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Evaluating the impact of electric vehicle charging infrastructure design alternatives on transport network performance

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Abstract

Plug-in electric vehicles (PEVs) are a rapidly evolving technology representing a potentially sustainable alternative to traditional internal combustion engine vehicles (ICEVs). By relying on electric power rather than petrol, these new vehicles will require a new infrastructure system for en-route charging options, be that fast charging stations or battery swap stations. PEVs will therefore generate mobile energy demands that must be met by regional power providers. Optimally designing infrastructure to meet these new energy demands will require knowledge of the spatiotemporal travel patterns, which are inherently dependent on the user's activities and travel behaviour. Furthermore, limited battery capacity will result in a distance constraint for PEV drivers, inevitably impacting individual's travel and activity patterns. This constrained behaviour must be incorporated into traditional traffic assignment models, requiring innovative routing algorithms. Previous work by Jiang et al (2012) introduced a novel distance constrained user-equilibrium-based assignment model which allowed charging requirements to be incorporated into the traditional traffic assignment problem. Using Jiang et al.'s assignment model, we evaluate the impact of PEV traveller's en route charging needs on the network system performance under various charging station location options. We identify key scenarios in which infrastructure planning decisions result in sub-optimal network performance, motivating the need for intelligently selecting charging station locations.

1. Introduction

Plug-in electric vehicles (PEVs) have attracted much attention as a potential alternative vehicle technology to help reduce both greenhouse gas emissions and reliance on fossil fuels. However, to successfully integrate this new technology into current transport systems, researchers and industry alike need to overcome many key barriers. One such issue results from the limited range of fully electric vehicles. A PEV's driving range is a function of the battery capacity and engine efficiency, both of which will increase as the available battery technology improves. Nonetheless, a limited driving range may result in range anxiety for potential PEV users, thus providing a disincentive to purchase the new vehicle technology. For those who do drive PEVs, the range limitation will restrict the set of route options available to them. To address these issues, it is vital that planners address the need for re-charging infrastructure, specifically the availability of charging stations.

It follows that the availability of PEV charging stations will be a key determinant in the ultimate success of these vehicles, both in terms of initial uptake, and once they are established on the road network. The location of the charging stations may impact drivers' route choice decisions, which will in turn impact the performance of the system. Therefore this paper focuses on evaluating the impact of charging station location on the overall performance of the regional transport system. A traffic assignment model accounting for the range limitations in PEV drivers is implemented, and various scenarios are developed and evaluated to quantify the impact of PEV charging station location decisions. This analysis motivates the more computationally intensive problem of optimally locating charging stations in a transport network by exposing the achievable system performance improvement from various charging station location alternatives. This work considers plug-in electric vehicles (PEVs) which rely solely on recharging a battery for energy, sometimes called battery electric vehicles or all-electric vehicles.

The remainder of the paper is structured as follows: Section 2 provides a literature review, Section 3 describes the problem definition and solution methodology, the numerical results are presented in Section 4. Finally, the conclusion and a discussion of future work is presented in Section 5.

2. Literature Review

This section provides a brief background to the problem addressed. First of all, the role of charging stations in the successful adoption of PEVs is discussed. Next, this section defines the constrained network equilibrium assignment model, followed by a summary of relevant literature related to PEV infrastructure design.

2.1 Challenges posed by electric vehicles

Much speculation exists in regard to the future of PEVs. Despite the environmental advantages that PEVs offer, they are currently subject to many barriers impeding their mass adoption. One of the most important issues is that PEVs have a limited driving range compounded by a lack of public charging infrastructure available.

Although internal combustion engine vehicles (ICEVs) also have a limited range, refuelling stations are abundant, negating any issues that may be imposed by fuel tank capacity. Numerous studies have identified charging infrastructure availability to have a significant impact on potential PEV consumers' purchasing decisions (Allan, 2012).

PEVs in Australia face a similar outlook. While trials in Perth have found that early adopters of PEVs are satisfied with their vehicles (Jabeen et al, 2012), still a majority of all trips were less than thirty kilometres in distance; this may partially be a reflection of range anxiety and a lack of charging infrastructure. Additionally, both Allen (2012) and Speidel et al (2012) identified similar challenges to PEVs in Australia: high operating and initial costs, technical limitations such as range anxiety, the lack of charging infrastructure, managing the added power demand on the electric grid, regulation and policy, and public education about PEVs. This work intends to motivate the importance of the charging infrastructure problem while acknowledging the issue of a distance constraint in PEV driver route choice.

2.2 Distance constrained network equilibrium assignment model

Network equilibrium assignment models are used in the trip assignment stage of the traditional four step transport planning process. However traditional network equilibrium assignment models do not account for the behaviour of PEVs in a network, because they do not impose a distance limitation on drivers. Traditional assignment models assume that users have perfect information and that they will choose the least cost path available to them (Wardrop, 1952); however, PEV users have the added consideration of ensuring that the path does not exceed the distance constraint of their vehicle.

This novel consideration means that a new type of equilibrium assignment model is needed to analyse networks in which PEVs are present. While previous works have examined the impact of a new class of PEV users without including this new behaviour (Duell et al, 2013; Gardner et al, 2013), Jiang et al (2012) address this issue by developing a distance constrained network equilibrium assignment model, which can be implemented to account for the behaviour of PEVs. The model assigns a range limitation to PEV users so that a route can only be chosen if the limit is not exceeded. It also allows PEV drivers to replenish their fuel when a charging station is available. The behaviour of PEVs can be represented because the shortest path algorithm in this model is a distance constrained shortest path algorithm. Note that this model does not account for the dwell time spent "recharging" a vehicle. Additionally, this model was extended to include a destination choice model (Jiang et al, 2013), although the impact of charging station infrastructure design using this algorithm has not yet been investigated.

2.3 Optimisation of charging station locations

Past work investigating the issue of optimal charging station location focused on different objectives, including maximising the demand covered by the charging stations (Xi et al, 2012), maximising service provided by the charging stations (Fraude et al, 2011), minimising the cost spent on constructing the charging stations (Kuby & Lim, 2005) and minimising average vehicle travel time in the network (Hess et al, 2012). Additionally, the approaches used to estimate the PEV demand on charging stations also differ, from the use of real data obtained from household travel surveys (McPherson et al, 2011), to the application of a traffic assignment model (Hanabusa & Horiguchi, 2011).

Kuby and Lim (2005) used a variation of the set covering model to solve for the optimal location of refuelling stations for vehicles, in the context of a vehicle routing problem, assuming that the vehicle flows are known a priori. The goal was then to provide refuelling to as many vehicles as possible while minimizing the total cost of constructing the infrastructures.

This approach was adapted to PEVs by McPherson et al (2011) and presented in the context of Australia. This work provides a sound methodological background, specifically examining the problem of battery switch stations. McPherson et al identify trips that are greater than 120 km in distance as the criteria for locating optimal battery switch station locations. While this approach does not account for behavioural changes due to the new charging stations, it does present a number of interesting, and relevant results, finding that in Melbourne and Sydney, about ten charging stations could capture 60% of long distance trips.

Frade et al (2011) performed a case study to determine the best locations for PEV charging stations in a neighbourhood in Lisbon, Portugal. The goal in this case, however, was to maximize the demand covered by charging stations when the demand was calculated from census data and the number of charging stations to be built in the future was determined by the government. Therefore the total cost of the charging stations was not taken into account in this study.

Xi et al (2012) addressed the planning problem using a simulation model that maximises charging station service rates. This model was then applied to a case study in the mid-Ohio region. The input data of this model, collected from vehicle usage data in 2010, was quite extensive. The analysis was done for maximising the amount of energy served and for maximising the number of PEVs serviced. However, the PEV flows on links were determined by assigning an PEV adoption probability to current vehicle owners. The candidate locations for charging stations were determined to be locations where users stay for extended period of time, such as shopping centres, work places and universities.

Worley et al (2012) also proposed an algorithm to find the optimal location for refuelling stations and the optimal set of routes for vehicles. Their approach was different from that of Kuby and Lim (2005) in that they utilized an integer programming model to solve the refuelling problem and the routing problem together. The problem, however is still based on the classic vehicle routing problem and the metric upon which optimality is measured is the total cost, which includes the sum of travel costs, recharging costs and costs of charging stations.

Hess et al (2012) evaluated the optimal locations for charging stations in a real network, which they solved using a genetic algorithm. They demonstrated this approach on the city centre network of Vienna, using the Krauss car following model for simulation. To reflect the range constraint of PEVs, additional decision logic was added in the Krauss model. This triggers the users' decisions to look for the closest charging station when their battery charge levels are low. The average trip time of electric vehicles, given by the sum of travel time and the recharging time spent was minimised by the aforementioned algorithm in this case study.

Hanabusa and Horiguchi (2011) developed an analytical method to solve for the charging station planning problem. This problem, in contrast, is based on the context of Stochastic User Equilibrium. The travel time of each PEV, including the waiting time it spent in charging stations, was to be minimised. An additional criterion was that the level of service for each charging station was also to be balanced. The range constraint effect was accounted for by applying an extra penalty cost on the link travel time.

Chen et al (2013) did a case study in finding the optimal charging station locations for the Seattle region. The PEV demand was assumed to be proportional to the current demand of light-duty vehicles, which was obtained from a household travel survey. The effect of land use attributes, parking durations and trip characteristics was also taken into account. This model minimises the total system travel time for potential PEVs in the Seattle region. While this work is closely related to that of Hanabusa and Horiguchi, Chen et al. used survey data to calculate the demand for charging stations while Hanabusa and Horiguchi obtained the demand from a traffic assignment model.

Among the reviewed literature the only work that utilised a network assignment model to assess PEV demand was by Hanabusa and Horiguchi. They used a common shortest path algorithm, which in itself does not consider the range constraint of the PEVs. The range constraint was reflected by an extra cost on links if the vehicle's total range is exceeded. This work provides a different angle of addressing the network assignment aspect of the aforementioned optimisation problem.

The network assignment algorithm by Jiang et al. requires that the locations of the charging stations are given as a priori. In this paper the locations of these charging stations are set by user input, and then the impact of these locations on the total system travel time is demonstrated. This could then motivate the need for the future development of an optimisation method that could search for the optimal locations of the charging stations, utilising the algorithm by Jiang et al. as its demand assignment model.

3. Problem Definition

The proposed model is based on the assumption that installing a charging station in a transport network will impact PEV driver's route choice, thus altering the link flows, and hence the performance of a given network. This is due to the inherent relationship between link flow volumes and congestion. The performance measure used in this study is the total system travel time (TSTT), which is the sum of the travel time experienced by all users in the network to travel between their respective origin and destination. The impact of charging station location on route choice is captured using the constrained shortest path with recourse algorithm by Jiang et al (2012), discussed in Section 2.2.

The link cost function may be any function that defines the relationship between the number of users travelling a particular link and the cost to travel that particular link (cost can be travel time, money, etc). While any link cost function could be substituted, a common link-cost function used in transportation literature and practice is the Bureau of Public Records (BPR) formulation (U.S. Department of Commerce, 1964), and is the function used in this paper for demonstration purposes. The BPR function is defined below:

$$t_a = t_f(1 + \alpha \left(\frac{v}{C}\right)^{\beta}) \qquad [1]$$

Where *t* is link travel time, t_f is free-flow travel time, *v* is hourly volume, *C* is hourly capacity, and α and β are parameters that depend on link geometry. It is assumed that $\alpha = 0.15$ and $\beta = 4$ for the analyses in this paper.

The location chosen for a charging station is expected to change the link flows. This is demonstrated through a selection of infrastructure design scenarios varying in number and location of charging stations. An evaluation of the network performance under each design scenario reveals the impact of charging station location on network system performance. Sensitivity analysis is also conducted to evaluate the impact of varying speed and travel demand.

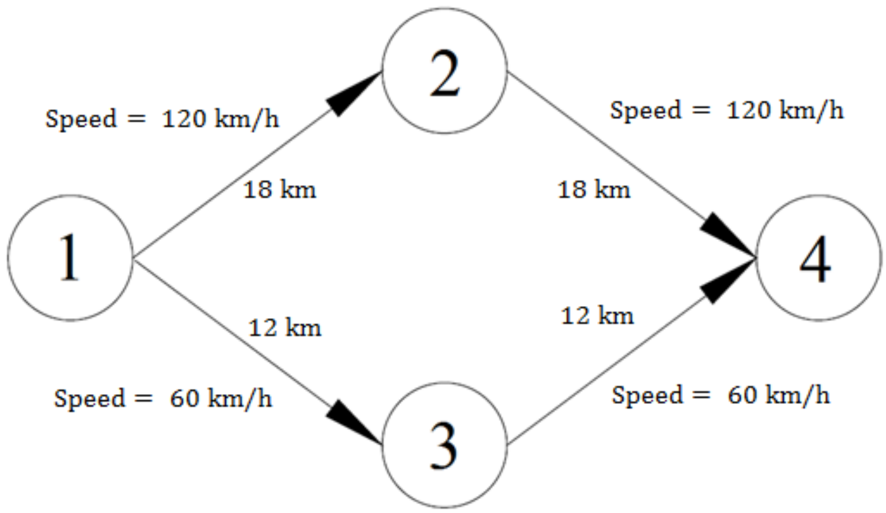
This paper uses two networks to demonstrate the model described. The first is a simple demonstration network with four links, similar to the Braess's Paradox network (Braess, 1969). This network serves to demonstrate the potential benefit that can be achieved by installing a charging station in a network. The second is a slightly larger example grid network that is large enough to capture the interaction between the demand from different origin-destination pairs and demonstrate the impact of infrastructure location decisions. The parameters for both test networks can be found in Appendix A.

4. Numerical Results

4.1 Demonstration Network

The 4-link demonstration network (shown in Figure 1) was analysed first. The change in network performance after installing a single charging station at node 2 is presented. In this example it was assumed all vehicles were PEVs.

Figure 1. Demonstration network



Scenario 1 - No charging station

In the demonstration network path 1-2-4 represents the existence of a highway option in the network, with a longer distance, but higher free flow speeds. However, when there is no charging station in the network, the path 1-2-4 exceeds the range of the PEVs so no one selects it. As illustrated in Table 1 all PEVs must path 1-3-4 and the travel time for any individual driver is 27.6 mins. The total system travel time (TSTT) is then 27.6 min *4000 veh = 110400 veh-mins.

Table 1. Network performance before charging station is installed

Path	*Flow*	*Individual travel time (mins)*
1-2-4	0	N/A
1-3-4	4000	27.6

Scenario 2 - A charging station at node 2

If a charging station is installed at node 2, the path 1-2-4 can now be utilised because PEVs can recharge at node 2. At equilibrium the flows on path are now 20.7 min*4000 veh = 82800 veh-mins, as presented in Table 2.

Table 2. Network performance after charging station is installed

Path	*Flow*	*Individual travel time (mins)*
1-2-4	4000	20.7
1-3-4	0	N/A

Therefore, installing a charging station reduced the TSTT by 25%, as shown in Table 3.

Table 3. Improvement in Network performance after charging station is installed

Scenario	*Charging station*	*TSTT (mins)*	*TSTT reduction*
1	No	110400	N/A
2	Yes	82800	25 %

This example illustrates how charging stations can allow PEVs to access longer alternative routes that were not available to them before, and hence reduce the travel time of PEV users.

Impact of speed of links on TSTT

The impact of charging stations is sensitive to parameters of the network, such as free flow speed. To demonstrate this, the speed of links (1,2) and (2,4) were varied to explore the sensitivity of network system performance to link speeds. When the speed on path 1-2-4 is varied the TSTT saving from installing a charging station (at node 2) can change drastically. This is illustrated for three different speeds, shown in Table 4.

Table 4. The speed on path 1-2-4 and the TSTT saving when charging station is installed

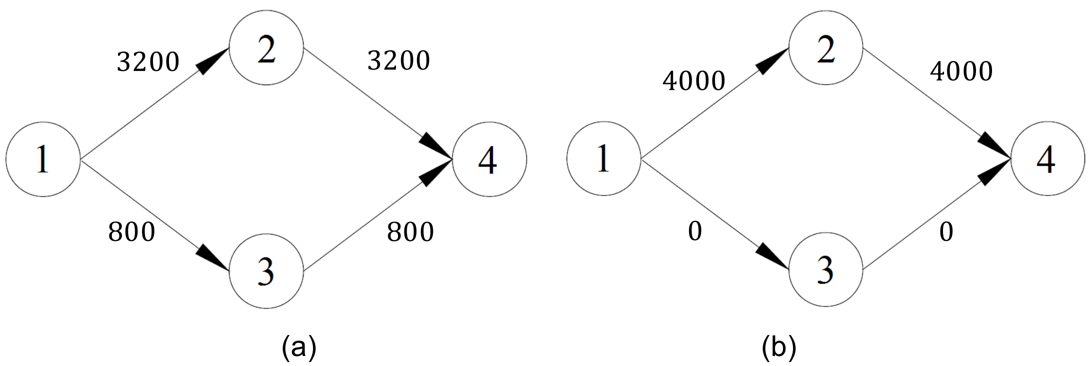
Speed on path 1-2-4 (km/h)	*% TSTT saving with CS installed compared to base case*	*Flow on path 1-2-4*	*Flow on path 1-3-4*	*Cost of path 1-2-4*	*Cost of path 1-3-4*
80	2.17	178	3822	27	27
90	12.23	2000	2000	24.2	24.2
100	13.04	3710	289	24	24

The speed of path 1-2-4 was increased at a constant increment of 10 km/h. The number of drivers that switched paths following every speed increment was nearly constant. The TSTT savings increased 10% when the speed was increased from 80 km/h to 90 km/h, but increased less than 1% when speed was increased from 90 km/h to 100 km/h. This behaviour results from the convexity of the BPR cost function.

When the speed increased from 80 km/h to 90 km/h users swapped from path 1-3-4 to path 1-2-4. This caused only minor increase in the congestion on path 1-2-4, yet reduced the travel time for path 1-3-4 significantly. On the other hand, when the speed was increased further from 90 km/h to 100 km/h, almost the same amount of users switched to path 1-2-4.However the congestion on path 1-2-4 was increased significantly, while further reduction in travel time for path 1-3-4 was minimal. Thus, the specific network properties, such as free flow speed, can significantly impact the resulting network performance under various infrastructure designs. However the resulting performance may be unintuitive, and requires traffic assignment models such as that proposed by Jiang et al. (2012) to explicitly evaluate potential design scenarios.

Furthermore, a paradox exists when there is a mix of PEVs and traditional ICEVs. Figure 2 illustrates this concept. Suppose that before the charging station was installed only 20% of the drivers going to node 4 are PEV drivers and the rest are ICEV users. The resulting network flows are illustrated in Figure 2. The 3200 ICEVs can use path 1-2-4 because they do not have a range limit. The 800 PEVs, on the other hand, need to use path 1-3-4. The total system travel time is 80344 mins.

Figure 2. Paradox Demonstration: (a) Link flows before the CS is built and (b) after the CS is built (right)



If a charging station is installed at node 2, the PEV users now have the option of using path 1-2-4. In order to minimize individual travel times all vehicles will use path 1-2-4 because it is shorter, resulting in a TSTT of 82800 mins. In this example the TSTT after the charging station is installed increases, making the system worse off. This is somewhat counter intuitive, as the charging station provided PEV users with an alternative path, and the ability to travel to their destination faster.

An additional sensitivity analysis was conducted to explore how TSTT savings brought by a charging station varied with the percentage of PEV users in the network. The results are presented in Figure 3. The horizontal axis represents an increasing percentage of PEV drivers, and the vertical axis represents the percentage decrease in TSTT as compared to the base case when there are no PEV drivers in the network. The results demonstrate the importance of considering various future PEV uptake scenarios (different proportional mixes of PEVs and ICEVs) when designing charging infrastructure, as the benefits of building a charging station at a given location can vary drastically.

Figure 3. Results from varying the percentage of PEVs in the network

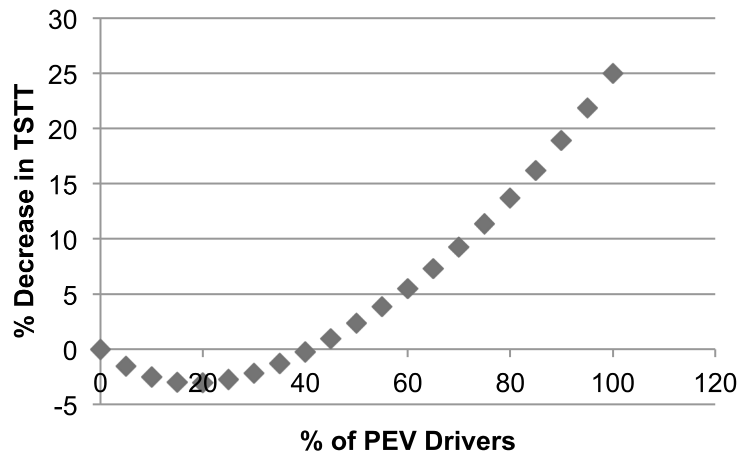
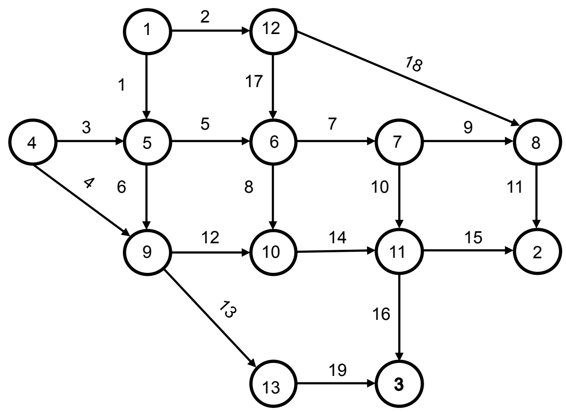


Figure 3 shows that when the vehicle fleet is more than 40% PEVs, building a charging station results in positive TSTT savings, and is maximized when all vehicles are PEVs. On the other hand, as the number of PEV users decreases below 40% a charging station will result in a decrease in network performance. More specifically, at least 1644 PEV users are required for a charging station to provide any system performance improvement. The proposed model therefore has the ability to quantify the penetration level of PEVs necessary for a given infrastructure design scenario to be of value, and similarly, quantify the system improvement possible under a given PEV penetration level.

4.2 Example grid network

The impact of charging infrastructure location is further explored on a medium size network with multiple origin-destination pairs and travel paths. The example network is based on the Nguyen-Dupius network, a common transportation test network. The network is illustrated in Figure 4. The distance constraint for PEVs in this network is 12 km. The specific link parameters are provided in Appendix A. As with the demonstration network, charging infrastructure location is shown to have a substantial impact on system performance, motivating the development for an optimal charging station location algorithm.

Figure 4. The Nguyen-Dupuis network



Similar to the demonstration network, the Nguyen-Dupius network performance varies based on the chosen location for installing a charging station. The base case is representative of the scenario where no charging station is installed. In all other design scenarios at least one charging station is installed in the network. The resulting TSTT is computed for various scenarios, and the results are shown in Table 6, where the TSTT savings are ordered from highest to lowest. The results illustrate that the achievable network TSTT savings can vary significantly dependent on the location where the charging station is installed.

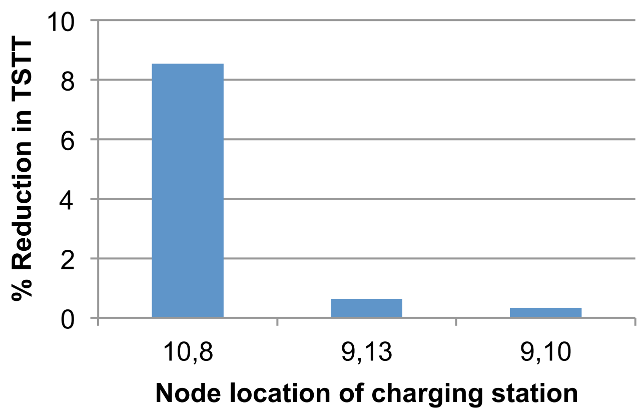
Table 6. The location of charging stations and the TSTT saving results

CS Location	*TSTT*	*% of TSTT saving*
N/A	110672	N/A
6	97311.4	12.07
7	97323	12.06
11	97508.6	11.89
5	97943.7	11.50
12	98989	10.56
8	101223	8.54
9	109976	0.63
13	109976	0.63
10	110670	0.00

Installing a single charging station at node 6 is shown to reduce the TSTT by 12%; while installing a charging station at node 10 does not improve the performance relative to the base case where there is no charging infrastructure. In order for a newly installed charging station to reduce the TSTT it must provide alternative route options for PEVs which result in network wide savings. This is accomplished with the installation at node 6. However, because node 10 already lies on a highly congested path, the addition of a charging station would only attract more users, increasing the congestion on the links around the node, thus reducing network performance. Therefore the addition on a charging station at node 10 does not alter the traffic patterns relative to the base case.

Next, the impact of multiple charging stations is explored. One might expect two charging stations to provide greater network savings compared with a single charging station, but this is not always the case. The network performance is evaluated for the installation of all combinations of two charging stations, which results in 105 combinations for this medium sized network. The range of TSTT ranged from 0% -12.2%, which is similar to the range from installing a single charging station. Therefore installing an additional charging station may not provide any further improvement in network performance. The percentage reduction in TSTT for three combinations of two charging stations are presented in Figure 5.

Figure 5. Results for two charging stations



Two examples where multiple charging stations have little system impact, (9,13) and (9,10) are represented in Figure 5. Additionally, installing charging stations at nodes 10 and 8 reduced TSTT less than installing a single charging station at node 6 or 7. This further supports the need for assignment models which account for user behaviour when comparing charging infrastructure design alternatives.

Finally. the impact of charging station location under demand uncertainty is explored. Three demand scenarios are evaluated: (i) the expected demand, (ii) deflated demand equal to 80% of the expected demand, (ii) inflated demand, equal to 120% of the expected demand. The results are presented in Table 7.

Table 7. Percentage Reduction of TSTT under deflated and inflated demand

CS Location	*Deflated Demand*	*Expected Demand*	*Inflated Demand*
6	6.03	12.07	16.27
7	6.04	12.06	16.21
11	6.10	11.89	15.96
5	6.03	11.50	14.92

12	5.02	10.56	13.33
8	4.13	8.54	11.34
9	-0.02	0.63	1.92
13	-0.02	0.63	1.92
10	-0.07	0.00	0.02

From Table 7 it is apparent that the achievable TSTT saving are dependent on the realized demand. Furthermore, the optimal charging station location varies with demand. For example, node 6 is the optimal location for a single charging station under the expected and inflated demand, while node 11 is optimal for the deflated demand. Thus, when the network demand varies the potential benefit of a potential charging station location can vary, as well as the optimal design alternative. Because future demand in inherently uncertain, it is important to identify charging infrastructure design alternatives which will be robust to future changes in demand.

5. Conclusion

This work investigates the system impact of PEV charging infrastructure design alternatives, specifically charging station location. This problem is important because electric vehicle technology has introduced a new distance constraint to its users. Therefore, new models that represent the behaviour of drivers will aid in more effective infrastructure design; a robust infrastructure of charging stations will influence both the uptake of PEVs and support these vehicles once a significant level of deployment has been achieved.

Demonstration networks provided insight into the complex behaviour of this problem, which results from constrained PEV drivers' route choice. The potential benefits achievable from selecting optimal charging station locations were quantified. Additionally, we identified the case where installing charging stations had no impact on the system performance. Finally, we explored the impact of demand uncertainty. The results from the analysis point to the following observations:

(I) Installing charging stations in a network can provide alternative paths for PEV users, thus reducing the total travel time for all users.
(II) The number of charging stations and location chosen for the charging stations may have a significant impact on the network performance.
(III) The network benefits from installing charging stations may be counter-intuitive. It is possible some design alternatives provide no benefit to the network. It is also possible installing two charging stations provides less benefit than installing a single charging station.
(IV) Network properties and parameters such as link speed, demand and the percentage of PEV users will impact the achievable performance of a given charging station location.

The analysis presented in this paper is intended to motivate future research efforts for developing an optimization algorithm to identify optimal charging station locations in large networks. Factors such as time spent recharging may also play a role in user route choice, and should be integrated into the distance constrained network equilibrium assignment model used in this paper. Finally, future models should investigate a more realistic proxy for the distance constraint of PEV drivers, such as energy consumption that is reflective of driving behaviour and network conditions.

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Appendix A: Nguyen-Dupuis Network

Table: **Origin-Destination Demand**

OD Demand		Destination	
		2	3
Origin	1	1300	1840
	4	1680	1450
Total Demand		6270	

Table: Network Parameters

Link no.	Start node	End node	Length(km)	α	β	Capacity	Speed(km/h)
1	1	5	2	0.15	4	800	60
2	1	12	3	0.15	4	800	60
3	4	5	3	0.15	4	800	60
4	4	9	4	0.15	4	800	60
5	5	6	4	0.15	4	800	60
6	5	9	7	0.15	4	800	60
7	6	7	7	0.15	4	800	60
8	6	10	5	0.15	4	800	60
9	7	8	15	0.15	4	1500	120
10	7	11	16	0.15	4	1500	120
11	8	2	5	0.15	4	800	60
12	9	10	5	0.15	4	800	60
13	9	13	10	0.15	4	800	60
14	10	11	13	0.15	4	1400	60
15	11	2	4	0.15	4	800	60

16	11	3	3	0.15	4	800	60
17	12	6	3	0.15	4	800	60
18	12	8	20	0.15	4	800	60
19	13	3	14	0.15	4	800	60

References

Allan, A (2012) The transport policy and planning implications of electric cars for Australian cities *Papers of the 35th Australasian Transport Research Forum 35(2)* Perth: ATRF

Braess, D (1969) Über ein Paradoxon aus der Verkehrsplanung. *Unternehmensforschung* 12, *pp.* 258–268

Bureau of Public Roads (1964) Traffic Assignment Manual, *U.S. Dept. of Commerce, Urban Planning Division, Washington D.C.*

Chen, T D, Kockelman, K M, Murray, W J, & Fellow, J (2013) The electric vehicle charging station location problem: A parking-based assignment method for Seattle *Proceedings of the 92nd Annual Meeting of the Transportation Research Board* Washington DC, USA

Duell, M, Gardner L, Waller S T (2013) Multiobjective Traffic Network Design Accounting for Plug-in Electric Vehicle Energy Consumption *Proceedings of the 92nd Annual Meeting of the Transportation Research Board: Washington DC, USA*

Frade, I, Ribeiro, ., Gonçalves, G, & Antunes, A P (2011) Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal *Transportation Research Record: Journal of the Transportation Research Board*, *2252*(-1), *pp.* 91–98

Gardner, L.M, Duell, M, Waller, S T (2013) A framework for evaluating the role of electric vehicles in transportation network infrastructure under travel demand variability. *Transportation Research Part A: Policy and Practice 49, 76-90*

Hanabusa, H, & Horiguchi, R (2011) A Study of the Analytical Method for the Location. *Lecture Notes in Computer Science in Knowledge-based and Intelligent Information and Engineering Systems, 6883(2001),* 596–605

Hess, A, Malandrino, F, Reinhardt, M B, Casetti, C, Hummel, K A, & Barceló-Ordinas, J M (2012) Optimal deployment of charging stations for electric vehicular networks *Proceedings of the first workshop on Urban networking - UrbaNe '12*, 1

Jabeen, F, Olaru, D, Smith, B, Braunl, T, Speidel, S (2012) Acceptability of Electric Vehicles: Findings from a Driver Survey *Australasian Transport Research Forum (ATRF), 35th, 2012, Perth*

Jiang, N, Xie, C, Waller, S T (2012) Path-Constrained Traffic Assignment: Model and Algorithm. *Proceedings of Transportation Research Board 91st Annual Meeting*.

Jiang, N, Xie, C, Duthie, J C, Waller, S T (2013) A network equilibrium analysis on destination, route and parking choices with mixed gasoline and electric vehicular flows. *EURO Journal on Transportation and Logistics*, 1-38

Kuby, M & Lim, S (2005) The flow-refueling location problem for alternative-fuel vehicles. *Socio-Economic Planning Sciences*, *39*(2), 125–145

McPherson , C, Richardson, J, McLennan, O, Zippel, G (2011) Planning an electric vehicle battery switch network for Australia *Papers of the 34th Australasian Transport Research Forum 34(31)* Adelaide: ATRF

Nguyen S, Dupuis C (1984). An efficient method for computing traffic equilibria in networks with asymmetric transportation costs, *Transportation Science, 18, pp.* 185-202

Speidel, S, Jabeen, F, Olaru, D, Harries, D & Bräunl, T (2012) Analysis of Western Australian electric vehicle and charging station trials. *Australasian Transport Research Forum (ATRF), 35th, 2012, Perth*

Taylor, M.A., Pudney, P., Zito, R., Holyoak, N., Albrecht, A., Raicu, R. (2011) Planning for Electric Vehicles in Australia–Can We Match Environmental Requirements, Technology and Travel Demand? *Australasian Transport Research Forum (ATRF), 34th, 2011, Adelaide*

Wardrop, J. G. (1952). *Some theoretical aspects of road traffic research*. Proceedings, Institution of Civil Engineers

Worley, O., Klabjan, D., & Sweda, T. (2012). Simultaneous vehicle routing and charging station siting for commercial Electric Vehicles. Electric Vehicle Conference (IEVC), 2012 IEEE International, IEEE

Xi, X., Sioshansi, R., & Marano, V. (2012). "A Simulation-Optimization Model for Location of a Public Electric Vehicle Charging Infrastructure." *Transportation Science*, Under Review