The System Impact of Travel Demand Variability in the Context of Electric Vehicles

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Abstract

The introduction of plug-in electric vehicles (PEVs) represents an unprecedented interaction between the road network and electricity grid. In this new integrated system, travel demand, behavior, and traffic congestion will influence the temporal and spatial characteristics of electricity usage and environmental impacts. Furthermore, uncertainty in the transport characteristics will manifest as a new uncertainty placed on electrical infrastructure. Overall, the realized system-level impacts depend on the eventual penetration of PEV ownership. However 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. 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. Implications are demonstrated on 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. However in order for this potential to be realized, it will be vital for research to investigate the way in which PEVs introduce a closer link between our transportation and electric power systems. By acting as a mobile source for energy demand, PEVs represent an unprecedented interaction between the road infrastructure and electricity grid, creating both the challenge and opportunity to appropriately plan across two traditionally non-interacting networks[1]. Thus,

research that explicitly considers the addition of PEVs into the traditional transport system as well as the broader impact across multiple infrastructure systems will be vital to the successful integration of this transformative technology, and furthermore to ensuring that PEVs are utilized to their fullest potential.

This work begins by providing a methodology for transport planners to quantifiably compare future infrastructure design scenarios with regards to both traditional transport goals and the impact of PEV drivers. In order to analyze different scenarios, traffic assignment models were implemented to characterize vehicle travel patterns, the results of which were used to quantify PEV energy consumption rates at the system level. 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 PEV energy consumption rates, an essential issue for regional energy providers. In order to explore this point, this work quantifies the variability in PEV energy consumption resulting from uncertain travel demand. 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.

Variability in PEV energy consumption has an impact at both the user level and the electricity system level. For example, complete daily charging of a PEV would more than double a typical household's electricity consumption in Australia [2]. Additionally, the aggregation of individual PEV energy consumption patterns with high variability may result in significant variations in energy demand at the system level. For example, highly correlated charging of 2 million PEVs in the Australian National Electricity Market, which serves around 8 million households, could conceivably require an additional 8GW of generation, more than 15% of current capacity, whilst also requiring very significant electricity network augmentation. Potential PEV deployment of this scale therefore has very significant

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[1] It is important to note that electrified transportation did play a key role in the early development of many electricity industries around the world and this includes not only heavy rail, but light rail and electric buses that share the road system with conventional vehicles

implications for electricity industry planners and key decision makers. 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 Figure 1.
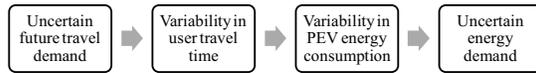

Figure 1. Relationship between travel demand uncertainty and PEV energy consumption rates

The remainder of this work summarizes the background information, describes the problem, mathematical formulation, and finally the Sioux Falls network is used to illustrate several important points about the behavior of system energy consumption of PEVs in networks accounting for deterministic or stochastic demand.

2. Background

Traffic assignment models are an integral part of the transportation planning process. The assignment algorithm implemented in this research follows the rules of user equilibrium [1, 14] 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. 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 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 estimation procedures which rely on average travel distances and driving cycles for energy consumption estimates [4].

The impact of travel demand uncertainty on transport planning is a well-established topic in the literature [3, 5, 13], although the problem has not been studied in the context of electric vehicles. In order to quantify the impact of travel demand uncertainty on PEV energy consumption, it is necessary to compute energy consumption rates. Past efforts to model vehicle energy consumption commonly use a dynamic vehicle simulation approach [8, 9]. However, this approach is limited by its complexity and reliance on driving cycles [10]. The EPA software MOVES2010a (Motor Vehicle Emissions Simulator) also estimates ICEV energy consumption rates, and is the method chosen for this work. The PEV energy consumption rates used in this model represent a battery electric vehicle (not a hybrid electric vehicle), and are based on data from Tesla Motors [11].

3. Problem description and methodology

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 variability. A static UE traffic assignment model is implemented which incorporates long-term demand uncertainty. Based on the resultant assignment patterns, the following performance measures are computed for the vehicles in the network:

1. Total system travel time (TSTT)
2. Standard deviation of total system travel time (TSTT STD)
3. Total system energy consumption (TSEC)
4. Standard deviation of total system energy consumption (TSEC STD)

These 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 source 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.

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.

In this analysis public charging infrastructure is unavailable, therefore PEV drivers only charge at home. This is consistent with current patterns of EV deployment in many places around the world and typical commute distances in urban areas lie within the home-work return trip range of EVs [6]. Therefore it is assumed that PEVs begin each trip fully charged with the same specified all-electric

range. 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 PEVs 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 the limited all-electric range of PEVs, and their respective energy consumption 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 each 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 two key challenges with regard to PEV deployment: 1) ensuring that available generation and network capacity is sufficient to meet the spatially- and time-varying electrical demand (MW) imposed by PEV charging, and 2) ensuring that available generation can reliably and economically meet the additional overall electricity consumption (MWh) of these PEVs. Thus, three key factors need to be considered:

- *Where* and *when* will the vehicles be available to be charged (that is, parked at a location with charging facilities);
- The *amount* of charging each vehicle will require and the total amount of PEV related electricity demand from a given location, which is related to the discharge of the battery from the previous trip;
- The charging *scheme* of the facility (i.e., smart-charging).

As an example, of the latter, having all vehicles commence charging immediately when they return home in the evening is a potentially problematic scenario from an electricity industry perspective. However such a scenario is greatly improved if this charging is *intelligently scheduled* so that even if vehicles are immediately plugged in upon return home at peak hour, the vehicles are actually charged in groups over the evening and night. 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 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 [12]. 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, etc). The estimates used here are based on MOVES default databases for urban arterial roadways in Travis County, Texas in the month of July. This data can be seen in Figure 2(a).
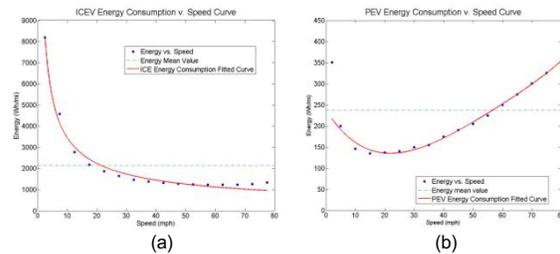

(a)   (b)

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

PEVs consume energy in a way that is fundamentally different from traditional ICE vehicles. 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 Figure 2(a)). 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 [11], and can be seen in Figure 2(b). 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 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.

3.3. Travel Demand Uncertainty

In this analysis, PEV energy consumption variability is the result of variation in long-term travel demand and PEV adoption rates. 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 [3].

To account for travel demand uncertainty, Monte Carlo sampling was implemented to select an origin-destination (O-D) specific demand profile from a normal travel demand distribution with a known mean and variance, of which a certain percentage of each O-D demand pair are PEV users. The realized demand was then fed into the static UE assignment model, from which the system performance measures were computed. Additionally, the variance for each of the system performance measures was computed based on the sample.

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 $G = (N, A, \mathbf{D}, \mathbf{Z}, \Omega, P)$ described by the notation summarized in Table 1.

Then 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. Then let V^ω represent the vector set of feasible link flows for demand realization $\omega \in \Omega$.

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

Let $T(.)$ 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 and is the function used in this paper for demonstration purposes:

Table 1. Summary of Notation

N	The set of all nodes in the network
A	Set of directed arcs, where $a \in A$ is the index for a particular link
$\mathbf{D}$	demand matrix with $|N|$ rows and columns, mapping the demand for travel from every node to every other node
$\mathbf{Z}$	A $N|x|N$ matrix representing the percentage of each OD demand made up of PEVs
Ω	Set of all demand scenarios such that $\omega \in \Omega$ is one particular realization
R	Set of all origins such that $r \in R$
S	Set of all destinations such that $s \in S$
K_{rs}	Set of paths connecting origin $r \in R$ and destination $s \in S$ with index $k \in K_{rs}$
z_ω^{rs}	Percentage of PEVs between OD demand scenario ($0 \leq z_\omega^{rs} \leq 1$)
f_{rs}^{kw}	Flow on path k connecting origin r and destination s in scenario $\omega \in \Omega$
v_a^ω	Total flow on link $a \in A$ under demand scenario $\omega \in \Omega$
$\delta_{a,rs}^{k\omega}$	Link path incidence variable

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

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. This function applies to both ICEVs and PEVs. 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:

$$(T(V^{\omega}*))^T (Y^\omega - V^{\omega}*) \geq 0 \forall Y^\omega \in V^\omega, \omega \in \Omega$$

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.

The energy consumption function, *TSEC(s)*, is based on data in Figure 2 as a function of average travel speed, *s,* and γ is the relative energy efficiency factor. The resulting link travel speed s_a^ω is used to calculate *TSEC* for all vehicles on a link as follows:

$$E_\omega(\Lambda(V^\omega *)) = \sum_{a \in A} \{TEC(s_a^\omega)v_{a\_ICEV}^\omega + \gamma TEC(s_a^\omega)v_{a\_PEV}^\omega\}$$

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

4. Numerical Analysis

Numerical analysis was conducted the well-known Sioux Falls network to demonstrate the importance of considering multiple performance parameters when selecting future transport infrastructure projects. In particular, this work aims to highlight the changes in network behavior due to the presence of PEVs, as well as the importance of considering new performance measures when selecting network improvement projects. The objective of this analysis is twofold:

1. Quantify the impact of demand uncertainty on system level energy consumption 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 energy system operators. However, 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.
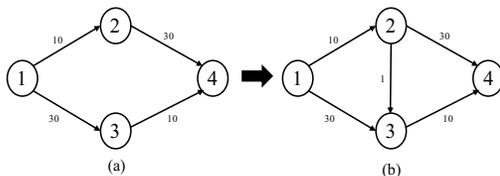

Figure 3. (a) Demonstration network and (b) with addition of crossover link

The demonstration network is similar to the well-known Braess's paradox example. In the initial scenario, the network has four nodes and four links, as in Figure 3a. Then a crossover link is added between links 2 and 3, as in Figure 3b. From the Braess's paradox, it is known that the TSTT

actually goes *up* with the addition of this link; however, the TSEC actually *decreases* by a significant 51%. Note that this decrease is far more dramatic for a network consisting of PEVs. This illustrates the counter-intuitive behavior of PEV energy consumption; transport planners must explicitly consider TSEC as a new performance measure when comparing network improvement options.

Table 2. Results from the demonstration network

	Original Network	Crossover link added between (2,3)	% Change
TSTT (minutes)	1104	1385.5	26%
TSEC (100% PEV) (kWh)	146.6	71.5	-51%
TSEC (100% ICEV) (kWh)	1102.5	1032.8	-6%

Next, this work will analyze the behavior of the two performance measures using the well-known Sioux Falls network, which can be seen in Figure 4. This network contains 24 nodes (all of which are origins and destinations) and 76 links. 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.
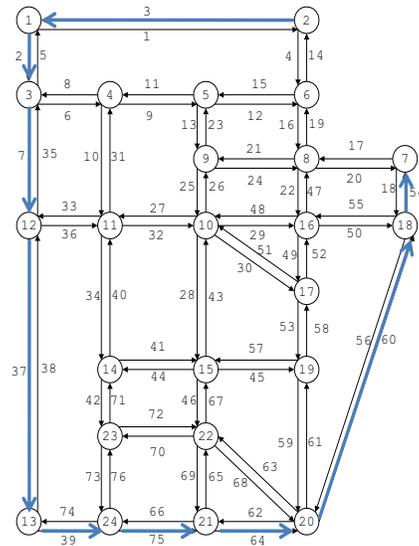

Figure 4. Sioux Falls Network, where bolded lines represent freeway links

As a method of demonstrating the importance of considering PEV TSEC, this work examined the impact of small network capacity enhancement projects on TSTT and TSEC. Two cases are examined. First, the unpredictable 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 is evaluated on each of the 76 different links, resulting in 304 different

design scenarios. Next a subset of the design scenarios 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. These links were chosen through sensitivity analysis based on the results from the deterministic cases. Unless stated otherwise, demand consists of 100% PEVs which have an all-electric range large enough to ensure that they would not run out of charge between any origin and destination. This assumption allowed us to isolate the impact of network design decisions on PEV energy consumption. Current PEV models typically have a maximum range of 100 to 160km; the focus of this work is planning for future transport systems at a time which the battery technology is expected to have improved by, and the range is expected to have increased. Because the electric range is specified as an input, the proposed model is also capable of evaluating the impact of PHEVs that will switch to gasoline-powered mode after an allotted all-electric range is exceeded. 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.

4.1. Deterministic Scenario Comparison

While the impact of demand uncertainty is one focus of this work, the relationship between drivers' travel patterns, TSTT, and TSEC is complex even for the case of deterministic demand, and will be explored first. The network improvement for the performance measures TSTT and TSEC for each design scenario relative to the performance in the original network (with no improvements) is represented as ΔTSTT and ΔTSEC respectively. In Figure 5, 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 Figure 5. 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
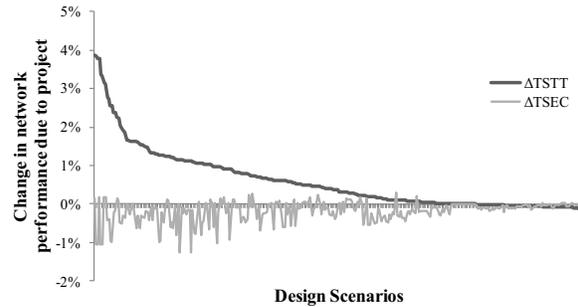
include PEVs.

Figure 5. Comparison of system performance improvement, ΔTSTT and ΔTSEC, for different design scenarios under deterministic demand for Sioux Falls

To reinforce the behavioral difference between PEV energy consumption and energy consumption of traditional ICEVs, Figure 6 illustrates the same results as Figure 5, 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. Again, these observations highlight the need for network planners to explicitly consider PEV energy consumption within the context of network
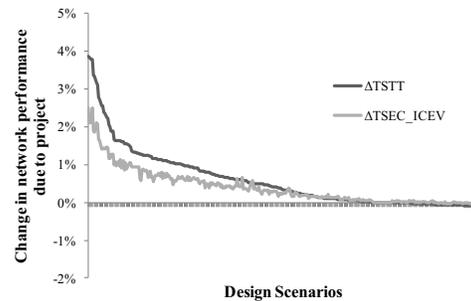
planning.

Figure 6. Comparison of system performance improvement for traditional ICEVs

4.2. The Role of Uncertainty

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. Due to the complexities associated with individual driver's routing behavior, variations in demand may result in extreme variations in system performance. Variability in TSEC is of specific concern for a network with a high penetration of PEVs because
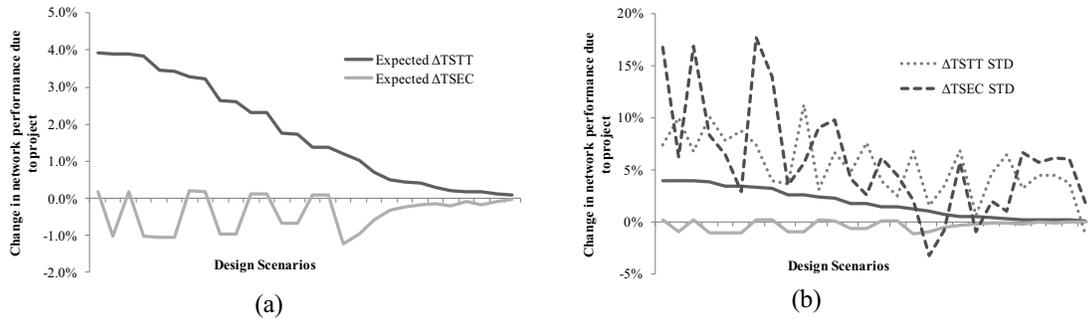
Figure 7. Comparison of system performance improvement under stochastic demand

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.

The impact of the set of small capacity enhancement projects were compared under stochastic demand, where the demand followed a normal distribution with a variance equal to 50% of the expected demand. The performance measures graphed in Figure 7 are Expected ΔTSTT and Expected ΔTSEC, the expected percentage improvements under demand uncertainty compared with the original network, 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 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 more moderate system impact relative to the same scenario under deterministic demand. In addition, the variability of the network performance measures were subject to dramatic fluctuations, represented by the dotted lines in Figure 7(b). Again the vertical axis represents the improvement in performance measures for each design scenario relative to the original network. Similar to the deterministic results in Figure 5, there was little correlation between Expected ΔTSTT and Expected ΔTSEC; many scenarios resulted in a slight increase in total energy use.

Figure 7(b) 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.

In contrast, the behavior of these 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.

4.3. Potential Applications

The preliminary model introduced here contains a framework that can be adapted to a wide range of applications. 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. Such models are now being developed that consider potential factors driving EV uptake including income, off-street parking and environmental awareness [7].

5. Conclusions and Future Research

Future potential PEV usage requires that long-term transportation planning models expand to explicitly account for relevant system impacts. Furthermore, due to the uncertain nature of PEV adoption and the novelty of PEV technology, 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. Such modeling insights could play a key role in electricity industry planning with regard to potential future generation and network investment requirements, and the value proposition for more intelligent 'smart grid' control of PEV charging. At the same time, potentially widespread deployment of PEVS will also mean that transport models will benefit from new techniques and insights on the implications of electrical networks for transportation planning. Some potentially relevant issues include spatiotemporal electrical network capabilities for providing shared charging infrastructure such as fast charge and battery swap stations in particular locations of the road network. 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 was developed and analyzed. From the modeling framework, four important insights were discussed:

i.   The potential of PEVs implies that transport analysis must consider multiple performance measures in a consistent modeling approach (at a minimum travel time, energy consumption and variability of each).

ii. 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 insight was shown to be even more critical in a multi-objective framework such as the one in employed for this work.

iii. *Variability* in system performance measures due to uncertain future travel demand is not correlated with the *expected* system performance. This further strengthens the realization that expected performance should not be considered the sole indicator of a project's desirability.

iv. 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.

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 both systems.

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 key electricity industry participants including network providers and operators to efficiently plan, 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 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. Additionally, dynamic models will be necessary to test the impact of smart-charging schemes. 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 (which is a function of energy consumption), subject to varying penetration rates of PEVs.

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. PEV energy consumption is a novel consideration because of technological advancements that mean PEVs will consume energy in a different manner from that of traditional vehicles. Energy systems operators will now be interested in predicting PEV travel demand in order to predict the induced electricity demand on the grid. Thus 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 given the lead times and capital intensive nature of the infrastructure. This research contributes toward achieving that goal.

ACKNOWLEDGEMENTS

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