✓	Captured flow and power loss	Genetic algorithm
Chen et al. (2016)	✓	×	Number of stations, charged vehicles, and investment costs	Agent-based simulation
Huang and Kockelman (2020)	✓	×	Station allocation and network profit	Genetic algorithm

There is a wide range of studies regarding the EV network and charging system both in transportation and power fields. Adding a new charging station to the power grid will impact voltage stability, peak load demand, power distribution quality, and the transformers' performance (Deb et al., 2018b). The effect of charging station power load on the network's reliability can be significant, so chargers' placement depends on the type of installed charger and the node's voltage (Deb et al., 2018a). By development of the Vehicle-to-Grid (V2G) technology with the load smoothing and revenues it can bring to the power system, the significance of the charging stations design has been extended (Deb et al., 2018b). Utilization of V2G and controlled charging strategy have proved to reduce emission up to 11% additionally (Xu et al., 2020) which is a booster approach to be considered in future charging facilities. Studies about the charging stations' power system typically focus on optimizing the system's costs or the grid's power load. Stabilizing the power load profile can control the grid's thermal rating and keep the voltage drop within a standard range (Liu et al., 2019b). A recent study has reviewed the impact of customers' charging behavior to optimize the power load in two phases and optimize the benefits of both EV owners and the power grid (Fu et al., 2018). Plus, the users' behavior and arrival rate of the EVs at the charging station will affect the system's power fluctuation, which needs to be planned (Chen et al., 2013a). Variation of charging behavior will result in different load on system which can influence the necessary planning for charging facilities (Crozier et al., 2021). Multiple studies have also studied the power load cost optimization of the distribution system, which is affected by the system's power grid features and demand load (Srithapon et al., 2020; Yan et al., 2019; Zhang et al., 2015). The cost reduction for both users and the system has been studied by simulation or revolutionary algorithms (Hafez and Bhattacharya, 2017; Liu et al., 2020; Zhenghui et al., 2014).

On the other hand, some studies emphasized the user experience and attempted to plan for the charging station system's transportation section. The EV charging system in urban planning relies on travel demand, costs, EV travel range, and parking facilities to cover the demand and allocate stations optimally (Chen et al., 2013b). The charging infrastructure studies also suggest integrating the charging facilities with other transit modes to optimize their impact on urban transportation. As the distance an EV can travel for each charging session is limited, the stations should be located so that EVs can still maximize the range of their trips (He et al., 2019). The optimization frameworks mostly use daily trip data and charging demand to find the stations' optimal sizing (Ahn and Yeo, 2015). However, the charging infrastructure is impacted by the power grid system and the transportation network. Therefore, the optimization model's ability to combine the power grid and the transportation network has been more of a focus lately. Frameworks that consider both power grid and traffic flow constraint develop a comprehensive optimization (Liu et al., 2019a). Moreover, the power grid limitations could be considered as constraints in the optimization model (Fazeli et al., 2020; Zhang, 2018).

However, studies integrate power and transportation network are mostly focused on human-driven EVs exclusively. On the other hand, studies that design charging infrastructure for AEVs are based on transportation network requirements (Chen et al., 2016). Studies with integrated models tried to evaluate a singular objective considering interest of each individual network. Although in the research by Liu et al. (2019a) both networks are included in the optimization model, vehicles SOC are neglected. The multi-objective optimization is solved by weighting objectives into one that might not reflect each network's significance in charging planning. Table 1 summarizes literature of integrated charging facilities and their outputs besides the objectives considered in their modeling.

Primarily, this study has included the station dispersion within the network compared to previous studies that consider both transportation and power networks. Scattering of the stations within the route ensures that AEV can complete the trip without running out of charge, especially for trips more than vehicle driving range. Checking the stations' dispersion distance prevents centralizing stations close to high-demand areas and ensures adequate stations along roads. Moreover, studies that include both power and traffic networks typically do not comprise either network interests in allocation optimization. In the literature, studies have traffic flow data and user-equilibrium (UE) to measure the charging power load on the grid and overlook the charging demand planning (Wei et al., 2018; Ucer et al., 2019).

On the other hand, the power grid objectives are ignored in charging planning, and power distribution constraints are only subjected in modeling (Alhazmi et al., 2017). Also, this study, unlike previous that use urban traffic data studies (Zhang and Yang, 2020; Zhang et al., 2020), uses actual trajectory data from a larger-scale network accounting for urban and long-distance trips. The latter point helps reflect the limited range of EVs in longer trips. In this study, an optimization model is developed to allocate charging stations for AEV. The contributions of this paper include:

Table 2
Features comparison between EV and AEV with different level of automation.

Attribute	EV (level 0–2)	Level 3 AEV	Level 4 and above AEV
Driver involvement	Fully	Fully to partially	Partially to none
Routing decision	Driver	AEV/Driver	AEV
Recharging requirement	Driver	Driver	AEV
Preference of charging at travel ends	No	No	Yes
Recharge en-route	Yes	Yes	Yes
Scheduled charging station	Fixed	Flexible	Flexible
Real-time charging network data	N/A	Yes	Yes
Flexible charging plan	No	No	Yes
Picking charging station	Driver	AEV	AEV

- A multi-objective optimization model that considers both power system and urban traffic network interests as objectives. The framework is developed based on both short and long trips for an integrated network and the range anxiety impact on planning policies.
- A novel modeling including both maximum covering problem and dispersion in locating stations to prevent the centralization of stations in zones with high traffic demands. Dispersion of charging facilities in the network enhances the accessibility of users for smart infrastructure and optimal land use.
- Generate charging station infrastructure for state of Utah as a case study using scaled GPS trajectories and standard distribution network. Multiple experiments have been done to understand the impact of the anticipated increase in driving range on AEV market penetration rate.

It is worthy of noting that vehicle automation involved in this study includes features both in lower levels of automation such as assisted driving (as in level 3) and higher levels (level 4 and higher) when a vehicle can be fully autonomous. Therefore, self-driving vehicles and human driving vehicle with some level of automation is the point of interest of this study. To distinguish the differences between conventional EV (level 0–2), AEV level 3, and AEV level 4 or higher, a table of features comparison is presented at Table 2. It shall be noted that level 1 and 2 AEV are only equipped with limited driving assisting technologies and require the driver's full attention. Therefore, it is considered to be the same as level 0 when studying the charging behaviors.

As shown in Table 2, the automation has enabled options such as providing routing decisions, real-time data of charging stations and their waiting time, and consequently providing suggested charging stations for vehicles to recharge. By progression of automation in driver-less AEV, vehicles can be sent to stations without requiring the driver to be present, which creates the flexibility of charging timing for users. This choice is influenced by the introduction of EV to AVs already available in the market and evolving technologies that will be present in the future AEV charging system. The following section will describe the overview of the methodology in the study.

3. Methodology

To find a realistic charging plan, charging facilities should be modeled in a CPT optimization framework to allocate the AEV charging stations in the optimal locations. The goal is to maximize the charging stations' demand coverage while minimizing the network's power cost. Minimizing the distribution network's power cost along the transportation network objective function creates a multi-objective optimization model. The consideration of both networks for the problem originates from the fact that both systems are tied in AEV charging system planning and could influence the results.

Traffic demand, power distribution grid details, drivers' behavior, travel patterns, and AEVs' battery features are factors that must be considered for the CPT network chargers allocation. In this study, each candidate station service range is evaluated using the AEV average remaining range and trip distances. Therefore, the flow capturing problem (FCP) is used to model the traffic network of the problem. The set of nodes covering a path will be determined by evaluating each station's service range. Charging demand is estimated based on the daily trip data and the state of charge's (SOC) randomness. Also, the number of vehicles that each station in a time frame can serve depends on the battery capacity and the current changing rate of chargers. The optimal locations of chargers are influenced by the power grid and the location of power buses (i.e., power nodes in the grid). Network power load can be fluctuated by chargers' locations and the level of power demand assigned to them. Interception of the transportation network and distribution network will select the potential locations of chargers, where the model's objective functions will determine the optimal nodes that can produce the best results from the CPT's perspective. The trade-off between objective functions will identify the optimal locations that meet both network purposes. An overview of the problem layout is demonstrated in Fig. 1. Also the table of notation is presented in Table 3.

3.1. Chargers allocation optimization model

The penetration rate of AEVs can be converted into the number of AEVs available on the transportation network. AEV market share has increased significantly during the past years, and it is estimated to expand exponentially in the future. EV market share in the US is reported to be 2.7% in 2019 and is forecasted to be around 20% by 2025 (Muratori, 2020). The rising number of AEVs

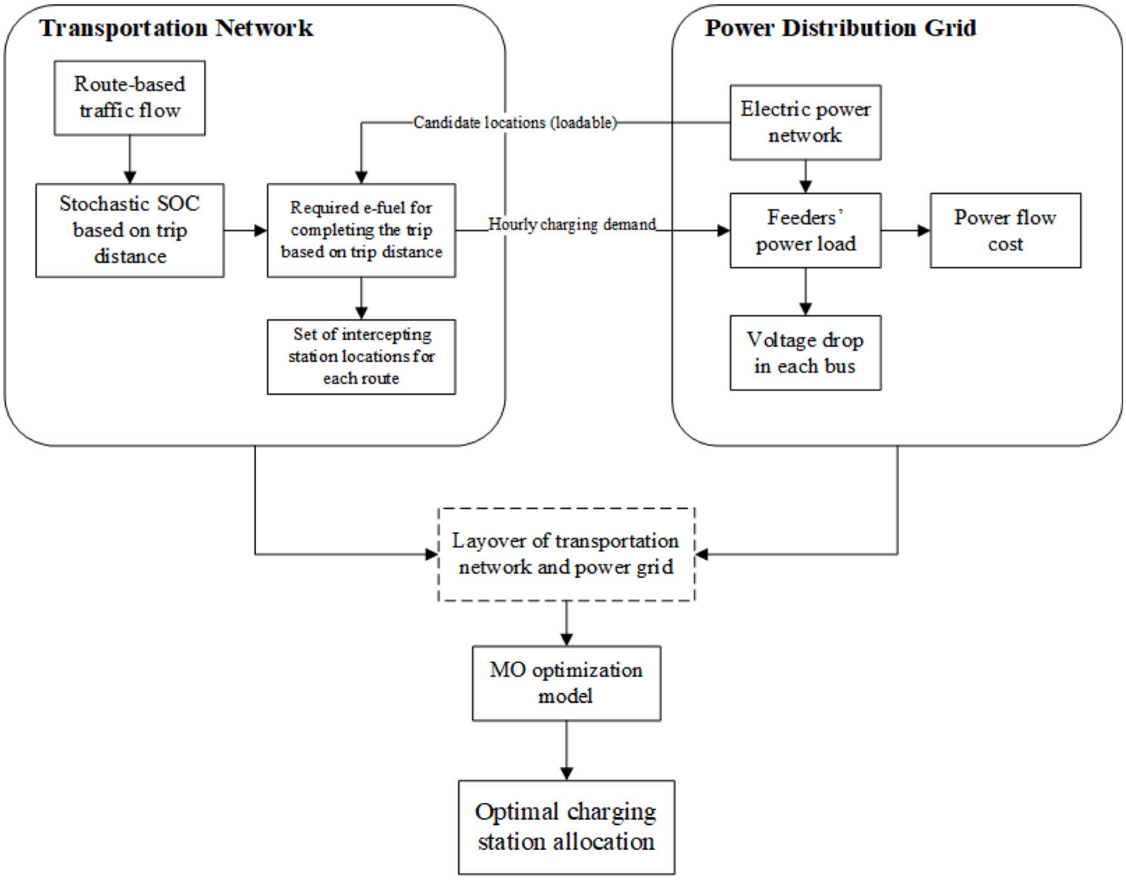


Fig. 1. Optimization scheme for optimal AEV charging station allocation.

Table 3
Table of notations.

Symbol	Description	Symbol	Description
Set and indices		Parameters	
F	Set of routes indicated by f	v	Voltage magnitude of feeders head (volt)
H	Set of nodes in power grid indicated by h	$X_{h,h'}/R_{h,h'}$	Reactance/Resistance of power line between nodes h and h' (Ω)
N_f	Set of nodes in H that can cover route f	Variables	
$\mathbb{C}$	Set of sorted nodes by distance from origin in N_f indicated by c[a]	d_f^t	AEV traffic demand on route f at t
h_c	cth bus node in set N_f	$l_f(.,.)$	Distance between power nodes on route f (miles)
T	Set of optimization time period indicated by t	ξ	Remaining battery of AEV
K	Set of automation level indicated by $k \in \{3,4,5\}$	t_{ch}	Time elapsed after last charging session (days)
U	Set of users in network indicated by u	$f_c(t)$	Probability of charging at t
Ω_h	Set of routes that can be covered by bus h	$\Psi^t(u,h)$	Probability of user u charging at node h at t
E_h	Set of buses directly connected to node h	$p_{h,d}(.)$	Charging demand power load at node h (kW)
S_h	Set of downstream power lines connecting to node h from feeders head	P_h^t/Q_h^t	Active/Reactive power load on node h at t (kW)
O/D	Indicator of origins/destinations	p_h^t/q_h^t	Active/Reactive demand power load on node h at t (kW)
Parameters		$p_{h,b}^t/q_{h,b}^t$	Active/Reactive base power load on node h at t (kW)
N_{ch}	Maximum number of facilities	V_h^t	Voltage magnitude of node h at t (volt)
L	Driving range of sample AEV (miles)	Decision variables	
α^t	Power rate cost at t (\$/kW)	x_f	Binary variable indicating coverage of route f
p_{ch}	Charging power current (kW/h)	y_h	Binary variable indicating charging station is setup at node h

[a] 1 indicates the closest and C in the furthest to origin.

demands corresponding planning for increased charging demand. Charging stations should be located to provide enough energy for AEVs driving through a specific path to complete their trips. Sufficient energy for AEVs can be provided by charging facilities distributed in a suitable range. From another perspective, each charging station should be placed to capture most traffic passing a specific route. This approach is formulated as the FCP that tries to find facilities' optimal location to maximize encountering traffic flow. In FCP, demand is a link-based variable in a transportation network and it can be captured if there is at least a facility located through the path.

Initially, the facility location problems were based on stationary demand in a set of origin and destination nodes (Kuby, 1987). Later, studies in this area debated that facilities are spots that will serve the demand in the form of traffic flow passing by the locations (Hodgson, 1990; Kuby and Lim, 2005). The latter fact brought up the need to locate facilities to serve the most demand, such as road intersections or heavily trafficked areas. Allocation of facilities, specially refueling location, and serving maximum demand can minimize the cost of infrastructure development and reduce chance of locating excessive facilities in the same area. Preventing individual facilities markets from overlapping creates a unique demand share for each station that will increase the profit for investors. Further, optimal locations can build a basis for future studies to equilibrate charging demand and manage stations congestion. Mirhassani and Ebrazi (MirHassani and Ebrazi, 2013) justified this problem by network expansion and refueling location optimization in the literature. Following the same line, Chung and Kwon (2015) further used the model for electric vehicle charging stations allocation. However, the limited travel range of AEVs needs to be considered in FCP since locating one facility along a path may not be sufficient for AEVs to have enough charge for long trips.

In transportation planning, the origin–destination (O–D) table shows the number of trips for each pair of connected nodes in the transportation network. Assuming drivers typically take the shortest path to get to their destinations, travel counts of each path can be estimated. The shortest path between each pair of nodes can be measured using Dijkstra's algorithm. Traffic demand on each path can be covered depending on the charging station's distance to each node on the path. As AEVs have a maximum range (L) that can drive, they need enough energy to complete their trips. Based on common sense refueling (MirHassani and Ebrazi, 2013), the distance between two successive charging stations should be less than L. Therefore, for two successive nodes on a path with distance more than L, there should be at least two stations to serve the AEVs. Also, the fact that AEVs are usually at least half-charged at the origin and destination raises the need for at least one station at a distance of $L/2$ from origin or destination (for round trips) at most. If a candidate node in the power network exists within criteria that AEV can complete their trip, those nodes can capture the routes' flow (Kuby and Lim, 2005).

This study assumes that the sample vehicle has a driving range of 150 miles and a battery capacity of 30 kWh. Moreover, the vehicles scholastically pick the stations within route based on their SOC and trip length. Later assignment is used to demonstrate the variable charging behavior within users. Also, it is considered that vehicles with less than 30% charge will look for a station to recharge the vehicle. Furthermore, it is assumed that EVs only consume real power while charging.

In the developed optimization model, a binary variable (x_f) is used, indicating if the path is covered. Since in this study, long trips are also considered, if there is a route that exceeds maximum driving range, at least two or more stations are needed to provide adequate energy for the trip depending on the trip distance. Confined driving range of AEVs contradicts the FCP rule for a minimum of one station to cover the flow. Thus, both trip's distance and available facilities determine if the flow is captured. At the same time, for trips longer than driving range stations needed to be dispersed with reasonable distance so the vehicle will not run out of charge. Considering the limited driving range of an AEV, the distance between two successive stations in a route should not exceed the L.

Assuming the set of nodes in power grid (N_f) that can cover the path f is sorted by distance from the origin, and h_c shows the node c th ($c \in \{1, 2, \dots, C\}$) in the set of covering nodes, the station dispersion distance requirements are shown in Eqs. (1)–(3). Maintaining a maximum distance between stations is the p-dispersion (Kuby, 1987; Capar and Kuby, 2012) problem which is required for locating facilities for AEVs for long distance trips. In order to find the set of candidate locations intercepting each route, maximum spacing between consecutive stations ($l_f^{max}(h_{c'}, h_{c'+1})$) must be less than driving range (Eq. (1)). Moreover, Eq. (2) ensures that there is at least one station less than maximum distance where M is a very large number.

$$l_f^{max}(h_{c'}, h_{c'+1}) \leq x_f L \tag{1}$$

$$l_f^{max}(h_{c'}, h_{c'+1}) \geq l_f(h_c, h_{c+1})(1 + M(1 - y_{h_c}) + M(1 - y_{h_{c+1}})) \tag{2}$$

$$l_f(O, h_1)x_f \leq \frac{L}{2} y_{h_1} \tag{3}$$

where, l_f denotes the length of path f; x_f is the binary variable that equals one if route f is covered and equals zero otherwise; y_{h_c} is another binary variable that indicates if a station is set up at cth power node in set of covering nodes; and N_f is the set of nodes that traffic demand of route f can be covered depending on the position of the power feeder. Eq. (3) determines if there is at least one station in $L/2$ distance of origin in each path to intercept the traffic. Also, a set of candidate locations that include the set of buses covering the path is defined. Considering the initial state of charge (SOC) of the AEV and driving range of the vehicle, the set of candidate location for each path is described as:

$$\forall\ h_c \in\ N_f\ :\ l_f(O, h_1) \leq L/2 \tag{4}$$

$$\forall\ h_c \in\ N_f\ :\ l_f(h_C, D) \leq L/2 \tag{5}$$

where O and D are the origin and destination nodes on the path f; and $l_f(O, h)$ and $l_f(h, D)$ denote the distance between the bus h and the origin and destination of the path f, respectively. However, for longer trips, the remaining SOC can be from L to zero (with rather low probability) in intermediate nodes of the path depending on the distance between consecutive nodes and the latest charging station location. Therefore, any power node that are no further than driving range from the latest candidate location can be considered as another candidate location. The latest rule will quantify locations within the L distance of intermediate candidate location within the route f as a candidate location to locate a charging station:

$$\forall\, h_c \in\; N_f \;:\, l_f(h_c, h_{c+1}) \le L \tag{6}$$

Due to the limited distance that AEVs can drive, charging stations should be placed to capture the most traffic flow with a fixed number of stations depending on budget constraints. In practice, depending on the power network distribution and AEV level of battery charge, the AEV drivers will pick the station based on the SOC and correspondingly remaining range of AEV. Hence, charging stations should be located at nodes that can serve the most vehicle in the area. Moreover, the charging stations' number is limited by the available budget and cost of a new charging station setup and available power feeders. The transportation section's optimization framework will be described as in Eqs. (7)–(11). $h \in H$ indicates the buses on the power network set of nodes (H).

$$\max_{x_f, y_h \in \{0,1\}} \quad \sum_{t\in T}\sum_{f\in F} d^t_f x_f \tag{7}$$

$$\text{s.t.} \quad \sum_{h\in H} y_h \le N_{ch} \tag{8}$$

$$l_f^{max}(h_{c'}, h_{c'+1}) \le x_f L; \forall (h_{c'}, h_{c'+1}) \in N_f, f \in F \tag{9}$$

$$l_f^{max}(h_{c'}, h_{c'+1}) \ge l_f(h_c, h_{c+1})(1 + M(1 - y_{h_c}) + M(1 - y_{h_{c+1}})); \forall (h_{c'}, h_{c'+1}), (h_c, h_{c+1}) \in N_f, f \in F \tag{10}$$

$$l_f(O, h_1)x_f \le \frac{L}{2} y_{h_1}; \forall f \in F, h_1 \in N_f \tag{11}$$

where, d^t_f is the traffic demand of path f in time slot t which in order to be covered, there should be at least one charging station at node $h \in N_f$ depending on the route length. Objective function of this optimization model (Eq. (7)) maximizes traffic demand captured by available charging stations. Eq. (8) shows the maximum number of charging stations that can be set up, depending on available power feeders, and the budget and average cost of new stations. Constraints (9)–(11) determines the distance between successive and ensure that first station (h_1) be located in $L/2$ of origin for the route to be fully captured. Due to the changing nature of charging demand over time, the model will be optimized over planning time T, and the best result is picked out of all optimal values in each time slot t. Value of time step t is based on battery capacity and charging rate where T is a set of time indexed with t.

3.2. Charging demand load

EVs' charging demand in the transportation network is influenced by travel patterns, distance traveled, battery capacity, and distribution network coverage. Drivers' daily driving distance implies vehicle usage and can demonstrate the remaining SOC of an individual AEV. In the literature, daily driven distance is studied in Plötz et al. (2017), Qian et al. (2011) based on vehicle travel data. Log-normal distribution is suggested for the probability distribution of vehicles' daily distance and gives more conservative results than the other distributions. Eq. (12) shows the probability density function of daily vehicle driving distance:

$$P(l) = \frac{1}{l\sqrt{2\pi\sigma_l}} e^{\frac{(\ln l - \mu_l)^2}{2\sigma_l^2}} \tag{12}$$

where, l is the daily driven distance by a vehicle, and σ_l and μ_l are standard deviation and mean of the log-normal distribution, respectively. The latest transportation survey data released by the National Household Survey Data (NHTS) reports that a private car's average daily distance is 23.5 miles, with a margin of error of 11.5 miles (McGuckin and Fucci, 2018). The distribution of daily trip lengths is displayed in Fig. 2.

SOC of an AEV depends on the battery capacity, trip distances in a day, and purpose of travel. Here, two groups of travelers are considered. The first group represents those who travel in shorter distances and use their vehicle for commuting and conducting personal matters inside urban areas. The second group has longer travel distances to travel between cities. Vehicle usage and daily trip distribution in each group vary depending on the travel purpose, which will influence drivers' SOC and charging behaviors. However, assuming the SOC is linearly related to the distance traveled (Qian et al., 2011), the initial SOC probability can be measured by Eq. (13), where initial AEV's SOC follows a log-normal distribution originating from the distance traveled in a day.

$$P(\xi) = \frac{1}{\frac{L}{t_{ch}}(1-\xi)\sqrt{2\pi\sigma_l}} e^{\frac{(\ln \frac{L}{t_{ch}} + \ln(1-\xi) - \mu_l)^2}{2\sigma_l^2}} ; \xi \in [0, 1] \tag{13}$$

where, ξ is the remaining battery of the AEV and t_{ch} is the time passed since the last time vehicle has charged fully in days. The maximum travel range of an AEV is considered to be 150 miles, and Fig. 3 shows the probability distribution of SOC of a personal AEV after two days.

Knowing the initial SOC and driving pattern, the probability of charging at time slot t is a random variable related to the temporal distribution of trips per day. Purpose of trip also specifies AEV's charging start time, which can determine the number of

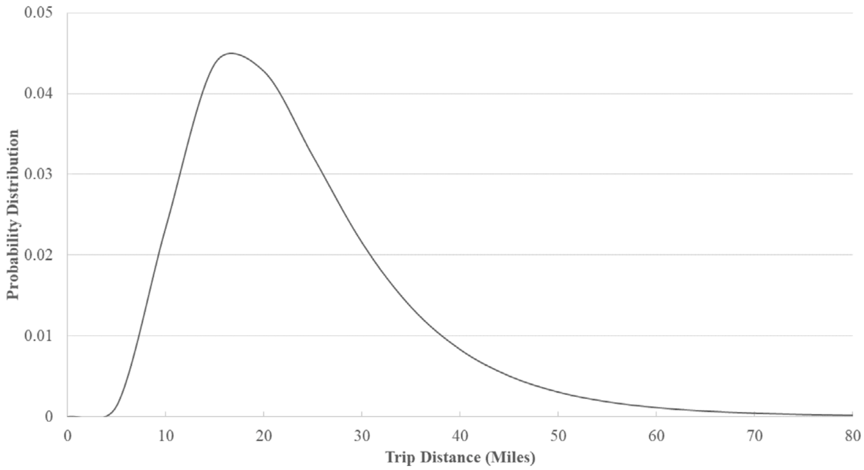


Fig. 2. NHTS probability distribution of daily distance drive driven for private vehicles.

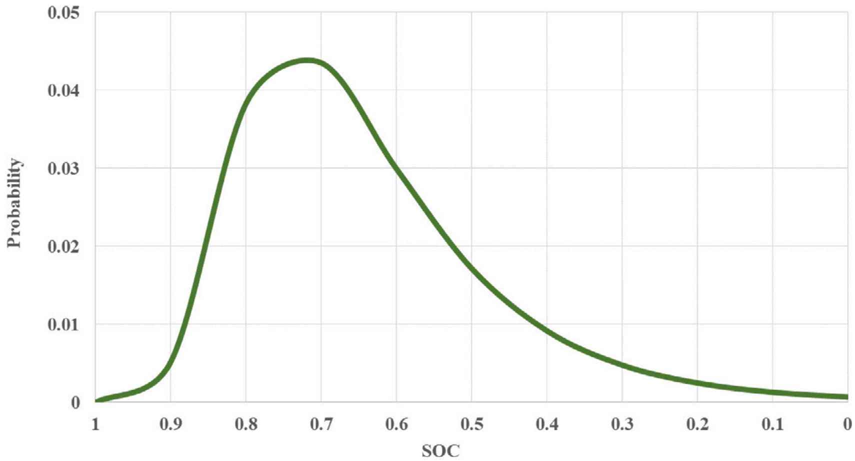


Fig. 3. Probability distribution of state of charge (SOC) for private vehicles.

AEVs charging at time t and power load of charging session on the distribution network. However, the critical variable in charging demand is the trip length, which will determine the time block a vehicle needs to recharge. Shorter trips require less initial SOC to guaranty the trip can be successfully made, while longer trips need a higher initial SOC to make the trip. Also, vehicles tending to drive more might need more frequent charging depending on the average daily traveled distance. Therefore, in the latest case, the initial SOC is lower than vehicles driving shorter distances in a day. Additionally, the longer the trip is, the higher chance there will be a need for charging.

As there are two types of trips in this study, the probability of charging is based on the group type and the initial SOC. Since the sample AEV's driving range is assumed to be 150 miles, the threshold of 50 miles per day is used to distinguish the long and short trips. Initial SOC of short trips is a random variable obtained by Eq. (13), and the latest time charged can be anytime from 2 days ago to recent (zero-day). Based on the initial SOC at time t by Eq. (14), it is assumed that vehicles with less than 30% remaining driving range will start to look for recharging within their paths. Therefore, the probability of charging at time t is described as:

$$f_c(t) = \begin{cases} 1, \xi_t \le 0.3 \\ 0, \xi_t > 0.3 \end{cases} \quad ; t \in T, l_f \le 50 \tag{14}$$

Moreover, in the long trips group, two scenarios may happen. Trips that are longer than 75 miles need more than 50% of the remaining range. However, based on refueling assumption, each vehicle will have at least 50% e-fuel at its origin, which forces the driver to recharge the vehicle. Therefore, it is assumed that vehicles with trips more than 75 miles will charge their cars in their path, making the probability of charging equals one. On the other hand, trips between 50 to 75 miles will consume 0.33 to 0.5 range, which assuming 0.2 to 0.3 remaining range is when drivers recharge their vehicles, an initial SOC of 70% on average is needed to complete the trip without recharging. The latest rule eventuates the probability of vehicles with less than 70% initial

SOC to recharge in their route:

$$f_c(t) = \begin{cases} 1, \xi_t \le 0.7 \\ 0, \xi_t > 0.7 \end{cases} \quad ; t \in T, l_f \in (50, 75) \tag{15}$$

However, the level of automation of vehicles can, in some cases, change these expectations. As a higher level of automation (i.e., level 4 and higher) requires no driver, users can plan to send their vehicles to stations in their origin or destination and they would not need to wait at the stations. Hence, if there is a station near the trip's origin or destination ($y_h = 1$), drivers prefer to send their vehicles to recharge at those stations. Probability of a user (u_k^f) with automation level k to recharge on route f at station h_c is demonstrated by Eq. (16). The chosen station depends on the vehicle SOC, trip distance, and availability of the charging facility. If no station is found in origin or destination, the vehicle will pick from the stations within the route ($h_{c\prime}$). It is considered that only a small portion of AEV have self-driving features for this purpose. For vehicles with lower automation levels ($k < 4$), the probability is estimated by Eq. (17). The latest value only depends on the availability of stations within route, SOC, and trips length.

$$\Psi^t(u_k^f, h_c) = \begin{cases} f_c(t) y_{h_c} \\ (1 - y_{h_c}) f_c(t) y_{h_{c\prime}} \end{cases} \quad ; k \ge 4, c \in \{1, C\}, c\prime \notin \{1, C\}, h_c \in N_f \tag{16}$$

$$\Psi^t(u_k^f, h_c) = f_c(t) y_{h_c} \quad ; k < 4, h_c \in N_f \tag{17}$$

Each feeder's power load profile in a time slot t consists of the power load of charging sessions at the chosen station at t. To evaluate the power load in each charging session, the battery needs to be charged to the desired SOC. The charging load and time need for recharging depend on the charging current and battery capacity. Direct current (DC) chargers are Level 3 chargers and the fastest one available that is one of the convenient options for long trips. DC fast chargers charge AEV batteries with a power load of 50 kW, which can be as high as 120 kW for some vehicles. Depending on the vehicle's battery capacity and the ambient temperature, DC chargers can take 20 min to an hour to charge an AEV. In this study, the AEV sample has a battery capacity of 30 kWh, and the charging power of stations is assumed to be 50 kW that will take about half an hour to recharge the battery fully. The aggregated power load is determined using the flow counts encountering stations. Since multiple stations can cover each flow, number of vehicles picking a station is assigned randomly from the traffic flow passing in the route willing to recharge their vehicles. Depending on SOC at origins, vehicles will be assigned randomly to one of the stations that can cover the route. Based on the arrival SOC at stations, and SOC at origins, battery capacities and the power loads of charging sessions will be evaluated. Also, it is assumed that vehicles recharge fully in each charging session. Eq. (18) shows the cumulative power load of AEVs at time step t, with charging power current p_c, and the probability of starting time of $f_c(t)$ at time t.

$$p_{h,d}(t) = \sum_{f \in \Omega_h} d_f^t \int_{t-1}^{t} \sum_{u_k^f} p_{ch} \Psi^t(u_k^f, h_c) f(\xi_t); h \in H \tag{18}$$

where Ω_h is the set of flows that can be intercepted by node h in power grid.

3.3. Distribution network optimization

In practice, the power grid constraints regulate the charging stations planning by the infrastructure and level of energy it can provides for the stations. Here, the charging stations are located optimally to minimize the network's power cost. As both traffic flow coverage and power cost are being optimized, the problem is a multi-objective optimization. However, considering the power distribution network will exhibit a more realistic solution when both transportation and power grid are affected. Optimization of the power grid includes balancing the flow on all nodes and reducing transmission lines' power load fluctuation. As the power generation rate is considered to be constant during distribution, the objective function considers charging cost in the distribution network. Therefore, the objective function can be expressed in Eq. (19):

$$\sum_{h \in H} \alpha^t P_h^t y_h \tag{19}$$

where, α^t is the power price rate at time t. The distribution network is assumed a radial network, and a linear distribution flow is used to demonstrate bus power, charging load, and nodal voltages (Liu et al., 2019b). To measure the power flows between each pair of nodes, Eq. (20) and Eq. (21), as introduced in the literature (Farivar et al., 2013), are used for both active and reactive for power bus pairs of h and h' of the set of the nodes $H(h, h' \in H)$:

$$P_h^t = p_h^t + \sum_{h' \in E_h} P_{h'}^t \tag{20}$$

$$Q_h^t = q_h^t + \sum_{h' \in E_h} Q_{h'}^t \tag{21}$$

where, P_h and $P_{h'}$ denote the injected real power at node h and h'; and p_h is the active demand power load on node h. The set of E_h denotes the nodes that are directly connected to node h at its downstream. Eq. (21) demonstrates the same equation for reactive power where Q_h and q_h are reactive power transmitted to node h and reactive part of the power load of node h, respectively. Power load on each node consists of baseline load and AEV charging demand power load. It is assumed that the charging load only includes real power (Liu et al., 2019b); therefore, each node's real and reactive power load is as Eq. (22) and Eq. (23).

$$p_h^t = p_{h,b}^t + y_h p_{h,d}(t) \tag{22}$$

$$q_h^t = q_{h,b}^t \tag{23}$$

Baseline power load can be looked up by the daily electrical consumption of the power network. Considering a single-phase linear optimal flow distribution (Arnold et al., 2016; Liu, 2019; Liu et al., 2019b; Wei et al., 2018), the optimization of power over the network is formulated as:

$$\max_{y_h \in \{0,1\}} \quad \sum_{t \in T} \sum_{h \in H} \alpha_t P_h^t y_h \tag{24}$$

$$\text{s.t.} \quad P_h^t = p_h^t + \sum_{h' \in E_h} P_{h'}^t ; h \in H, t \in T \tag{25}$$

$$Q_h^t = q_h^t + \sum_{h' \in E_h} Q_{h'}^t \tag{26}$$

$$|V_h^t|^2 = |v^t|^2 - 2 \sum_{h,h' \in S_h \cap S_{h'}} R_{h,h'} p_h^t - 2 \sum_{h,h' \in S_h \cap S_{h'}} X_{h,h'} q_h^t \tag{27}$$

$$V_h^{min} \le V_h \le V_h^{max} \tag{28}$$

where, $R_{h,h'}$ and $X_{h,h'}$ are the resistance and reactance of line segment h and h'; S_h (S_h') is the set of downstream line segments connecting to node h (h') from the feeder's head; $|V_h|^2$ denotes the bus voltage magnitude of node h; $|v|^2$ is the feeder's head (node 0) voltage magnitude; p_h and q_h show the active and reactive power load on node.

The combination of Eqs. (7)–(11) and Eqs. (24)–(28) forms the optimization problem of the current problem. The optimization problem in the transportation network is trying to find the optimal locations among candidate locations in the distribution network that captures the maximum encountering traffic demand, increasing the chance of a driver finding a charging station within the trip. This is while the number of new stations is limited, and their allocation must ensure that drivers can travel to their destination without running out of fuel. On the other hand, the optimization problem in distribution network seeks to minimize the charging demands power load cost by assigning stations to locations that will keep the voltage profile stable. Undoubtedly, the last objective can be achieved by choosing the locations that their corresponding charging demand will not drain the distribution network.

To find the optimal AEV charging stations' allocation, considering demand coverage and power flow optimization, the problem is solved as a multi-objective optimization. Since the optimization is an NP-Hard problem, it is solved using the nondominated sorting genetic algorithm (NSGA-II) (Deb et al., 2002). NSGA-II is an elitist EA using individuals' domination and closeness to their neighbors, called crowding distance, as ranking values. NSGA-II has less computational complexity, better convergence, and spread of solutions compared to previous versions. In the next section, an optimal charging station allocation using the developed model on Utah's transportation network and using the single-phase IEEE-37 Node Test Feeder is presented.

4. Numerical results

In this section, the CPT framework is used to find the optimal AEV charging station locations in Utah. The traffic flow data is obtained from the existing study (Miller et al., 2020; Yuan et al., 2021), which uses the GPS trajectory data of Utah and scales them to match the actual traffic counts by sensors all over the state. For the case study, the scaled traffic counts for one day within Utah are extracted. The origin–destination (OD) patterns are obtained at the county level to simplify the calculations, including intercounty and inside county trips of all 29 counties in Utah. Accordingly, the traffic network is illustrated by 29 nodes and 435 individual OD pairs (flows). Fig. 4 represents the diagram showing the number of trips between pair of counties and the concentration of trips for each county. Chord diagram on the left side demonstrates the ratio of inner and external trips of individual counties. Width of the bars connection each pair shows trips between the pair proportionally. Also, the hanging ribbon indicates the number of intra-county trips, which has the highest value in most counties. The diagram on the right side of 4 exhibits the logarithm of aggregated trips in each area.

Trip lengths are used to estimate the initial SOC for each vehicle in which the distribution is exhibited in Fig. 5. Distribution shows that the majority of trips are short distances (<50 miles), and longer trips have a lower density in comparison.

However, to determine the number of AEVs traveling in the network, flow counts are multiplied by the AEV market share in Utah, which is predicted to be 2% in 2020. According to trip lengths, AEV flow counts, and the results of the Eqs. (14)–(16), cumulative AEV charging session power load is evaluated. Also, the baseline load is extracted from Utah's power grid daily consumption in summer 2018 from US electric system operating data and scaled for optimization. The latest data resulted in power load profile depicted in Fig. 6, which shows the highest demand for charging is between 2 to 6 PM and is critical to monitor the voltage drop in this period.

The optimization is applied to the layover of the traffic network and distribution grid (Blank and Deb, 2020). Power distribution network from IEEE is adjusted to suit the traffic network, including nodes arrangement and lines' length. The capacitor banks and switch are eliminated from the power grid, and some lines are relocated to fit the Utah map. Both power and transportation networks

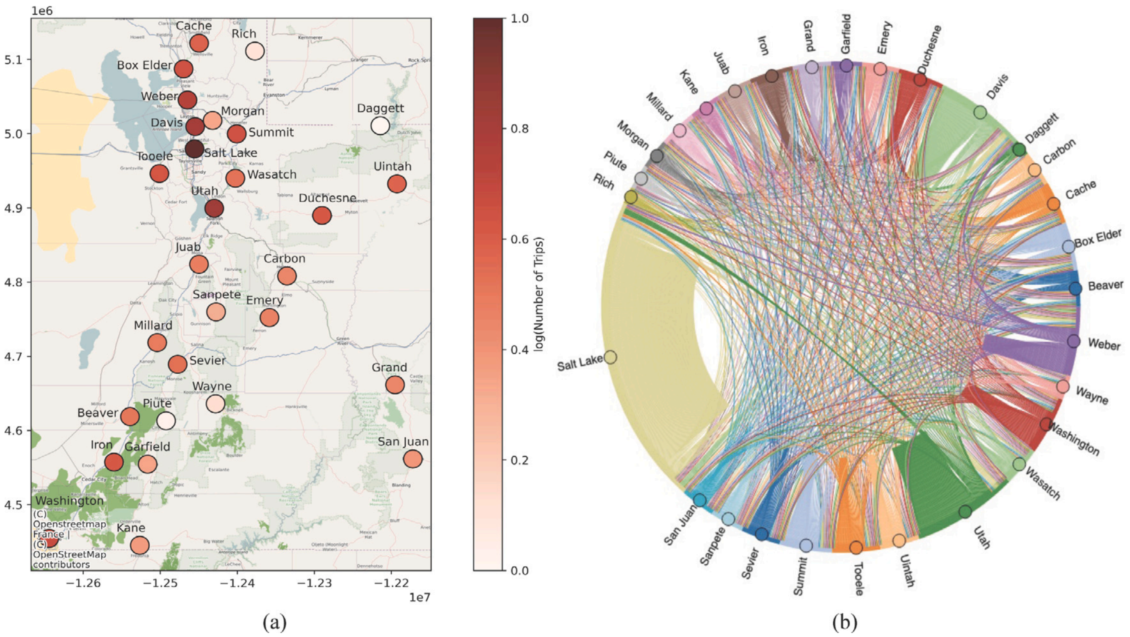


Fig. 4. OD trips by GPS trajectory data (a) logarithm of number of trips counties (b) OD pairs of the counties.

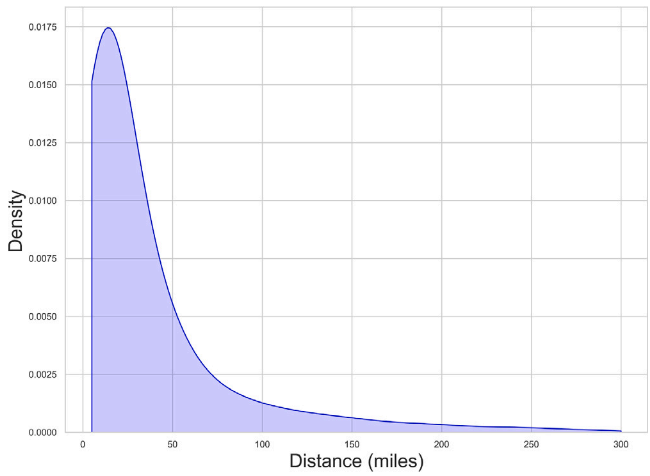


Fig. 5. Trips distance distribution from Utah trajectory data.

are displayed in Fig. 7. Node 0 is the feeder's head, and nodes 1, 3, 12, 18, and 22 are not among candidate locations to set up a charging station. The case study power grid has an operating voltage of 15 kV (Kersting, 2001) and is loaded in a single phase.

A set of optimal solutions is generated by optimization model that are solutions that outperformed in non-domination ranking. Pareto front solutions of both functions are displayed in Fig. 8. Considering the constraint and objectives of model, the best solution has been picked within optimal series of solutions. f_1 represents aggregated flow count that can be supplied by available stations, and f_2 is the total cost of charging power load in network.

By confining the number of station to 15 and driving range to 150 miles, the CPT optimization shows that 64% of the traffic flow demand will be covered, and the daily power consumption cost is $11,432. The allocation of stations using 24-hour AEV traffic flow and their power load on the distribution grid is described in Table 4. Total 13 fast-charging stations are set up for the traffic network that is mostly concentrated in the north. The fact that the counties in the north of Utah are the most populated ones and 10% of the recorded trips belongs to inner-city trips in Salt Lake justifies assignment of more stations in the northern area. Table 4 also demonstrates that nodal voltage drop due to charging load in new station does not exceed 0.029 p.u. which satisfies the voltage variation of ±0.05 p.u. in the distribution grid. For a better overview, the feeders' nodal voltage in the distribution network during the optimization time range is illustrated. Fig. 9 shows the voltage magnitude of buses where a station is assigned. The minimum

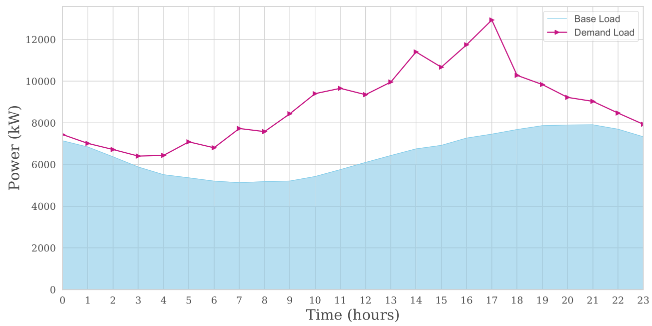


Fig. 6. Power load profile of 37 feeder distribution grid.

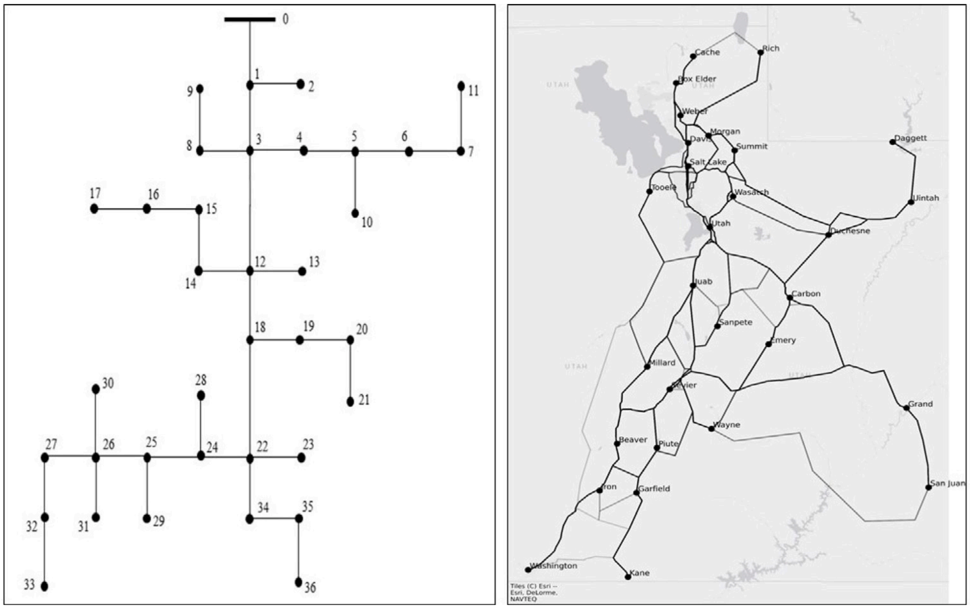


Fig. 7. IEEE-37 node test feeder (left), routes and counties of Utah traffic network for case study (right).

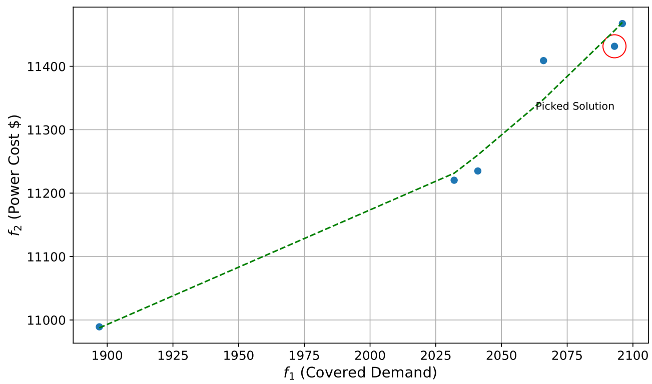


Fig. 8. Pareto front solutions of the optimization model.

voltage magnitude of the power grid of the optimization time slot is 0.969 p.u. which is within limits. For further restriction of voltage magnitude, the charging demand needs to be controlled by suitable policies so that both demand coverage is guaranteed and voltage fluctuation gets smoother.

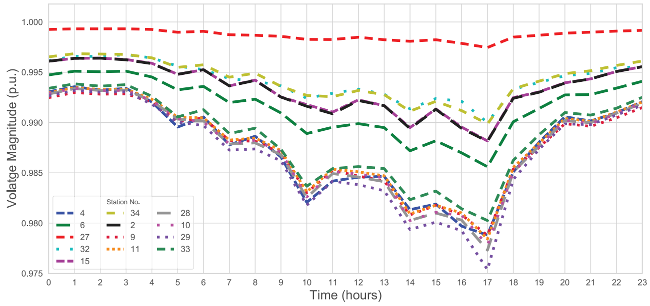


Fig. 9. Nodal voltage magnitude under AEV charging Loads for feeders with charging station.

Table 4
CPT optimal charging station locations and power load impact of charging sessions.

Station location on power grid	Number of AEV charging sessions	Max voltage drop (p.u.)
4	329	0.023
6	10	0.021
27	63	0.003
32	279	0.01
15	687	0.012
34	110	0.101
2	28	0.012
9	113	0.021
11	22	0.022
28	160	0.023
10	154	0.022
29	88	0.025
33	156	0.02
	2199	Sum

Table 5
Integrated model vs. base model results.

Results	Base model (GA)	Integrated model (NSGA-II)	Difference (%)
Stations ($\sum y_h$)	14	13	−8
Coverage (%)	71.2	64	−11
$V^t_{h,min}$ (p.u.)	0.95	0.97	2
Cost ($\times 10^4$ \$)	15.35	11.43	−34
$\bar{P}_h$ (kW)	754	638	−18

Results show that routes with much-frequented traffic volume are captured by 13 stations located in the power grid. Also, the stations located close to areas with more demand like Salt Lake County, Utah county, and Southern Utah have captured the most demand among the stations. The overlay of stations on Utah's map and routes that have been captured by optimal charging stations are displayed in Fig. 10. The optimal allocation based on fueling rules ensures that both inter-county trips and intra-county trips complete their trips with enough e-fuel. In view of the fact that a test feeder is picked to represent the approximate distribution network, some stations might be further from main roads, which do not indicate the exact location of the stations and just define the estimated area.

In order to show the efficiency of integrating the model in charging stations design, a basic model focusing on transportation network solely is studied. The base model tries to maximize the encountered flow while maintaining the maximum distances of stations within the path. Latest model is solved using genetic algorithm (GA), compared with the initial results of the integrated model. Results of base model show that more stations can be built, which increases the covered demand by 11%. More charging sessions will be done, increasing the average load on the system by 18%. Increased power load, drop the voltage to 0.95 p.u., makes the distribution grid unstable. It will result in a reduced charging rate in stations and adds up to individual charging time. This fact may reduce stations charging service rates. Consequently, fewer charging sessions will be done in one hour with fewer covered demand in practice. Detailed results of the base model in comparison to integrated model by this study are presented in Table 5. Accordingly, integration of distribution network and traffic demand ensues a stable charging network and proves the enhanced performance of integrated model over single objective models.

The previous result assumes an average AEV type with a driving range of 150 miles, despite the fact that there are AEV types that have less driving range or even more. AEVs' driving range will influence charging planning, such as station coverage, initial SOC, and

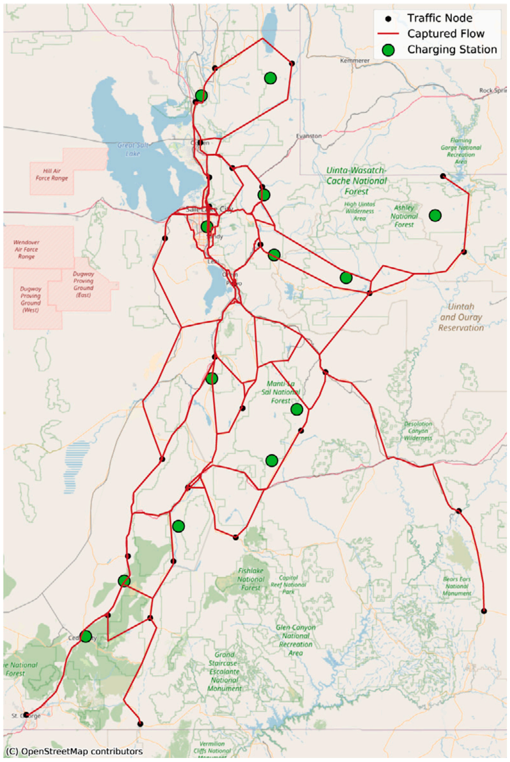


Fig. 10. Optimal location of charging stations and captured routes (red line).

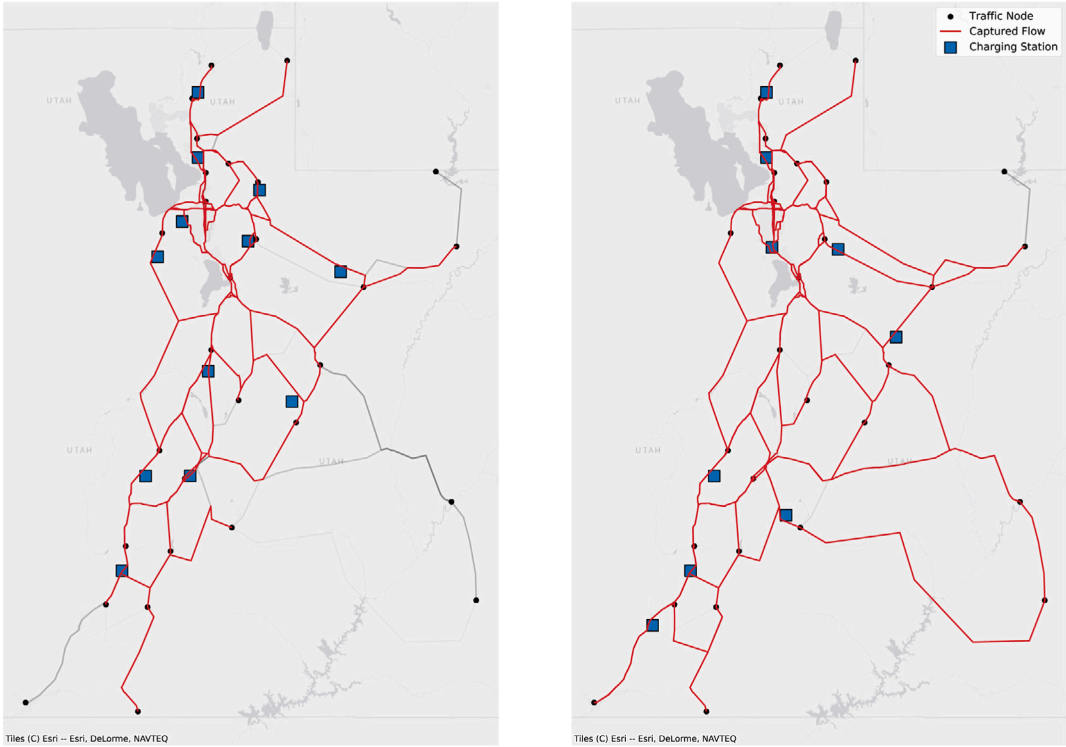
Table 6
Optimization results for variable AEV market share.

AEV penetration rate (%)	Power load cost (Thousands $)	Number of stations	Coverage (%)
2	11.431	13	63.94
3	15.975	15	52.11
5	26.204	14	38.95
10	53.567	13	20.58
20	108.943	13	9.92
30	190.146	13	7.23
40	193.331	12	5.49

charging session frequency. All recent variables will also change the optimal allocation of charging stations. Fig. 11 demonstrates the optimal allocation of charging stations for a driving range of 100 miles and 200 miles. If the driving range is decreased to 100 miles, 12 stations are needed to maximize the demand coverage, while by increasing the driving range to 200 miles, the number of stations will decrease to 9. In the case of 100 miles driving range, the stations will cover 46% of demand, which shows that the more limited range will impact the AEVs' mobility and requires a more extensive charging network. However, if the vehicle's average driving range is improved to 200 miles, up to 81% of the AEV charging demand will be supplied. Red lines in Fig. 11 show the covered routes by the stations, which are expanded by enhancement of the driving range.

EV charging management needs to consider the fast growth of AEV penetration rate forecast to grow significantly in next years. Therefore, to demonstrate the relation of AEV market share in charging planning, the CPT optimization is applied to multiple scenarios with various penetration rates (PR). A set of 3%, to 40% PR rate is used to find the optimal allocation of charging stations and the objective function margins in response to more AEV flow counts. Development of AEVs in traffic network will increase nodal voltage fluctuations, power load, and correspondingly the cost on the power grid, which will require a more extensive power grid with the necessary equipment to balance the load. Additionally, the available stations will serve a more limited number of vehicles as the AEVs flow level increases. Latest conclusion is based on the fact that the number of stations will be limited to the same value, which in this experiment was 15. Results of optimization are shown in Table 6.

The latest experiment results are based on the assumption that each station is limited to serve a fixed number of AEVs in a day. Limitation of charging stations might be due to the limited number of charging posts available, power grid limitations, battery capacity, and stations' charging power. By obtained results, current infrastructures are not sufficient to supply the growing demand.



(a) 100 miles range (b) 200 miles range

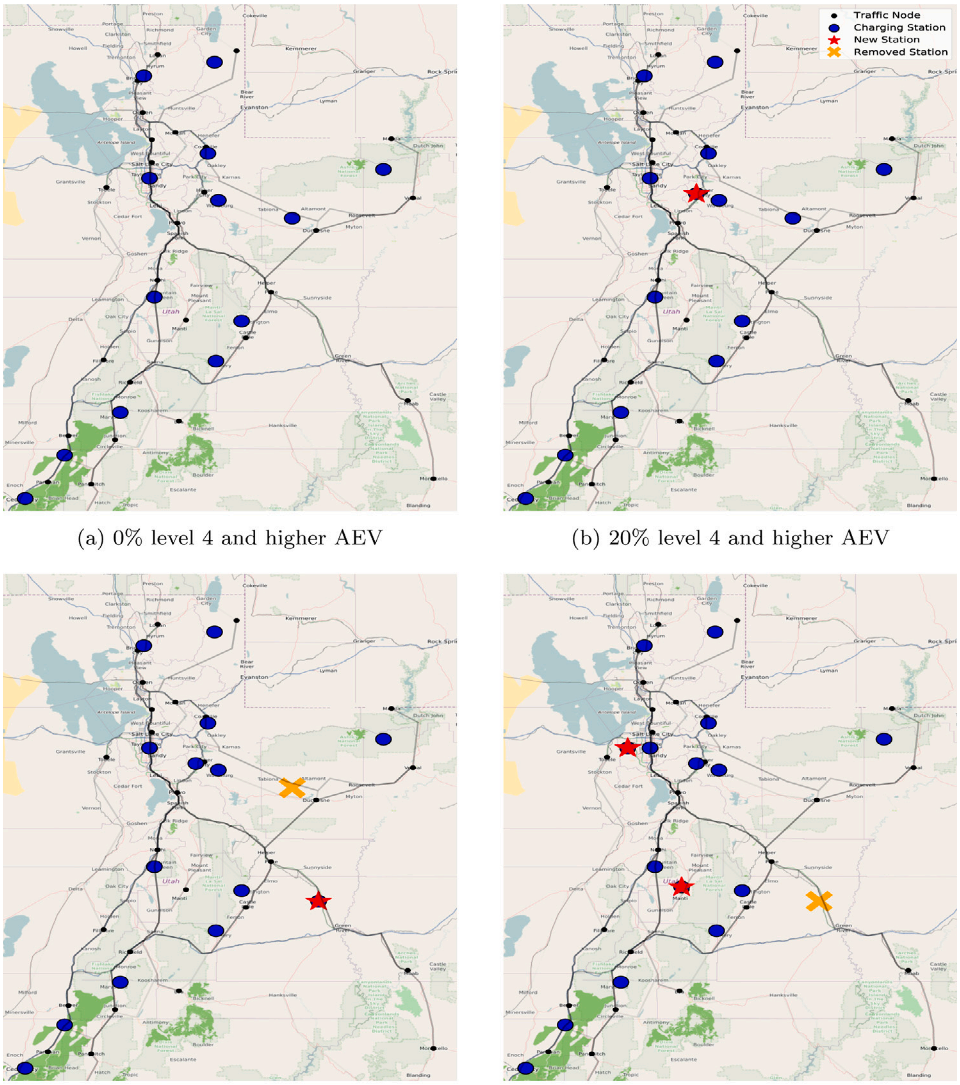
Fig. 11. Optimal location of AEV charging station for driving range of (a) 100 miles, and (b) 200 miles.

A more extensive charging network is required to maintain the coverage level at least as good as the present situation. A counter-intuitive finding is that a lower number of stations is determined for a higher demand due to the reciprocal increased power load on the distribution network. The increased power load from more charging demand will increase voltage drop on power grid. Excessive voltage drop on nodes experiencing power consumption more than capacity is a barrier in distribution network to inaugurate more stations than lower demands. Therefore, those stations are not included in optimal station allocation to keep power and voltage levels in the distribution grid in the standard range.Though, the increase in the number of stations to 5% PR is observed, which indicates the requirement of more stations to cope with increased demand. But increased demand will also impact the power grid, which prevents the system from setting up new stations and limit the number of facilities.

To show the effect of automation and driver's role elimination from the charging network, charging stations' optimal setting using the employed model is examined. For this purpose, it is assumed that level 4 and higher AEVs with a market share of 20%, 40%, and 100% are available on the road. Results of charging network location are shown in Fig. 12 which is also compared with the case where there are only level 3 AEV on road (Fig. 12(a)). Introduction of driver-less charging will result in more stations close to traffic nodes, focusing on spots with higher demand. Also, as higher levels increase on roads, the number of stations to supply the charging demand is shown to be increased. By 40% penetration rate (Fig. 12(c)), as there are AEVs on the road that requires to be charged en-route and station close to traffic nodes will be occupied mainly through driver-less AEV, another station is added within the route. The latter fact aspires from this framework layout designed to allow long-distance trips and ensure spacing between stations for a higher service rate. As all vehicles become fully automated, the model locates a station close to all traffic nodes within the criteria of power grid and transportation network limitations.

5. Conclusions

In this study, a new framework is developed to plan for optimal allocation of AEV charging stations. The main contribution of this research is to develop a fine-tuned optimization framework for the location of charging stations. The optimization model is based on both traffic network and power grid to find the best allocation of stations in order to serve the most demand while minimizing power cost. Considering the maximum distance among stations has resulted in an evenly distributed facilities that ensure the drivers can complete their trips, especially long-distance ones. Besides, the tie of objectives assisted in finding the feeders for stations that will not overload the network and maintain the nodal voltage in acceptable range. The AEV flows are also modeled to power load using travel patterns inferred from Utah GPS trajectory. Optimization model is solved by using an EA, NSGA-II that is a type of genetic algorithm. The power grid used in the case study is a demonstration of a small section of the distribution network and is



(a) 0% level 4 and higher AEV

(b) 20% level 4 and higher AEV

(c) 40% level 4 and higher AEV

(d) 100% level 4 and higher AEV

Fig. 12. Optimal charging stations locations for AEV with level 4 and higher automation level penetration rates of (a) 0%, and (b) 20% (c) 40% and (d) 100%.

used as power grid to erect charging stations for more extended trips. Moreover, the model is optimized over time to consider the hourly power load and flow pattern to reduce framework uncertainties.

Results of the study demonstrate that stations will be mostly located close to routes with high traffic and shorter distances and traffic nodes with high inner traffic demand. The concentration of stations along the shorter routes is due to the limited range of AEVs. However, the stations with the highest demand will experience more voltage drop in peak hours. Meanwhile, outputs of the modeling excluding power grid indicated that overlooking the power infrastructure constraint may result in an unstable network. Creating an over capacity network, charging rate will decrease and prolong the charging time and limit the chargers' service rate. Latter conclusion requires a more detailed analysis of the power grid, which is out of the scope of this study. However, increased average load for a slight demand coverage indicates the significance of charging demand in distribution performance. Integration of both networks creates a more evenly distributed power load within a full day of service that intercepts overloading on the grid in peak hours. Besides, using fast chargers in charging stations will drop vehicle queues for charging, and more demand can be captured in a day compared to other charger types. Changing the driving range of AEVs shows that fewer stations can cover more charging demand if the driving range is increased, which can help the financial aspects of planning and reduce power load on the grid. Although increased range, increases the maximum distance withing facilities and station coverage which is another expression for less station in such case. As this study also considers the automation of vehicles that might be more of concern in the near future, the option of scheduling vehicle to recharge at convenient facility locations. This feature is one of the benefits of automation in a charging system that takes out range anxiety and makes users charging behavior more deterministic and predictable. Self-driving vehicles might increase the demand at facilities close to traffic attraction zones (TAZ) which require a further demand management plan. On the other hand, AEV charging behavior creates certain ground for charging planning which makes it manageable.

Eventually, considering the growth of AEV market, less demand will be served without an appropriate expansion of the charging network. Results of the study show that higher penetration rates require an extended power grid to cope with increased demand and stable charging service rate. Based on the results, due to aggregated power rate on the grid, feasibility of charging stations become more restricted as charging load becomes escalated. On the other hand, reflection of maximum facility distance in the model and flow based demand is followed by locating facilities on heavily flowed routes rather than high demand centers. Overlaying of OD trips and stations locations demonstrate the scattering of sources within those zones with higher inter demand. Also, it prevents establishing multiple facilities on intersection of busier routes. Location of charging facilities is highly dependent on power feeders placement particularly. Yet, optimal allocation of chargers in the case study shows that areas with more than 10% trips require at least one facility in the vicinity of $L/2$. On the other hand, for zones less than 10% trips stations should be dispersed along the routes to zones with higher attraction. In this paper, the optimization model only considers the fast-charging stations. For further studies, all other types of charging options need to be considered to supply part of the charging demand. The user's driver uncertainties, such as limited time blocks for charging, are also suggested to be added to the model for more realistic results.

CRediT authorship contribution statement

Bahar Azin: Methodology, Investigation, Visualization, software, Writing - original draft. **Xianfeng (Terry) Yang:** Conceptualization, Validation, Writing - review & editing. **Nikola Marković:** Data curation, Validation, Writing- review & editing. **Mingxi Liu:** Conceptualization, Writing - review & editing.

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