Charging station design and location studies

K. Nissy[1], R. Swathi[2]

Abstract

Electric vehicles are believed to be an effective solution for reducing greenhouse gas emissions. Despite extensive study on the attributes and characteristics of electric vehicles and their charging infrastructure design, the development and network modelling of electric vehicles are still evolving and limited. This article provides a comprehensive review of electric vehicle studies and identifies existing research gaps in the aspects of theories, modelling approaches, solution algorithms and applications. This article first describes the electric vehicles' concepts, market share, characteristics and charging infrastructures. Then, the studies on traffic assignment problem with electric vehicles in the network and limited charging facilities are particularly discussed. We conclude that it is of great importance to take into account electric vehicles' special characteristics (e.g. range limit) in predicting their routing behaviour and charging infrastructure design networks.

Keywords

Introduction

Carbon-based emissions and greenhouse gases (GHGs) are critical issues that policy-makers have sought to address globally since the Kyoto Protocol issued in 1998.[1] The transportation is 98% dependent on fossil oil which is exceedingly affected by changes in energy resources.[2] Governments and automotive companies have recognized the value of alternative fuel vehicles (AFVs) for green

transportation[3] and have been implementing economic policies to support electric vehicles' (EVs) market.

Plug-in hybrid electric vehicle (PHEV) is one of the AFVs which can reduce GHG emissions.[2] The hybrid gasoline–EV is greatly promising in future since it can reduce gasoline consumption and GHG emissions from 30% to 50% without the need of changing the vehicle class.[4] However, a more widespread use of EVs is still hindered by the limited battery capacity, which allows cruising ranges between 150 and 200 km.[5] In addition, the chicken and egg problem[6]– who will build and buy the AFVs if a refuelling infrastructure is not in place and who will build the refuelling infrastructure before the AFVs are built – remains the most intractable barrier.

The driving range limit inevitably introduces a certain level of restrictions to battery electric vehicle (BEV) drivers' travel behaviours, considering the insufficient coverage of recharging infrastructures in a foreseeable future time period. The widespread adoption of plug-in electric vehicles (PEVs) calls for the fundamental changes of the existing network flow modelling tools in capturing the potentially changed behaviours, as well as the induced constraints on forecast of travel demands and evaluation of transportation development plans.[7]

In this article, we explore various topics with respect to the network modelling of EVs. The structure of this article and main focus are described as follows:

a. In section 'Charging station design and location studies', the studies on battery charging station and battery-swapping station (BSS) location, as well as their design, are briefly introduced. These aspects are mostly concerned for the development and acceptance of EVs' market.
b. In section 'PEV market potential, demand and behaviour study', the PEV market potential and its demand are reviewed from the aspects of EVs' infrastructure, challenges and opportunities. Then, the characteristics of EVs and EV drivers' behaviour are discussed by comparing with the traditional gasoline vehicles.
c. In section 'TAP of vehicles with range limit', the studies on traffic assignment problem (TAP) for EVs' network with limited charging infrastructure are summarized. Shortest path problem (SPP) is a sub-problem of TAP, and extra

constraints, such as driving range and availability of charging, need to be taken into consideration as the EV SPP. The vehicle routing problem (VRP) of EVs, which is a logistic issue that generalizes the well-known travelling salesman problem and usually takes distance or energy-constrained SPP as its subroutine, is discussed.

d. In section 'Network design and bi-level model', the network design problem (NDP) of EV and the bi-level models in solving the TAP are discussed. In bi-level model, the upper level can be seen as charging facility location problem, while the lower level is TAP.

e. Finally, the research gaps in network modelling of EVs are identified and potential future research direction is suggested.

Charging facilities are essential for EV drivers. Suppliers, such as EV companies and governments, are concerned about where to locate charging stations and what type of charging station to locate because of the high cost of building these facilities. Although many cities are planning the construction and expansion of BEVs' charging infrastructures, it is likely that BEV commuters will need to charge their vehicles at home most of the time in the foreseeable future.[8] For many EVs, such as Nissan Leaf or Chevrolet Volt, the current method of recharging the vehicle battery is to plug the battery into the power grid at home or office.[9] The battery requires an extensive period of time to recharge, and this largely constrains the EVs' usage only for short distance travel. EV companies are trying to overcome this limited range requirement with fast charging stations where a vehicle can be charged in only a few minutes. Bai et al.[10] proposed an optimum design of a fast charging station for PHEVs and EVs to minimize the strain on the power grid while supplying vehicles with the required power. Qiu et al.[11] analysed the characteristics of EVs' arriving time and charging duration in fast charging stations and established a queuing system model to optimize the allocation number of EV chargers using the stochastic service system and queuing theory. Compared to the gasoline vehicles, the EVs take more time to recharge and the fast charging station costs more to operate.[12] These inherent problems, combined with a lack of recharging infrastructure, highly inhibit a wide-scale adoption of EVs. These problems are especially apparent for longer trips such as inter-city trips. Range anxiety (a driver may be afraid that the vehicle will run out

of charge before reaching the destination) is a major hindrance for EVs' market penetration.[13] Hybrid vehicles, which have both an electric motor and a gasoline engine, can alleviate the range anxiety to some extent. However, these vehicles do not fully mitigate the environmental consequences since hybrids still require gasoline.[14]

Another refuelling infrastructure design is to have quick battery exchange stations (BESs) or BSSs. These stations will remove a pallet of batteries that are nearly depleted from a vehicle and replace the battery pallet with one that has already been charged.[15] This method of refuelling has the advantage that it is reasonably quick. The unfortunate downside is that all of the vehicles served by the BES are required to use the identical pallets and batteries. It is assumed here that the developers of these battery pallets will coalesce around a single common standard. BESs have been tried out by taxi vehicles in Tokyo in 2010.[16] Denmark is investigating the possibility of having sufficient battery exchange locations so that the country relies on none, or very few, gasoline-powered vehicles.[17]

There is a complementary location problem with regard to where to locate these 'refuelling' stations including battery recharging, battery exchanging and other alternative refuelling options. The problem of optimally locating such refuelling stations has been investigated by several researchers using flow refuelling location model.[18–20] To enable mobility of EVs, models of the placement of least charging stations on the shortest path are proposed to avoid detours for charging.[21,22] A conceptual optimization model is proposed to analyse travel by EVs along a long corridor. The objective is to select the battery size and charging capacity (in terms of charging power at each station and the number of stations needed along the corridor) to meet a given level of service in such a way that the total social cost is minimized.[23] Wang and colleagues[24,25] proposed a refuelling station location model based on vehicle routing logics using a set cover concept with consideration of both inter-city and intra-city travels. MirHassani and Ebrazi[26] presented a flexible mixed-integer linear programming model by reformulating the flow refuelling location model. The model can obtain an optimal solution much faster than the previous set cover version and it can be solved in the maximum cover form. Xi et al.[27] developed a

simulation–optimization model that determined where to locate EV chargers to maximize their use by privately owned EVs. Dong et al.[28] studied EV charging station location problems and analysed the impact of public charging station deployment on increasing EVs' travel miles.

PEV market potential, demand and behaviour study

With respect to PEV market potential, the car of the near future is the hybrid gasoline–EV, and it will likely become the dominant vehicle platform by the year 2020.[4] Global positioning system (GPS) data of the households were used to illustrate how PEVs can match different household (single-vehicle or multiple-vehicle) needs. Cost comparisons between the PHEV and conventional gasoline vehicle were conducted and the annual savings were given.[29] The reduction that a PHEV provides in both transportation costs and GHG emissions with respect to a comparable conventional vehicle was also discussed.[30] Smart and Schey[31] analysed the Nissan Leaf, which is a BEV, and concluded that the drivers drove 6.9 miles per trip, 30.3 miles per day on average and the average number of charging times was 1.05 per day, as well as 82% of charging events were conducted at home. Chargers and the associated cords are categorized by voltage and power levels: Level I is 120 V alternating current (AC) up to 20 A (2.4 kW); Level II is 240 V AC up to 80 A (19.2 kW) and Level III, which is yet to be defined fully, will likely be 240 V AC and greater at power levels of 20–250 kW. The SAE J1772[32] standard defines a five-pin configuration that will be used for Level I and Level II charging. A Level III connector and the use of the current connector for direct current (DC) power flow are under development. Markel[33] summarized the components of the PEV infrastructure, challenges and opportunities related to design and deployment of the infrastructure and potential benefits. Dong et al. proposed a stochastic modelling approach to characterize BEV drivers' behaviour using longitudinal travel data. It accounts for a more realistic analysis of the charging station impact on BEV feasibility. The actual range of a BEV is formulated as a Weibull-distributed variable, while the between-charge travel distances is formulated using a Poisson–gamma distribution.[34] Hidrue et al. analysed customers' willingness to pay for EVs and their attributes using a stated preference study. It showed that the driving range, fuel cost savings and

charging time rank as the most important factors and battery cost must drop significantly before EVs find a mass market without subsidy.[35] He et al.[36] proposed a model that captures the interactions among availability of public charging opportunities, prices of electricity and destination and route choices of PHEVs.

TAP of vehicles with range limit

In general, traffic assignment is characterized as an uncapacitated nonlinear multi-commodity network flow problem under some given optimal or equilibrium routing principle. It is the last step of the traditional four-step travel demand modelling process and widely used an evaluation tool for a variety analysis of urban and regional traffic network.[37]

The standard TAP can be solved efficiently using a Frank–Wolfe type algorithm within which the linearized sub-problem is to find shortest paths between each O–D pair. The problem of finding the shortest path for an EV was initially discussed by Ichimori et al.,[38] where a vehicle has a limited battery and is allowed to stop and recharge at certain locations. Lawler[39] sketched a polynomial algorithm for its solution, which makes EV SPP polynomially solvable. Although several studies considered EVs in traffic assignment, they only restricted the EV travel distances and assumed no refuelling.[40] Adding refuelling stations to the shortest weight-constrained path problem (SWCPP) is a NP-complete problem[41] which has been discussed by Laporte and Pascoal.[42]

EV SPPs considering various EV special constraints are extensively studied in EV VRP. These can be incorporated into TAP as a subroutine with EV network to enrich the family of TAP with EV network. Numerous works have addressed the classical VRP with capacity and distance constraints.[43] Erdoğan and Miller[44] extended the VRP to account for the additional challenges associated with operating a fleet of AFVs considering the driving range limit as well as the limited refuelling infrastructure. Adler et al.[45] proposed an EV shortest-walk problem to determine the shortest travel distance route which may include cycles for detouring to recharging batteries from origins to destinations with minimum detouring. Cabral et al. studied the network design problem with relays (NDPR) on an undirected graph, which

generalized the SPP with relays and the weight-constrained SPP. The length between two consecutive relays does not exceed a pre-set upper bound.[46] The problem of energy-efficient routing of EVs has been addressed, and the polynomial time algorithms have been developed in the literature by considering the limited cruising range and regenerative braking (i.e. the EV increases its level of energy when braking) capabilities of EVs which is actually a special case of the constrained SPP.[47] Ryan and Miguel[48] introduced a recharging VRP where vehicles with limited range are allowed to recharge at customer locations. A large body of work on optimal route planning for EV is proposed.[49–51]

Some other issues regarding battery-swapping service have also been discussed under various frameworks. Mirchandani et al.[52] discussed some new logistics relevant to the design and operations of a fleet of EV vehicles operating within a battery-exchanging infrastructure from the operational research perspective. Besides, Jiang et al.[7] presented a network equilibrium problem with a combined destination, route and parking choices subjected to the driving range limit and alternative travel cost composition associated with BEVs.

Network design and bi-level model

The NDP is concerned with the modification of a transportation system, by adding new links or improving existing ones to minimize the total system costs consisting of system travel costs and investment costs.[53] In the EV scheme, it means locating EV charging station in the traffic network and minimizing the total cost of charging station investment and travel cost. The bi-level programming technique can be used to formulate this equilibrium NDP.[54] Wang et al. developed a global optimization method for a discrete NDP which can be applied in EV network design. It is formulated as a bi-level programming model, where the upper level aims to minimize the total cost (sum of total travel times and investment costs) and the lower level is a traditional Wardrop's user equilibrium (UE) problem.[55] Bi-level model has been applied in various congestion pricing schemes to design the toll for transport network.[56–60] These models and solution algorithms[61,62] can also be extended for EV scheme considering their similar framework and constraints.

Future developments

Although there is a large literature related to the EV scheme, the EV network modelling (see Table 1) study is limited and evolving, including the EVs' limited driving range, different charging facilities and lack of charging facilities. On this basis, the following research directions are proposed with direction no. 1, 2 and 7 which are the extensions of existing models, while others are future research directions.

Table 1. Overview of EV network modelling literature in the past 5 years.

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Extensions of the static traffic assignment model of EVs to stochastic traffic assignment or dynamic traffic assignment considering elastic demand

There have been few researches on the stochastic or dynamic traffic assignment of EV as well as those considering elastic demand. The driving range limit and the lack of charging infrastructure are the two main characteristics of EVs at the current stage. To our best knowledge, it remains unsolved about how to develop the general stochastic user equilibrium (SUE) traffic assignment model or dynamic traffic assignment model with path distance constraints as well as the corresponding solution algorithms. Take stochastic traffic assignment model for example, it turns out that simply adding path distance constraints into Daganzo's model, which is an unconstrained minimization model, cannot yield an optimization one of the generalized SUE conditions.

Extensions of BSS network model in which batteries can be treated as goods in traditional logistic management and transported from distribution centre to swapping stations

There have been few studies found on the operating mode of the BSS which incorporates logistic management into the battery pack transportation. For now, the EV users have their batteries swapped at the swapping station, and the depleted batteries are then charged at that station with DC fast charger which usually takes around 1 or 2 h to charge to the full capacity. This kind of operating mode has a lot of disadvantages. First, it is hard to accurately predict the demand of battery-swapping service or the EV-arriving pattern (e.g. more EV users may swap during peak hours or public holidays) at each station, thus making it a hard choice to decide the number of chargers and battery inventory at each station. It is a waste of money and resource if the chargers are over built. If the number of chargers is less than what we need, it means that the EV drivers may have to wait for hours to get a full-energy battery which will discourage the user and eventually influence the market penetration. Second, DC fast charger needs a power of around 100 kW per charger for DC fast charging or Level 3 charging. Building one charger at a station is already a great burden for local electricity power grid; not to mention, it usually needs more than that. So, it will make few locations available for building new BSSs or rebuilding the existing gas station restricted by the power grid and the safety issue. Finally, the fast charging causes damage to the battery itself and reduces the battery life. By contrast, building a battery distribution centre can help to solve all the problems above to ensure the acceptable level of service via the proper operation of logistic management and inventory information system. Also, the existing gas station can be reconstructed by just adding a battery-swapping facility and a warehouse for battery storage. A battery distribution centre can give more flexibility to battery usage with regard to spatial and temporal distributions of the demand by adjusting the battery shipment scheme, thus reducing the number of batteries needed in the system by leveraging the battery transportation cost and battery manufacturing cost. Therefore, it is of great value to do this research towards developing a new operating mode for BSS, especially along the corridor between cities for the optimal design of future

battery-swapping systems which would help in improving the level of service and attracting more drivers to the EVs.

Bi-level model that incorporates an upper level of EV charging facility network design and a lower level of stochastic traffic assignment of EVs

Bi-level model has been used successfully in many applications, such as NDP[54,64] and congestion pricing scheme.[56–60] Most of the bi-level models that involve traffic assignment are deterministic models in which there are no uncertainties of model inputs and the input values are fixed and known. However, the inputs of the upper level model can be the output of the lower level models that may be inaccurate if simple static traffic assignment model is used. Therefore, it is necessary to extend these bi-level models to consider uncertainties or perception errors of the EV users. One possible research direction is to incorporate recent stochastic modelling into these models considering EVs' special behaviour including range limit or charging requirement. Moreover, one can define and incorporate various objective functions in terms of different cost composition or coverage need to evaluate upper level objective functions and adopt the extension of Wardrop's principles in the lower level, so as to develop a new and more realistic framework for EV.

Multi-class users and corresponding multi-class charging stations

Little previous research has been done on multi-class EVs. There are various types of EVs and different EVs have different battery capacities or range limits. Besides, the corresponding charging system (e.g. connectors and plugs) differs. For example, three types of DC fast charging exist today. CHAdeMO is the most common one used by the Nissan Leaf and Mitsubishi vehicles. Recently, the Chevy Spark and the BMW i3 came to market with the SAE J1772 combined charging system (CCS), which uses a single port for either AC Level 1 and 2 or DC Level 2 charging. Additionally, Tesla is rapidly expanding their supercharger network, which is based on their own connector and currently can only charge Tesla vehicles. Each of these three standards operate at a variety of DC voltages, and each has a different maximum power level but replenish miles of range at roughly the same rate on average.

The issue of multi-class users is quite crucial for both the charging facility location design and the TAP. Different user class means different vehicle routing behaviour and different charging facilities. At the initial stage, the existing research has assumed that all the EVs use the same battery standard, and the charging facilities or swapping facilities are compatible for all types of EVs. There is a presence of charging facility location design with only different charging levels (e.g. AC Level 1, AC Level 2, DC fast charging and battery swapping) but without any consideration of multi-class users. Therefore, it is of considerable importance to perform in-depth research on the multi-class EV user problem because the battery technology is a main competitive factor in the EV market, and it is impractical for all the manufacturers to employ the battery with the same capacity and standard.

Stochastic range anxiety

There has been little research considering that different EV users have their own tolerance of 'range anxiety' which means that drivers will not always charge their batteries until the batteries are running out. Stochastic range anxiety of EV drivers will affect the charging station location scheme because people will react differently when they arrive at a charging station. So, it is important to consider the range anxiety as a stochastic term which differs among the user group so that battery demand forecast can be more accurate and the EVs' arriving pattern can be more predictable.

Efficient, convergent and robust algorithms for stochastic traffic assignment with path distance constraints for large-scale network

The objective function of the SUE model with path-specific constraints has path-specific term without explicit mathematical expressions, leading the resultant model to more difficulty in solving the global optimality than the classical traffic assignment models. Moreover, existing solution algorithms for stochastic traffic assignment with side constraints have only been applied to small networks. The robustness of the algorithms has not been tested yet. For large-scale network, distributed computing system could be of considerable significance to fulfil satisfactory execution time and accuracy level for probit-based SUE problem.[65] So, developing global convergent

and efficient algorithms for solving such models with side constraints for large-scale EV transport networks is a challenging research direction in the future.

Microscopic EV behaviours and impact of EVs' signal priority

Signal priority is an effective way to reduce vehicle delay at signalized intersections.[66] Many cities around the world have taken steps to promote EVs' market share, including government subsidy, free parking and signal priority. However, the potential impact of these measures above remains unclarified. In addition, behaviours, such as car following, overtaking and lane changing, may occur differently across EV classes. A car following model has been proposed to explore the influences of the EVs' driving range on the driving behaviour.[67] Take links with different numbers of lanes for example. It has been found that the platoon dispersion of traffic flow in low-friction conditions is affected by the number of lanes.[68] So, the special microscopic EV behaviours also remain to be a potential worthy direction in the future.

Potential impacts when attributes are related to EV change

Recent advances in technology suggest that driving range can be extended, charging time shortened and battery cost lowered. Also, after a few years of massive production, the unit cost for EVs, like most new technologies, is likely to fall.[35] Attributes related have great impacts on various aspects of EVs' adoption. Oil and electricity prices will affect fuel cost saving, while the charging time and driving range concern about range anxiety. So, it is important to understand the market for EVs in the future when there are large push and sizable investment of resources in favour of EV.

Charging station location on urban freeways

Urban freeways have been deemed to be important transportation infrastructure.[69–72] Recent research of charging station location problem mainly focused on urban area or Central Business District (CBD) area, using standard p-median, p-centre, maximum covering, flow capturing and flow interception model to maximize

coverage. Considering EVs' driving range, locating charging stations on urban freeways is more important and encouraging to eliminate range anxiety. Thus, there is an urgent need to develop optimal charging station location model on urban freeways, especially for inter-city trips.

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