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A framework for evaluating the role of electric vehicles in transportation network infrastructure under travel demand variability

Lauren M. Gardner [a,*], Melissa Duell [b], S. Travis Waller [c]

[a] CE 112, School of Civil and Environmental Engineering, The University of New South Wales and NICTA, Sydney, NSW 2052, Australia
[b] CE 113, School of Civil and Environmental Engineering, The University of New South Wales and NICTA, Sydney, NSW 2052, Australia
[c] CE 110, School of Civil and Environmental Engineering, The University of New South Wales and NICTA, Sydney, NSW 2052, Australia

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ABSTRACT

The introduction of plug-in electric vehicles (PEVs) represents an unprecedented interaction between the road network and electricity grid. By replacing the traditional fuel source, petrol, with electricity, PEVs will increase the demand for electric power in a region and change emission profiles. Overall, the impacts depend on the eventual penetration of PEV ownership, but the true market share of PEVs in the future is highly unclear and radically different scenarios are possible. This added forecasting volatility makes long-term transport models that explicitly consider travel demand uncertainty even more critical. This work utilizes transport modeling tools in order to quantify the relationship between the travel patterns of PEV drivers and PEV energy consumption rates, as well as the corresponding environmental impact (measured by emissions savings relative to traditional internal combustion engine vehicles). Furthermore, this research explicitly addresses the relationship between long term travel demand uncertainty and system level energy consumption variability, an essential issue for regional energy providers and planners. Results and implications are discussed on both a small demonstration network and the Sioux Falls network.

1. Introduction and motivation

Plug-in electric vehicles (PEVs) are a rapidly evolving technology that represents a potential partial solution to global concerns related to petroleum dependence, energy security, and human contribution to climate change, particularly from the transport sector. PEVs are therefore of interest to researchers, policy-makers, consumers, and industry alike – a fact that is reflected by the vast efforts taking place to support the development of these vehicles. In addition, the ongoing PEV-related projects span a wide spectrum of fields. This research places particular emphasis on an aspect of PEVs that is often less recognized than the aforementioned issues: their potential to more closely link our transportation and electric power systems.

PEVs represent an unprecedented interaction between the road infrastructure and electricity grid, creating the opportunity to combine the two traditionally disconnected networks. This will aid in the design of a smarter, safer system to meet the needs of users in the most effective way possible. Thus, research that explicitly considers the addition of PEVs into the traditional transport system as well as the broader impact across multiple systems will be vital to the successful integration of this transformative technology, and furthermore to ensuring that PEVs are utilized to their fullest potential.

* Corresponding author.
E-mail addresses: l.gardner@unsw.edu.au (L.M. Gardner), m.duell@unsw.edu.au (M. Duell), s.waller@unsw.edu.au (S.T. Waller).

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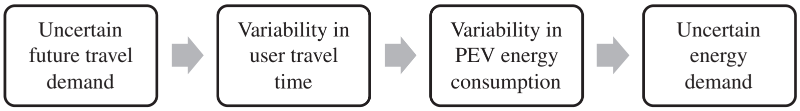

Fig. 1. Relationship between travel demand uncertainty and PEV energy consumption rates.

However, as of yet, relatively little work has been done in transportation modeling that explicitly accounts for the presence of PEVs. To address this growing domain, this work begins by providing a methodology for transport planners to quantifiably compare future transport network design scenarios with regards to both traditional transport goals and the impact on PEV drivers. In order to analyze different network designs, traffic assignment models were implemented to characterize vehicle travel patterns for a weekday peak period travel demand. The resulting travel patterns were used to quantify PEV energy consumption rates at the system level by aggregating consumption across all PEVs in the network during the period modeled. The amount of energy consumed by a single PEV during a trip is assumed to vary with travel speed, and is further detailed in Section 2.3. The availability of public charging infrastructure is not considered in this analysis.

As travel demand is inevitably stochastic in nature, this research explicitly addresses the relationship between long-term travel demand uncertainty (and correspondingly, uncertainty in varying PEV penetration levels) and variability in PEV energy consumption rates, an essential issue for regional energy providers. Additionally, the differences in PEV technology as compared with the energy consumption of traditional internal combustion engine vehicles (ICEVs) mean that energy consumption is a novel performance measure that needs to be considered by transport planners.

Provided travel demand is uncertain, traditional robust network designs are sought to maximize reliability of travel routes in terms of travel time. Analogously, travel routes that are reliable in terms of energy consumption are of importance to PEV drivers due to the limited range imposed by the electric battery capacity. However the impact of travel demand uncertainty on PEV energy consumption, and furthermore its potential role in both the transport and electric-power-grid system design process, is an issue that has not yet been addressed. In order to explore this point, this work quantifies the variability in PEV energy consumption resulting from uncertain travel demand. Under the same network conditions the environmental impact is also evaluated in terms of emissions.

Variability in PEV energy consumption has an impact at both the user level and the system level. Because PEV travel is constrained by the battery capacity and state of charge, range anxiety may result in PEV drivers preferring more reliable travel routes in terms of energy consumption to minimize the probability of getting stranded. At the system level the aggregation of highly variable individual PEV energy consumption patterns can result in significant variations in regional energy demand, making it difficult for electric-grid systems operators to allocate resources optimally. Therefore understanding the relationship between PEV energy consumption with regard to travel time variability (resulting from demand uncertainty) is a necessary first step in determining the spatiotemporal demand distribution. The basic relationship between travel demand variability and energy demand variability is summarized in Fig. 1.

In addition to the stated objectives this work seeks to answer the following questions:

1. How should traditional transport models accommodate the added presence of PEVs?
2. How should traditional power systems prepare for the added presence of PEVs?
3. What is the impact of travel demand uncertainty (in terms of total travel demand and PEV penetration levels) on PEV energy consumption?
4. How might transport network design differ when PEV energy consumption and energy variability are also accounted for?
5. How sub-optimal are the transport network designs when PEV energy consumption and energy variability are disregarded?
6. How can this sub-optimality be quantified?

The remainder of this work is organized as follows: Section 2 contains a literature review. Section 3 defines the problem properties and the modeling tools utilized in this work in detail. Section 4 presents the mathematical formulation of the problem and solution methodology. Section 5 further motivates the problem with a sample demonstration, and provides a case study of Sioux Falls to illustrate the behavior of system energy consumption under stochastic demand. Section 6 concludes the work with a brief review and discussion of future research.

2. Literature review

This research combines and applies previous transport modeling methodologies in a novel way that highlights several important aspects of PEVs. In particular, this work seeks to illustrate the impact of network-level travel patterns on PEV energy consumption levels. The research areas addressed in this work include static traffic assignment, demand uncertainty, travel time variability, electric vehicle technology, vehicle energy consumption and emissions rates, as well as electric power plant emissions rates. A complete literature review in just one of these fields is a daunting task of its own, and a comprehensive review is infeasible. Therefore the literature introduced in this section aims to provide the necessary background for the proposed research, and to highlight the pieces of literature directly applicable to the problem at hand. Consequently, the literature review first covers basic traffic assignment models, particularly those that have incorporated PEVs, followed by the role of demand uncertainty in travel assignment models. Finally, approaches to compute energy consumption rates and emissions modeling are discussed.

2.1. Traffic assignment models accounting for PEVs

Traffic assignment models represent an integral part of the transportation planning process. Given a network structure and the origin–destination travel demands, traffic assignment models are implemented to determine link-level flow patterns based on the travel routes chosen by drivers. The assignment algorithm implemented in this research follows the rules of user equilibrium (Wardrop, 1952) which assumes travelers seek to minimize their own cost, and once the network reaches equilibrium no user can lower their own travel time by unilaterally changing routes. Beckman et al. (1956) are credited with the first mathematical formulation of user equilibrium, which was further refined by Sheffi (1985).

At present there is a dearth of transport modeling literature that explicitly incorporates PEVs into traffic assignment models and accordingly evaluates the system impact. This gap in research relating traditional transportation methodologies and PEVs can be attributed to two main reasons: (1) The impact of PEVs on the system will be dependent on PEV driver behavior and preferences, which are unknown, and difficult to capture in a transport planning model and (2) Significant market penetration of PEVs is likely 20–30 years in the future, if that, and thus PEVs are just gaining momentum in the academic community Two papers that address the integration of PEVs and travel assignment models include Artmeier et al. (2010), who applied PEVs to the vehicle routing problem. The authors use a constrained shortest path formulation and solve with a prefix bounded shortest path tree. They note that PEVs change the problem because negative path costs (i.e., regenerative braking that recharges the battery) are possible, which eliminates traditional methods of solving the problem. Jiang et al. (2012) formulate a path-constrained traffic assignment model that could be used to represent the distance limitations of PEVs in a congested network. They solve using an algorithm based on the Frank Wolfe method that also incorporates a single resource constrained shortest path algorithm to efficiently find the set of possible distance constrained paths with each iteration. This relatively simple model and solution method is the first step toward adapting traffic assignment models to account for the presence of PEVs, and offers significant insight toward later efforts at more complex models.

This work implements a static traffic assignment model to characterize the driving patterns of PEVs and then tracks the vehicles through the network. This enables vehicle energy consumption and emissions to be computed at the link level based on average link travel speeds and travel volumes. While the use of a static model neglects the impact of certain congestion effects like bottlenecks, acceleration, and deceleration, the approach taken in this work represents a significant improvement compared to the traditional regional level energy and emissions estimation procedures which disregard travel patterns entirely, instead relying on average travel distances and driving cycles and corresponding per mile energy consumption and emissions estimates (Ford et al., 2011).

2.2. Travel demand uncertainty

As with all traffic flow modeling, travel demand is a key factor in determining network performance, yet inherent uncertainties in travel demand modeling make it difficult to properly account for. Issues such as changes in land use (e.g., suburban sprawl), increasing population, and changing gas prices are just a few of the reasons that making accurate predictions of long term travel demand is virtually impossible. An additional complexity associated with this work results from the uncertainty in PEV uptake levels. At the present time, PEV market penetration rates 20–50 years from now are highly speculative. Estimates regarding annual market penetration rates for the year 2050 (for plug-in hybrid electric vehicles (PHEVs)) vary from almost nothing to about 90% (Karplus et al., 2010; Musti and Kockelman, 2011; Ford et al., 2011). For the remainder of this work travel demand uncertainty will include uncertainties in both total travel demand and PEV penetration rates.

Accounting for demand uncertainty entails network analysis under a variety of possible scenarios rather than the unrealistic assumption of deterministic conditions. Given the long-range planning application discussed here, this work is concerned with long-term travel demand uncertainty and its impact on energy demand via PEV energy consumption patterns. Thus, the travel demand realization is unknown, but after some time the actual demand is realized and the users equilibrate deterministically. This assumption is motivated by the idea that users gain knowledge of the actual demand level through their own driving experience, and over time have learned the optimal route minimizing their travel time. The impact of demand elasticity is not considered explicitly, as the focus of this work is to specifically isolate the effects of uncertainty.

Studying the impact of demand uncertainty on the traffic assignment problem is a well documented research topic. Waller et al. (2001) showed that neglecting the impact of long term demand uncertainty by using a single fixed estimate of future demand can result in significant underestimation of the future system performance, which could further result in sub-optimal network design decisions (Duthie et al., 2011). Clark and Watling (2005) examine the impact of travel demand uncertainty on travel time reliability using a combination of statistical techniques. Gardner et al. (2008) develop a robust pricing scheme that accounts for the effects of uncertain demand. Ukkusuri and Waller (2010) develop closed form approximate analytical expressions for expected value and variance of network performance resulting from uncertain travel demand. Duthie et al. (2011) compare six sampling techniques to generate future demand, finding that Antithetic sampling leads to the least bias and error, while emphasizing the importance of accounting for correlation between zones of travel demand, lest suboptimal planning decisions be made. While many of these works have potential implications for PEVs, to the authors' knowledge no works have addressed the relationship between travel demand uncertainty and PEV energy consumption directly.

2.3. PEV energy consumption rates

In order to quantify the impact of travel demand uncertainty on PEV energy consumption, it is necessary to compute energy consumption rates. Many past efforts to model vehicle energy consumption utilize a dynamic vehicle simulator approach. This kind of model is based on a standardized driving cycle, which is an estimated series of data points representing the speed of a vehicle versus time based on driver and road characteristics. While standardized (usually to represent the behavior of different drivers, e.g., urban, rural, aggressive), driving cycles are often criticized as arbitrary in nature and unrepresentative of real world driving (Joumard et al., 2000). A well-known example of a dynamic vehicle simulator comes from the Argonne Labs commercial software ADVISOR (Markel et al., 2002). This software and other programs of its nature use an iterative approach to match the speed estimates to energy use estimates based on empirical calculations. While accurate in nature, this approach is limited by both its computational complexity and its use of driving cycles. In addition, programs like ADVISOR are only available for a hefty commercial fee.

The EPA software MOVES2010a (Motor Vehicle Emissions Simulator) also estimates energy consumption rates, and is the method chosen for this work to estimate ICEV energy consumption. The software calculates vehicle energy consumption estimates as part of finding emissions estimates, which is its primary purpose. MOVES contains detailed default databases of meteorology, vehicle fleet composition, vehicle activity, fuel characteristics, and emission control program data for the United States. Energy calculations in this software are based on data such vehicle miles traveled (VMT), vehicle age distribution, vehicle populations, sales and VMT growth rates. MOVES applies a 10-step algorithm that estimates the total activity generated for a distribution of vehicle operating behaviors (e.g., operating hours, number of vehicle starts, extended idle hours, etc.), and calculates energy consumption rates as a function of average travel speed and various other vehicle properties. The PEV energy consumption rates used in this model represent a battery electric vehicle, and are based on data from Tesla Motors (2012).

2.4. Emissions estimation procedure

A final measure examined in this work is vehicular emissions. Internal combustion engine vehicles (ICEVs) are well-documented as a significant source of green house gas (GHG) emissions. Replacement of ICEVs with PEVs has the potential to significantly reduce GHG emissions from the transport sector, especially if the required energy is generated using renewable and clean sources (Kempton and Tomić, 2005; Schwanen et al., 2011). Certain tailpipe pollutants like carbon monoxide and some particulate matters (both of which have harmful human health ramifications), are eliminated at the vehicle level with PEVs (although still result at a small scale from upstream power generation). Of main concern are the vehicular emissions (the main three being CO_2, SO_X, and NO_X) which are redistributed upstream to where the electricity for the vehicles is generated. A common concern with PEVs is the upstream emissions from "unclean" sources like coal and natural gas that are commonly used to power the electric grid. However, previous studies have found that even in the worst-case scenarios (i.e., black coal, increased demand, few advances in technology), PEVs reduce emissions as compared to traditional ICEVs (although not necessarily compared to hybrid-electric vehicles) (Kintner and Pratt, 2007; Samaras and Meisterling, 2008; Elgowainy et al., 2010; Ford et al., 2011). The environmental assessment portion of this work seeks to quantify the emissions savings by replacing traditional ICEVs with PEVs while accounting for the additional emissions produced by electric power plants which generate the electricity to charge the PEVs.

This analysis requires computing emissions rates for both PEVs and ICEVs. Determining realistic emissions output from an ICEV is an arduous task. On one hand, all vehicles perform differently according to an array of internal characteristics: engine performance, age, make and model, among others. Additionally it is difficult to model emissions accurately because of the many external factors that play a role: climate, weather conditions, geographic location, time of year, altitude, the driving cycle, braking, accelerating, traffic conditions, and travel time. Meanwhile emissions rates from different kinds of electric vehicles are a direct outcome of their upstream energy provider. While the authors are unaware of any previous works that have explicitly accounted for the environmental impact of PEVs in traffic assignment models, a number of researchers have studied the well-to-wheels life cycle analysis for PEV energy consumption and emissions at a regional level. One of the most influential of these was performed by Argonne National Labs, which combined the software programs PSAT (which models vehicle powertrains using a dynamic simulation approach) to calculate fuel economy and the modeling software GREET to measure upstream emissions specific to the location where PEVs were plugging in (Elgowainy et al., 2010). To calculate the energy consumption by PEVs, Argonne (and most other studies of its kind) used data from the 2001 National Household Travel Survey to determine vehicle characteristics and annual miles driven, and then implemented the utility factor method to determine the percentage of miles driven in 'charge depleting' mode and 'charging sustaining' mode. In this work the amount of energy consumed by the PEVs is used to calculate their upstream emissions based on power plant generation rates. Because this work assumes a linear relationship between PEV energy consumption and emissions, energy consumption can be used as a direct proxy for emissions generated. Therefore the rest of this paper will focus on energy consumption rather than emissions, although the methodology used to calculate emissions will be provided and discussed.

3. Problem description

This work aims to explicitly incorporate PEVs into the transport planning process, with a focus on the relationship between travel demand uncertainty and PEV energy consumption. In this analysis, peak hour PEV energy consumption variability is the result of unknown future travel demand and PEV adoption rates. Therefore a static UE traffic assignment model is implemented which incorporates long-term demand uncertainty, i.e. the demand loaded onto the network is representative of a potential peak period traffic volume which may be realized in the future. If the number of demand realizations is large or infinite, one can estimate the system performance measures using sampling techniques; a comparison of sampling techniques for transportation networks with uncertain demand can be found in Duthie et al. (2011).

To account for future travel demand uncertainty, Monte Carlo sampling was implemented to select an origin specific demand profile from a normal travel demand distribution with a known mean and variance. The demand originating from a particular origin zone to each destination is aggregated to form the origin specific demand. The origin specific sampling assumes a future increase in a zone's population will increase travel to all destinations from the given origin proportionally. The problem further assumes the proportions between a certain origin and its corresponding destinations will remain the same in the future. Additionally a specified proportion of each O–D demand is PEV users. This parameter was included to explore the impact of varying levels of market penetration. The realized demand was then fed into the static UE assignment model, from which the following performance measures and their corresponding variances are computed for the vehicles in the network:

1. Expected total system travel time (TSTT).
2. Standard deviation of total system travel time (TSTT STD).
3. Expected total system energy consumption (TSEC).
4. Standard deviation of total system energy consumption (TSEC STD).
5. Expected system emissions produced.

Each of these performance measures is specific to a peak travel period for a single day. In this work the entire analysis (i) demand sampling, (ii) UE assignment and (iii) system performance calculations were repeated for at least 1000 iterations and the resultant expected system performance measures and respective standard deviations were computed based on the sample.

The performance measures can then be used to quantitatively evaluate and rank different network design scenarios according to specific objectives. Of specific interest is the variability in PEV energy consumption (TSEC STD) across the network; PEVs essentially create a mobile source of energy demand, the supply of which will come from the electric grid. Energy systems operators must be able to predict this demand in order to efficiently supply the energy to a region. The proposed model provides a framework for quantifying the expected energy demand and associated variability required by PEVs in a given region at the end of a typical day.

Section 3.1 states the behavioral assumptions made in this work. The following two sections detail the process for computing the vehicular energy consumption and emissions rates.

3.1. Traffic assignment modeling

The UE assignment model formulation with demand uncertainty is provided in Section 4. The incorporation of PEVs into the assignment model can be thought of as introducing a new vehicle class with associated behavioral assumptions and driver characteristics. Throughout this work the following assumptions apply:

I. PEVs charge at home only.
II. PEV drivers behave in the same manner as non-PEV drivers, particularly in regard to route choice.
III. There are only two vehicle types, PEV and non-PEV.
IV. All PEVs have the same distance range.

In this analysis public charging infrastructure is unavailable, therefore PEV drivers only charge at home. This is consistent with current patterns of PEV deployment in many places around the world and typical commute distances in urban areas lie within the home-work return trip range of PEVs (Hemphill, 2011). For the purposes of this analysis PEVs can be assumed to begin charging at the end of the day when they return home. Therefore it is assumed that PEVs begin each trip fully charged with the same specified all-electric range. For this analysis the PEVs have an all-electric range large enough to ensure that they do not run out of charge between any origin and destination in the network evaluated. Current PEV models typically have a maximum range of 100–160 km; the focus of this work is planning for future transport systems at a time when the battery technology is expected to have improved, and the range is expected to have increased. It follows then that because these drivers have no motivation to change their routes (no charging or parking incentives are accounted for in this evaluation), these drivers will behave identically to drivers of conventional vehicles with regards to route choice. Under this assumption the traffic assignment model tracks all PEV vehicles in order to identify their travel patterns (routes, speeds), but does not distinguish them from ICEV drivers in a behavioral context. However the two vehicles types, PEVs and non-PEVs, are distinguished by their respective energy consumption and emissions rates.

Implementation of the assignment model returns travel routes, link volumes (including both vehicle types), and link travel times. A single average speed is then associated with the entire link. From the equilibrium-state link speeds and volumes, the TSTT is computed.

3.2. PEV energy consumption evaluation

Electricity industry planners and operators face key challenges with regard to PEV deployment, which must ensure that available generation can reliably and economically meet the additional overall electricity consumption (MW h) of these PEVs. The key factors which need to be considered include:

1. *Where* and *when* will the vehicles be available to be charged.
2. The *amount* of charging each vehicle will require which is related to the discharge of the battery from the previous trip.
3. The total amount of PEV related electricity demand from a given region.

Extensive spatiotemporal transport system data will be required for these models, including patterns of travel (source and destination), the energy consumption associated with these trips, PEV penetration levels, user driving behavior, travel patterns, and road conditions. While the current model is not able to account for smart-charging of vehicles, it represents a first step in quantifying the relationship between the travel patterns of PEV drivers and PEV energy consumption rates. In doing so the model accounts for speed-variable energy consumption and travel patterns of both PEVs and ICEVs.

The data for the ICEV speed variable energy function was obtained from MOVES. The purpose of this software is to estimate vehicles emissions for government environmental impact assessments, particularly accounting for a large spectrum of locale-specific variables (EPA, 2009). The emissions estimates are based on extensive data collection programs conducted by the EPA. This software calculates energy consumption estimates as one step of finding vehicle emissions; it is these energy estimates that are used in this work to measure the energy consumption of ICEVs. However, exact energy consumption estimations are difficult for any project because of the number of influential factors specific to the location of the project (e.g., atmospheric conditions such as temperature, humidity, geographic conditions such as gradient of terrain). The estimates used here are based on MOVES default databases for urban arterial roadways in Travis County, Texas in the month of July during the hours of 8–9 AM. This data can be seen in Fig. 2a. The relationship between speed and energy consumption for ICEVs was extracted from MOVES in a tabular format from which a regression model was produced using MATLAB.

PEVs consume energy in a way that is fundamentally different from traditional ICEVs. Due to their use of an electric motor and battery, PEVs represent a novel form of energy consumption in the transport system. For example, ICEVs' energy efficiency is a function of the rolling resistance, air resistance, and acceleration power requirements from the engine, and they are more energy efficient at higher speeds (see Fig. 2a). On the other hand, PEVs are more energy efficient at lower speeds (the speeds at which traditional ICEVs are least energy efficient) partially because they experience fewer losses when converting energy from the motor. The data used for the PEV energy consumption equation was obtained from Tesla Motors (2012), and can be seen in Fig. 2b. Finally, note that this energy consumption model does not account for potential energy regained from regenerative braking, which could make PEVs even more efficient in congestion conditions. The contradicting

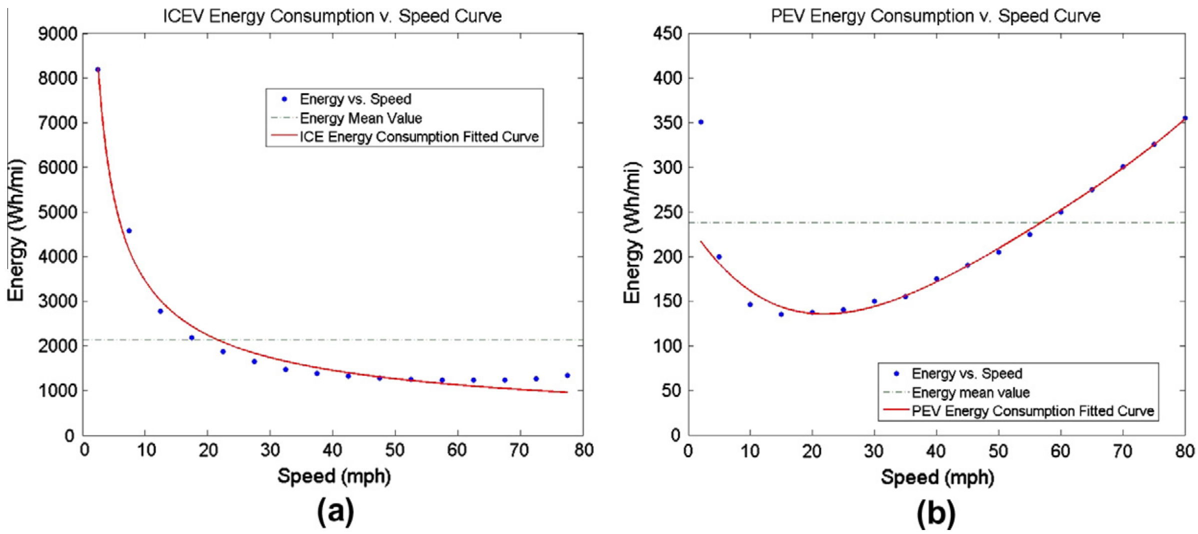

Fig. 2. Comparison of functional form of (a) ICEV energy consumption vs. (b) PEV energy consumption.

Table 1
Energy consumption functions.

Energy consumption (TEC) (kW h/mi)	Adjusted R^2 value
$TEC_{ICEV}(s) = 14.58s^{-0.6253}$	0.9846
$TEC_{PEV}(s) = 1.79e{-}8s^4 - 4.073e{-}6s^s + 3.654e{-}4s^2 - 0.0109s + 0.2372$	0.9651

Table 2
MOVES based Emissions functions for ICEVs.

Pollutant	Emissions function (g/mi)	R^2 Value
CO_2	CO_2 (s) = $3158s^{-0.56}$	0.948
VOC	VOC (s) = $1.3647s^{-0.679}$	0.965
NO_X	NO_X (s) = $2.5376s^{-0.42}$	0.892

Table 3
Average U.S. electric power plant emissions rates.

Pollutant	Number of facilities	Collective emissions rate (kg/MW h)
CO_2	899	893
NO_X	897	1.66
SO_2	836	3.79

energy consumption behavior complicates future transport planning because infrastructure improvements will impact PEVs and ICEVs differently. For this reason, PEVs need to be explicitly incorporated into transport planning models.

The resultant energy consumption functions for both PEVs and ICEVs in kW h/mi as a function of the average travel speed on a link, *s*, are shown in Table 1.

Again the results from the UE traffic assignment model (i.e., average link speeds and volumes) can in turn be used to calculate the energy consumption at the link level, which are aggregated across all links to compute the network level performance measure, TSEC.

3.3. Environmental impact assessment

The third performance measure in this analysis is system emissions. The tradeoff between tail pipe emissions (from ICEVs) and smoke stack emissions (produced to generate the energy required by PEVs) is of particular interest in this work. CO_2, NO_X and SO_2 emissions were computed for both ICEVs and PEVs. The process to generate ICEV emissions as a function of average travel speed, *s*, was similar to that used to calculate energy consumption rates. Speed-emissions relationships were extracted from MOVES, and a best fit function was generated in Microsoft Excel. The same default databases were used for emissions as for the energy consumption. A combination of national data, allocation factors, and some default local data (e.g., meteorology data) was used. The resultant emissions produced by each vehicle in g/mi as a function of average travel speed on a link, *s*, are shown in Table 2. Each of the resultant functions is a power law where the emissions rates decrease as the speed increases.

The UE traffic assignment model (i.e., average link speeds and volumes) was again utilized to calculate the emissions produced at the link level, which are aggregated across all links to compute the system level emissions for each pollutant for all ICEVs in the network.

While PEVs do not produce tailpipe emissions, they are still responsible for emissions indirectly via the electricity generating plants that supply their energy. Power plants have a notorious reputation for polluting the atmosphere, particularly coal fired plants. Although the infrastructure is already in place, a significant increase in PEV adoption would require additional energy to be produced, thus increasing electric power plant emissions. To account for the environmental impact of PEVs, the total energy consumed by the vehicles previously computed was multiplied by electric power plant emissions rates in kg of pollutant per MW h of energy produced. The result is the total emissions produced by generating the amount of energy consumed by all PEVs. The average U.S. electric power plant emissions rates, published in an analysis by the Commission for Environmental Cooperation of North America, were used. The data included emissions information reported by facilities as part of the EPA's Clean Air Markets program in March 2004 (Miller and Van Atten, 2004). The emissions rates for CO_2, NO_X, and SO_2 were considered in this study and are shown in Table 3.

4. Solution methodology

The formal mathematical formulation of the UE assignment model and system performance measures are presented in this section. Consider a stochastic transportation network $G = (N, A, \mathbf{D}, \mathbf{Z}, \boldsymbol{\Omega}, \mathrm{P})$ consisting of a set of nodes N; a set of directed arcs A; a demand matrix $\mathbf{D}$ with $|N|$ rows and columns, mapping the demand for travel from every node to every other node. The demand matrix $\mathbf{D}$ represents the aggregate demand for both ICEVs and PEVs. The percentage of each origin destination demand consisting of PEVs is denoted by the $|N| \times |N|$ matrix $\mathbf{Z}$. Let Ω denote the set of all demand scenarios and $\omega \in \Omega$ be an index for one particular demand scenario. Let R and S represent the set of all origins and destinations respectively. $r \in R$ and $s \in S$ are indexes representing one particular origin and destination respectively and d_{rs}^{ω} denotes the value of one particular demand realization between origin $r \in R$ and destination $s \in S$. The percentage of each origin–destination demand realization that are PEVs is z_{rs}^{ω} $(0 \leqslant z_{rs}^{\omega} \leqslant 1)$, which is specified a priori. Let K_{rs} represent the set of paths connecting origin $r \in R$ and destination $s \in S$ and $k \in K_{rs}$ is an index for one path. Let A denote the set of all arcs and $a \in A$ is an index for one particular arc in the network. $f_{rs}^{k\omega}$ represents the total (ICEV and PEV) flow on path k connecting origin r and destination s in scenario $\omega \in \Omega$. Let v_a^{ω} represent the total link flow on link $a \in A$ under demand realization $\omega \in \Omega$ and $\delta_{ars}^{k\omega}$ is the link path incidence variable. Let V^{ω} represent the vector set of feasible link flows, v_a^{ω}, for demand realization $\omega \in \Omega$.

$$V^{\omega} = \left\{ v_a^{\omega} \forall a \in A : v_a^{\omega} = \sum_{rs} \sum_{k \in K_{rs}} \delta_{ars}^{k\omega} f_{rs}^{k\omega}, \sum_{k \in K_{rs}} f_{rs}^{k\omega} = d_{rs}^{\omega} \qquad \forall r \in R, \quad s \in S \right\} \tag{1}$$

Let $T(\cdot)$ represent the vector of link cost functions for all links in the network. The link cost function may be any function that defines the relationship between the number of users traveling 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:

$$t = f_0 \left[1 + \alpha \left(\frac{v}{C} \right)^{\beta} \right] \tag{2}$$

where t is link travel time, f_o is free-flow travel time, v is hourly volume, C is hourly capacity, and α and β are parameters that depend on link geometry. Under the assumption that ICEV and PEV drivers behave identically there is no need to differentiate them in terms of route choice behavior, therefore this function applies to both ICEVs and PEVs. However the vehicle types are distinguished for tracking purposes throughout the assignment process in order to calculate their link level emissions and energy consumption independently once a state of equilibrium is reached.

In this work, we seek a collection of flow vectors $V^{\omega*}$ for user equilibrium link flow that depend on the demand realization, and satisfy the following inequality:

$$(T(V^{\omega*}))^T (Y^{\omega} - V^{\omega*}) \geqslant 0 \qquad \forall Y^{\omega} \in V^{\omega}, \quad \omega \in \Omega \tag{3}$$

The constraint represents the set of equilibrium link flows given demand realization ω and link cost functions t. The model output specifies the ICEV and PEV link level flows, $v_{a\_ICEV}^{\omega}$ and $v_{a\_PEV}^{\omega}$ respectively, and link travel times t_a^{ω} (thus link average speed, s_a^{ω}) for each demand scenario. Based on the resultant assignment pattern for each demand scenario, the system performance measures are calculated.

$F_{\omega}(\Lambda(V^{\omega*}))$ represents a function of total system travel time for every realization $\omega \in \Omega$ which is computed based on the resultant link travel flow and link travel costs. $E_{\omega}(\Lambda(V^{\omega*}))$ represents a function of total system energy consumption for every realization $\omega \in \Omega$. For each realization the total energy consumed is computed by summing the energy consumption for all vehicles on a link, for all links in the network. $TEC_{PEV}(s)$ and $TEC_{ICEV}(s)$ are the energy consumption rate functions for PEVs and ICEVs respectively, and correspond to data in Fig. 2 as a function of average travel speed, s. The resulting link travel speed s_a^{ω} is used to calculate $TSEC$ for all vehicles on a link as follows:

$$E_{\omega}(\Lambda(V^{\omega*})) = \sum_{a \in A} \{ TEC_{ICEV}(s_a^{\omega}) v_{a\_ICEV}^{\omega} + TEC_{PEV}(s_a^{\omega}) v_{a\_PEV}^{\omega} \} \tag{4}$$

The next set of functions defines the system emissions. $CO_{2_{\omega}}(\Lambda(V^{\omega*}))$, $SO_{2_{\omega}}(\Lambda(V^{\omega*}))$ and $NO_{X_{\omega}}(\Lambda(V^{\omega*}))$ represent the functions for total system CO_2, SO_2 and NO_X emissions for every realization $\omega \in \Omega$. For ICEVs the system emissions are calculated using the emissions function in Table 2. For PEVs the emissions are a function of the total energy consumed on the network, and computed using the electricity generation emissions rates in Table 3. The same analysis holds for each pollutant. The calculation is shown for CO_2 and is directly translatable to the other pollutants.

$$CO_{2\omega}(\Lambda(V^{\omega*})) = \sum_{a \in A} \{ CO_2(s_a^{\omega}) v_{a\_ICEV}^{\omega} + e_{CO2} TEC_{PEV}(s_a^{\omega}) v_{a\_PEV}^{\omega} \} \tag{5}$$

For each demand scenario, each of these system level measures was computed. Based on the sampling approach described in Section 3, the expected value and variance was computed for each performance measure.

5. Numerical analysis

Numerical analysis was conducted on both a demonstration network and the well-known Sioux Falls network to demonstrate the importance of considering multiple performance parameters when selecting future transport infrastructure projects. The system performance measures and their respective variations due to uncertain PEV travel demand are compared for different network design scenarios. The objective of this analysis is twofold:

1. Quantify the impact of demand uncertainty on system level energy consumption, emissions and variability.
2. Quantitatively compare different network design options in terms of the system performance measures.

This section begins by illustrating the contrasting behavior of the two performance measures of interest – TSTT and TSEC – on a small example network. As discussed previously, the introduction of PEVs makes energy consumption of greater interest to electric power system operators. However, as discussed PEV energy consumption can also act as a proxy for emissions output, and so a network that plans for lower energy will also be environmentally favorable.

5.1. Demonstration network

The importance of considering both user costs and energy consumption rates when comparing network design options is first demonstrated on a small sample network (shown in Fig. 3). In the figure the link numbers represent the link length. All links have equivalent capacities, free flow speeds and parameters α and β equal to 10, 50, 0.15 and 4 respectively. The link costs are calculated according to the Bureau of Public Roads cost function (2). In addition there is a single origin, node 1, and a single destination, node 4, and the expected demand between the two nodes is 20.

The demonstration network is representative of Braess's network (Braess, 1969), consisting of four nodes and five links. Without the crossover link (2,3) the network has symmetrical path costs, and at equilibrium users will split equally among the two paths (1–2–4) and (1–3–4). With the addition of the crossover link a new shorter path option is made available (1–2–3–4). Based on this network alteration the well know result follows; some users will now opt to take the new path resulting in an increase in path costs for all users, thus increasing the TSTT. The issue of interest here is the impact of such a network change on the performance measures, TSTT, TSEC and system emissions.

The focus of the demonstration is on comparing TSTT and PEV TSEC for two different network design options, with and without the crossover link (2,3). Demand is set at 20. The system performance measures were calculated and the results are illustrated in Table 4. In order to isolate the relationship between TSTT and PEV energy consumption the initial analysis assumes 100% PEV market penetration.

From the Braess's paradox, it is known that the TSTT actually increases with the addition of this link (by 26%); however, the TSEC actually *decreases* by a significant 51%. Note that this decrease is far more dramatic for a network consisting of only PEVs. For a network with 100% ICEVs the energy consumption *decreases* by 6%, which is more consistent with the TSTT behavior. It is also worth noting the increase in energy consumption for a network with 100% PEVs would results in a similar increase in emissions (produced by electric power plants) because 51% more energy would be required by the electric vehicles. Based on the inverse relationship between speed and energy consumption rates in Table 1, higher average travel speeds (which generally translate to lower TSTT) would intuitively translate to lower system level energy consumption. The counter intuitive outcome in the demonstration is a result of the complex relationship between traveler behavior, congestion, and energy consumption. This example serves to highlight the importance of considering multiple performance measures when comparing road network design scenarios for transport systems likely to be utilized by PEVs.

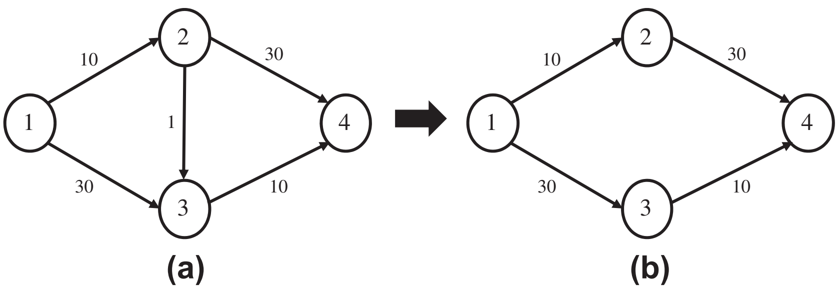

Fig. 3. Example network (a) with crossover link and (b) without crossover link.

Table 4
Performance measures for the demonstration network with and without the crossover link, including the change in TSTT and TSEC and respective standard deviations.

	Original network	Crossover link added between (2,3)	% Change
TSTT (min)	1104	1385.5	26%
TSEC (100% PEV) (kW h)	146.6	71.5	−51%
TSEC (100% ICEV) (kW h)	1102.5	1032.8	−6%

5.2. Sioux falls network

The second network used in the analysis of this work is the well-known Sioux Falls network, and can be seen in Fig. 4. Network data, including travel demand, were obtained from Bar-Gera (2012). This network contains 24 nodes (all of which are origins and destinations) and 76 links. Again the demand is assumed to be normally distributed, with a specified variance; demand is also truncated at zero to ensure non-negativity. Travel times are given by the BPR cost function, with shape parameters 0.15 and 4.

5.2.1. Impact of stochastic demand

The network performance measures varied significantly between the deterministic case and the case of stochastic demand. The original network performance measures under both the deterministic and stochastic cases are illustrated in Table 5. In the stochastic cases the standard deviation was set to 20% of the expected origin demand value. The performance measures were averaged over 10,000 iterations to ensure model convergence, and are shown in the second row of the table labeled *expected value*. The third row provides the *standard deviation* of each performance measure for the stochastic demand case. The standard deviation represents the variability of the performance measures under the case of demand uncertainty, or the robustness of the network.

5.2.2. Deterministic scenario comparison

The relationship between drivers' travel patterns, system travel time, and system energy consumption is complex even for the case of deterministic demand. To demonstrate the importance of considering PEV TSEC, multiple design scenarios, specifically small network capacity enhancement projects, were evaluated for the Sioux Falls network. The unpredictable

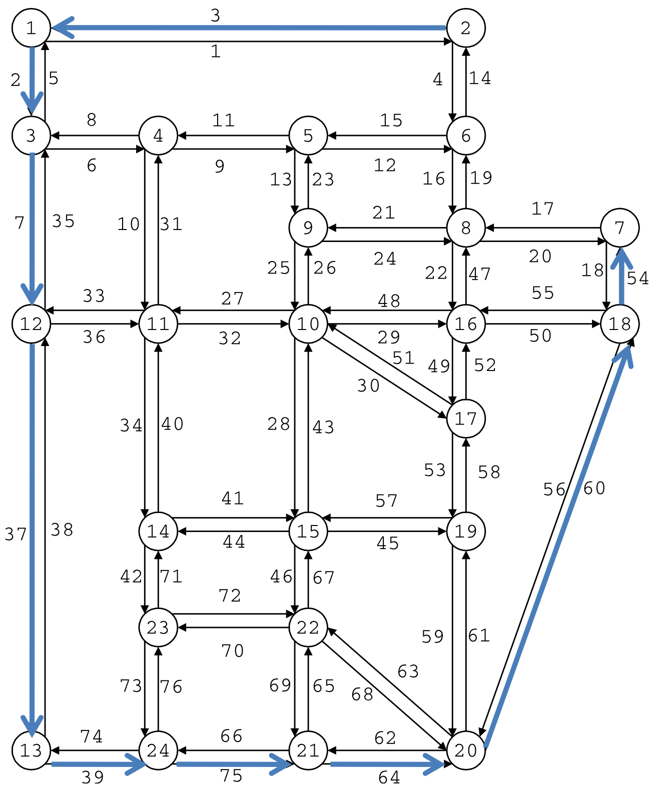

Fig. 4. Sioux Falls Network, where bold lines represent freeway links.

Table 5
Results for original network under deterministic and stochastic demand.

	Original network		
	TSTT (min)	PEV TSEC (kW h)	ICEV TSEC (kW h)
Deterministic case	7,471,185	580,354	6,115,102
Expected value	7,781,710	587,142	6,117,210
Standard deviation	1,105,936	22,828	648,220

relationship between TTST and TSEC under the assumption of deterministic demand is illustrated by comparing a number of scenarios that increase the capacity on a given link by either 1000, 1800, 3000, or 4000 vph. Each capacity improvement was evaluated on each of the 76 different links, resulting in 304 different design scenarios. Unless stated otherwise, demand consisted of 100% PEVs. This assumption allowed us to isolate the impact of network design decisions on PEV energy consumption. The results highlight the need to consider multiple measures of network performance in addition to demand uncertainty for future transport planning which includes electric vehicles.

The percent improvement in the performance measures TSTT and TSEC for each design scenario relative to the original network is represented as ΔTSTT and ΔTSEC. In Fig. 5a the vertical axis represents this percentage improvement in each performance measure; thus, a positive increase in performance means that the overall system cost went down. The horizontal axis then represents each discrete design scenario, as ordered by decreasing ΔTSTT.

There are two important observations which can be drawn from the results in Fig. 5a. Firstly, ΔTSTT and ΔTSEC do not appear to have any correlation. Two projects that both increase ΔTSTT may impact ΔTSEC differently. Secondly, these results reveal that a majority of the scenarios actually decreased ΔTSEC by a small margin, which implies that the total energy consumption actually increased. While this increase in energy consumption is not substantial, it is reasonably consistent (occurring in 79% of the tested scenarios). Therefore, planners need to be aware of this possible consequence when choosing between proposed improvement projects in networks that include PEVs.

To reinforce the behavioral difference between PEV energy consumption and energy consumption of traditional ICEVs, Fig. 5b illustrates the same results as Fig. 5a, but for a network with no PEVs. For a network comprised of 100% ICEVs there is a positive correlation between system energy consumption and travel time, and none of the design scenarios decrease TSEC. The difference in PEV and ICEV vehicle energy consumption illustrated in Fig. 5a and b further highlights the need to explicitly consider PEV energy consumption within the context of network planning.

This is reinforced by the following example for the larger Sioux Falls network. In Table 6 two design scenarios are compared. Again, the $\Delta(\cdot)$ values represent the improvement in the performance measures in percentages compared with the original network (positive values represent a decrease in costs and energy consumption). Due to the linear relationship between PEV energy consumption and PEV CO_2 emissions, the change in emissions will be directly proportional to the change in energy consumption, and for that reason is not included in the tables. But it is important to acknowledge that a network design which reduces energy consumption will result in the same percentage reduction in system CO_2 emissions relative to the original network.

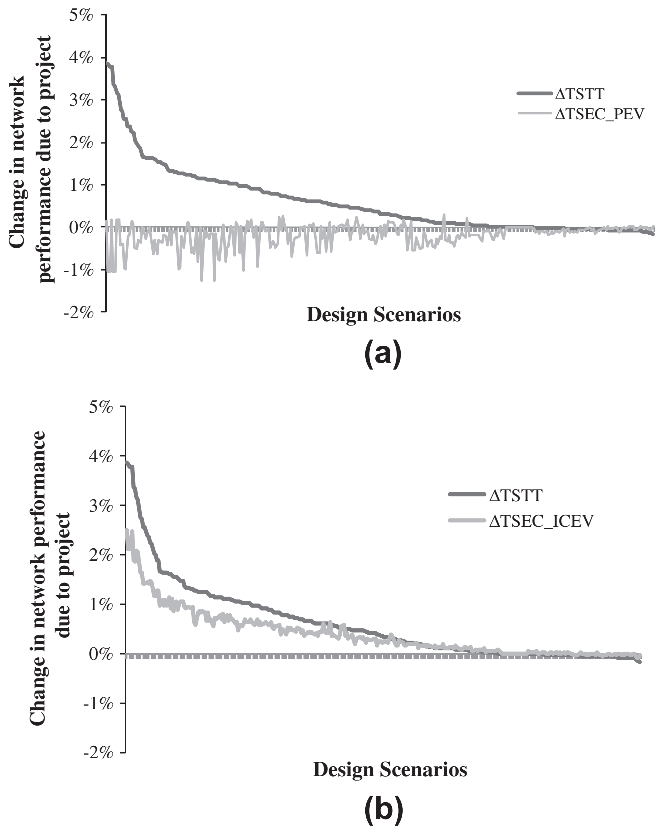

Fig. 5. Comparison of system performance improvement, ΔTSTT and ΔTSEC, for different design scenarios under deterministic demand for Sioux Falls under (a) 100% PEVs and (b) 100% ICEVs.

Table 6
Deterministic project comparison for Sioux falls network.

	Δ(TSTT) %	Δ(PEV TSEC) %
Scenario 1: Add 3000 capacity on link 19		
Deterministic case	3.33%	−1.04%
	Δ(TSTT) (min)	
Scenario 2: Add 3000 capacity on link 48		
Deterministic case	3.16%	0.19%

In scenario 1 a capacity of 3000 veh/h, which could represent the additional of a new lane and improved signal timing plan, is added to link 19 in the network. In scenario 2 a capacity of 3000 veh/h is added to link 48. Both scenarios provide a similar improvement in TSTT, about 3.2% compared with the original network. However scenario 1 increases the energy consumption by 1%, where as scenario 2 results in a slight decrease in PEV TSEC. While these energy system savings are small, they are again the result of a minor change to the network, and they represent a potential tradeoff between two competing performance measures. Under these conditions scenario 2 may be more desirable, but would not have been selected if TSTT was sole indicator of network performance.

5.2.3. The role of uncertainty

Scenarios 1 and 2 were both evaluated under deterministic conditions. Due to the complexities associated with individual driver's routing behavior, variations in demand may result in extreme variations in system performance. Therefore changes made to the network may appear to improve the system performance measures for a deterministic demand value, but may result in negligible improvements under varying demand scenarios, or even reducing certain performance measures. When designing a future transport network it is important to consider the role of demand uncertainty because future travel demand is inevitably stochastic, and cannot be known with certainty at the time of planning. Variability in TSEC is of specific concern for a network with a high penetration of PEVs because the energy must be supplied by the regional electric power provider. Electric power systems operators must therefore be able to predict the energy demand generated by PEVs. Network design under stochastic conditions has two objectives: (i) maximize the expected system performance and (ii) minimize the variance of system performance. These objectives can be quantified by the mean and standard deviation of the performance measures identified: TSTT, TSEC, and system CO_2 emissions produced.

A subset of the design scenarios from the deterministic analysis was evaluated under stochastic demand to evaluate the impact of demand uncertainty on network performance. Capacity increases of 1000, 1800, 3000, or 4000 on links 16, 19, 26, 29, 30, 48, and 69, were considered, resulting in 28 scenarios. The links with the maximum potential for system travel time improvement were chosen based on the results from the deterministic analysis.

The impact of the set of small capacity enhancement projects were compared under stochastic demand, where the origin demand followed a normal distribution with a standard deviation equal to 20% of the expected demand. The performance measures graphed in Fig. 6a are Expected ΔTSTT and Expected ΔTSEC, the expected percentage improvements under demand uncertainty compared with the original network, as well as ΔTSTT STD and ΔTSEC STD, the percentage change in standard deviation under demand uncertainty compared with the original network. In all cases positive values represent an improvement, or decrease in total costs and energy consumption for a given scenario. Negative numbers in the table represent a decrease in system performance, or increase in travel time, energy consumption, or variability.

In general a given design scenario under stochastic demand saw a slight improvement in network performance as compared to the deterministic case. However, the variability of the network performance measures were subject to dramatic fluctuations, represented by the dotted lines in Fig. 6b. Again the vertical axis represents the improvement in performance

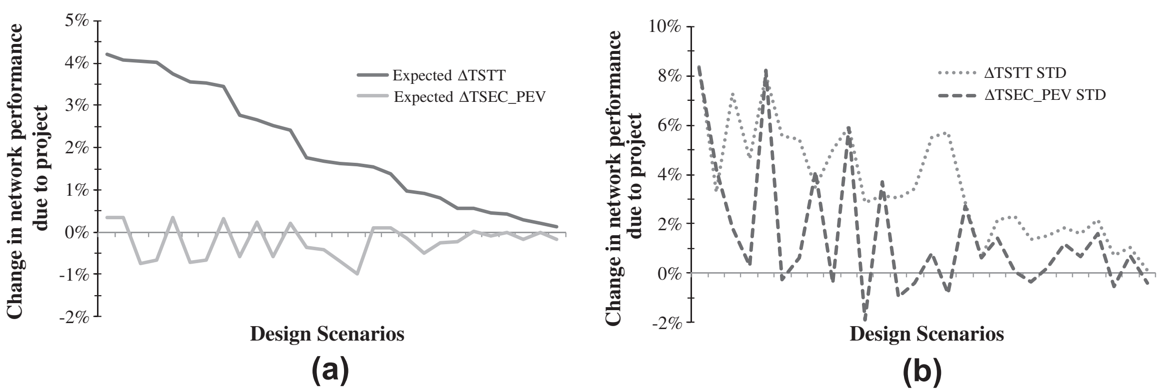

Fig. 6. Comparison of (a) expected system performance improvement and (b) variability of system performance for different design scenarios under stochastic demand for Sioux Falls.

Table 7
Project comparison for Sioux falls under stochastic demand.

	Δ(TSTT) %	Δ (PEV TSEC) %
Scenario 3: Add 4000 capacity on link 48		
Deterministic case	3.86%	0.15%
Expected value	4.06%	0.33%
Standard deviation	3.26%	4.22%
Scenario 4: Add 4000 capacity on link 19		
Deterministic case	3.78%	0.17%
Expected value	4.21%	0.33%
Standard deviation	8.38%	8.32%

measures for each design scenario relative to the original network. Similar to the deterministic results in Fig. 5, there was little correlation between Expected ΔTSTT and Expected ΔTSEC; many scenarios resulted in a slight increase in total energy use.

Fig. 6b illustrates the behavior of the remaining two performance measures, ΔTSTT STD and ΔTSEC STD, which quantify the variability of system performance for each of the design scenarios evaluated. A greater ΔTSEC STD translates to a more robust network. Robust networks are particularly desirable with the added element of PEVs because the energy demand can be predicted with greater certainty. In addition the highly variable performance measures reveal the challenge of ranking proposed design projects when demand uncertainty is considered; many projects may appear to have similar expected system performance improvements, but the actual performance can vary significantly under specific future demand realizations. To add to this challenge there appears to be a lack of correlation between the performance measures and their respective variabilities.

An example of this phenomenon is illustrated for the Sioux Falls network in Table 7. Again the values in the first row (*deterministic case*) is the improvement in the performance measures as compared to the original network for the deterministic case. Similarly the values in the second row (*expected value*) is the percentage improvements under demand uncertainty compared with the original network. The final row (*standard deviation*) represents the percentage change in standard deviation under demand uncertainty compared with the original network. In all cases positive values represent an improvement, or decrease in overall costs and energy consumption for a given scenario. Negative numbers in the table represent a decrease in system performance, or increase in travel time, energy consumption, or variability. Two scenarios are compared which have similar expected performance under uncertainty, however scenario 4 is a much more robust design, with a smaller standard deviation for both performance measures. This is represented in the table as a larger percentage decrease in standard deviation relative to the original network. As previously stated, the robust design would be more desirable for systems operators who need to predict the energy consumption of PEVs. However, projects could be incorrectly ranked without explicitly considering both travel time and energy related network performance measures.

5.2.4. PEV market penetration

In contrast to PEVs, the behavior of the two metrics, ΔTSTT STD and ΔTSEC STD, is closely correlated for a network with 100% ICEVs (under stochastic demand). This is expected due to the similar functional forms between TSTT and TSEC_ICEV. The same consistency in behavior applies to the Expected ΔTSTT and Expected ΔTSEC_ICEV, further reinforcing the concept that PEV energy consumption is a fundamentally new performance measure that transport planners will need to consider.

At the present time, it is impossible to predict the level of market penetration that PEVs will achieve in the next 20–50 years. Therefore, the performance measures were evaluated for the Sioux Falls network under stochastic demand for varying levels of PEV penetration ranging from 0% to 100% of each realized origin specific demand. In the proposed model varying PEV proportions do not impact the TSTT because the proportion of PEV drivers does not impact the total demand on the network.

A linear relationship between PEV penetration level and each performance measure resulted due to the model assumptions; specifically (i) PEV drivers and ICEV drivers were not differentiated in terms of driving behavior and (ii) PEV penetration levels were uniformly applied across all OD pairs. While a uniform penetration of PEVs is unrealistic for a given region, the value of the proposed model lies in the ability to quantify the system level impact of varying PEV penetration levels at the OD level. Such an analysis was excluded from this work due to the lack of spatial market penetration data. However, with detailed information on the spatial uptake of PEVs for a given region, this model could be implemented to quantify the environmental and economic impact of various design scenarios under specific PEV adoption scenarios.

6. Conclusions and future research

Future potential PEV usage requires that long-term transportation planning models expand to explicitly account for relevant system impacts. Further, due to the uncertain nature of PEV adoption as well as their cross-cutting characteristics, there is an increased need for new techniques and insights related to travel demand uncertainty, energy consumption, and environmental impact. This paper has begun to address these items by developing an evaluation framework and examining multiple performance measures (e.g., travel time, energy consumption) while explicitly accounting for the variability of each metric as a function of travel demand uncertainty. Specifically, a model incorporating user equilibrium based traffic assignment, stochastic demand, speed-variable energy consumption and emissions rates was developed and analyzed. From the modeling framework, five important insights were discussed:

1. The potential of electric vehicles implies that transport analysis must consider multiple performance measures in a consistent modeling approach (at a minimum travel time, energy consumption and environmental impact).
2. Projects evaluated for a deterministic demand can appear to improve network performance but may have negligible or negative impacts under varying future demand realizations. This is even more critical in a multi-objective framework such as the one in employed for this work.
3. *Variability* in system performance measures due to uncertain future travel demand is not correlated with the *expected* system performance. This was illustrated in Fig. 6, where a number of design improvements reflected similar expected improvements in TSTT and TSEC but erratically different TSTT STD and TSEC STD behavior. This further strengthens that realization that expected performance should not be considered the sole indicator in a project's success.
4. The robustness of each network design alternative is important to consider when ranking future infrastructure projects. A robust project may be more desirable than an alternative project with slightly higher expected performance, but higher performance variability as well.
5. PEVs have the potential to significantly reduce both total system energy consumption and system-wide emissions but one metric cannot be used as a straightforward proxy for the other.

The results from the numerical analysis imply that ignoring future travel demand uncertainty can result in unrealistic performance expectations of a project across all examined metrics. In addition, a sub-optimal project may be selected over a better alternative if certain system performance measures are excluded from the decision process. Such implications will be increasingly important for transport planners and electric-grid operators alike if PEVs gain market penetration, increasing their impact on the system.

As noted previously, to facilitate the potential future convergence of transport and electricity domains, one long term goal of this work is to quantify spatiotemporal energy demands for PEVs based on their regional travel patterns. This information is necessary for electric power systems operators to efficiently design and manage the electric grid. The model as presented contributes towards this goal, but offers many opportunities for improvement. For example the traditional static assignment model can capture the complexity between travel patterns and energy consumption, but it cannot account for emissions and energy consumption factors such as acceleration or gradient. A dynamic model will be better able to realistically represent the relationship by accounting for the actual vehicle trajectories, and will be applied for future applications of this research. Secondly, the proposed model can incorporate varying levels of PEV penetration across a region, which was not addressed in this work. This is due to a lack of information on PEV adoption patterns in a region. The concurrent development of discrete choice models to predict PEV adoption patterns at the household level can provide the necessary input for the model. Infrastructure design scenarios under specific spatial distribution patterns of PEVs can then be evaluated. Furthermore, this model can be used to measure the environmental impact of various network design alternatives in terms of energy use and emissions output, subject to varying penetration rates of PEVs.

An additional extension of this model will incorporate alternate sources of uncertainty inherent to the transport network. As an example, capacity unreliability from traffic incidents or extreme weather could have unexpected ramifications on the system performance measures. The possibility of these types of events in conjunction with PEV energy consumption rates and limited driving range could influence PEV driver behavior differently than traditional ICEV driver behavior. Evaluating this impact of supply uncertainty in transport networks on PEV driver behavior is a topic of ongoing research.

In conclusion, the introduction of PEVs into the transport system brings a new level of uncertainty into an already volatile system. Additionally, PEVs connect the transport system with the electric power system in a fundamentally new way that is omitted in traditional transport models. However it is critical for planners to begin considering these interactions in order to ensure the efficacy of future infrastructure. Although a significant market penetration of PEVs may be in the distant future, the strategic long term planning process of our transport systems requires planners to begin considering the system effects early on. This research contributes toward achieving that goal.

Acknowledgements

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