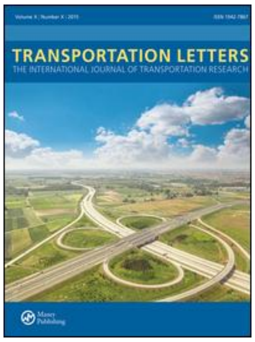

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Policy implications of incorporating distance constrained electric vehicles into the traffic network design problem

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ABSTRACT
To exploit the potential of electric vehicles (EVs) as a sustainable form of transport, the technology must be integrated into the traditional transport planning process. EV energy consumption will also become an essential issue for regional energy providers who will need to adapt to the additional electricity demand created by EVs. This study presents research to facilitate planning for EVs by incorporating travelers' behavior and energy consumption into the evaluation process by introducing a novel framework for the network design problem (NDP) which employs a previously introduced constrained shortest path algorithm that accounts for the distance limitations imposed on EV drivers. For certain design scenarios, the total travel time and total energy consumption are shown to be conflicting objectives. In addition, a new equity issue that arises in networks comprised of mixed classes of vehicles is explored. Results illustrate that a given design scenario can impact vehicle user groups differently.

KEYWORDS
Traffic network design problem; electric vehicles; traffic assignment; constrained shortest path algorithm

Introduction

Transport-based research efforts relating to electric vehicles (EVs) are experiencing a surge in popularity due to advancements in technology, their potential to reduce harmful emissions originating from traditional petroleum-fueled vehicles, and a greater emphasis on global sustainability in many sectors. While the beneficial environmental impact provides ample motivation for investigation, it is also important to note that EVs introduce a closer tie between the road network and the electric power system that will require collaborations and modeling tools to effectively exploit that do not exist today. Traditionally, electric power systems operators have needed to predict energy demand that results from static sources (e.g. households, buildings, industries). However, when EVs achieve a small but significant level of market penetration, the aggregate mobile energy use generated by users' driving patterns will comprise a substantial new form of energy demand. Predicting this new source of energy demand requires a model based on a cross-disciplinary platform that captures vehicle driving patterns, EV energy use, EV market locations, and spatio-temporal charging behavior.

The transport problem of interest in this work is a specific variation of the well-known network design problem (NDP), which is called the discrete multiclass equilibrium network design (DIMEND) problem. The objective of the DIMEND is to identify the optimal set of link capacity additions to minimize a stated objective. Such capacity additions can be used to represent of the set of infrastructure design scenarios under consideration. This work considers the traditional NDP objective, which is to minimize total system travel time (T), as well as an additional objective, to minimize total system energy consumption (E), where the energy is generated by EV mobility activities in a network.

The addition of EVs into the system introduces important behavioral modifications that are not addressed in traditional transport planning models (i.e. traditional user equilibrium (UE)). Specifically, EV drivers now face a distance constraint due to both range anxiety and the limited energy capacity of the vehicle battery. For this reason, the subproblem of the DIMEND problem evaluated in this study is a distance constrained UE assignment model (Jiang, Xie, and Waller 2012), which is able to capture the effect of EVs' route choice on the performance of a network. The route choice algorithm will be introduced and described in Section 3.

This work includes two classes of vehicles. EVs, which are differentiated by the use of the special constrained shortest path routing algorithm, and traditional internal combustion engine vehicles (ICEVs) that are not subject

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to any distance constraints. The energy consumption of each vehicle type is calculated using a speed-variable model that is based on real data from reputable sources in industry (Tesla 2012). These energy consumption rates are combined with the vehicular trajectory outputs from the UE assignment model in order to compute a set of metrics to evaluate a given network design scenario, where a network design scenario refers to the number of links to which to add capacity and the amount of capacity to add (e.g. three links, 1500 vph). An evolutionary-based heuristic method is then implemented to solve for the optimal set of links for each network design scenario. The trade-off between total system travel time and total system energy consumption is compared under different design objectives and different budget constraints. The results reveal differences in network design decisions when considering EV drivers in addition to traditional ICEVs.

Hence, the motivation for this work is twofold: to explore the effects of an additional performance measure (vehicle energy consumption, particularly for EVs) on network design decisions, and to advance research that will aid the potential convergence of the transportation road network and the electric power system. Furthermore, dozens of cities around the world are conducting projects to evaluate the potential of EVs in their region. An essential component of such a forecast is tied to the energy consumption which directly leads to additional demand on the electric grid at the household, neighborhood, and regional levels. Given the novelty of EV technology, these forecasts are generally based on highly aggregated data such as average annual vehicle travel distances and static energy consumption rates, or estimated battery capacities. This work provides a more accurate estimation of the additional demand generated by EVs by exploiting each driver's disaggregate travel patterns based on an equilibrium model adapted to account for EV driver route choice. This type of analysis is an integral first step in predicting regional demands for power systems. Furthermore, energy consumption can be used as a proxy for emissions production and thus a network that minimizes energy consumption will also be environmentally beneficial.

This work begins with a short literature review focusing on the NDP. Next the mathematical model for the problem is introduced, followed by a discussion of the solution methodologies employed in this research. Next, the computational results are presented and finally this work concludes with a discussion of future directions for research.

Literature review

In order to analyze the impact of EVs on traffic design policies, this work focuses on the DIMEND problem, with the additional consideration of calculating the energy consumption of vehicles in the network based on their route. Network design traditionally addresses the problem of finding the optimal location(s) to enhance a network given a limited 'budget.' In this work, such enhancements are road capacity improvements that can have a variety of interpretations, from the discrete additions (e.g. lanes, roads) to projects that may have a more continuous nature (e.g. optimized signal timing plans, other projects like widening of shoulders, elimination of parking, etc.). The NDP is traditionally formulated as a bi-level mathematical programming problem, where the upper level represents the 'planner's' perspective that measures the impact in the network due to the change, and the lower level represents the users' reaction to those changes (Yang and Bell 1998). Due to the nonconvex cost function resulting from the addition of capacity, the NDP can't be solved by traditional optimization techniques and therefore heuristic methods are necessary. Formulations and solution algorithms for the traditional traffic NDP exist in many variations and applications (see Yang and Bell (1998) and Wismans, Van Berkum, and Bliemer (2011) for in depth reviews).

The application of the DIMEND addressed in this study is unique in the way it considers the constrained behavior of EVs. Furthermore, the design decision in this study is to select the best project from a discrete set of capacity enhancement scenarios, rather than charging station location. The NDP in the transport setting is well established and heuristic solution methods have been used by other researchers to solve the bi-level traffic NDP for a number of applications including multi-objective signal timing (Sun, Benekohal, and Waller 2003), accounting for demand uncertainty (Ukkusuri and Waller 2008), optimal toll pricing strategies (Gardner, Unnikrishnan, and Waller 2008), environmental justice considerations (Duthie and Waller 2008), evacuation planning (Abdelgawad and Abdulhai 2009; Ng and Waller 2009), and minimizing emissions (Ferguson, Duthie, and Waller 2012; Sharma and Mathew 2011).

EVs are a popular topic in the research, from topics such as promoting market uptake (Bakker, Maat, and van Wee 2014) to analyses of consumer behavior (Bunce, Harris, and Burgess 2014), range behavior (Franke and Krems 2013), and optimal location of charging infrastructure (Chen, Kockelman, and Khan 2013; Dong, Liu, and Lin 2014; Riemann, Wang, and Busch 2015). Researchers began analyzing EVs from an aggregate perspective based on historical data or in transport planning models without accounting for the changes in behavior. For example, Raykin, Roorda, and MacLean (2012) evaluated a range of driving patterns on the tank-to-wheel energy use of plug-in hybrid EVs for multiple travel routes between a single origin–destination pair. They used traffic assignment to identify the routes and link conditions, and driving cycles to compute energy use. Artmeier et al. (2010) introduced a vehicle routing problem where EVs can use regenerative braking to regain battery power and extend their range.

However, researchers have also recognized that EVs will impact not just physical characters of driving such as fuel economy, but also route choice behavior. Jiang (2012) and Jiang, Xie, and Waller (2012) formulated a constrained shortest path problem to account for range anxiety, and implemented it within a traffic assignment model that was solved using a Frank–Wolfe-based algorithm. This model was additionally applied to model combined destination, route, and parking choices (Jiang et al. 2014) and to account for drivers choosing between gasoline vehicles and EVs (Jiang and Xie 2014). Adler et al. (2016) represent the driving behavior of EVs with the 'shortest walk' problem, which is a shortest path problem intended to minimize the detouring costs due to refueling for EVs. They formulate this problem as an integer program with the objectives of minimizing traveling distance with an unlimited number of stops or a maximum of p stops are allowed. He, Yin, and Lawphongpanich (2014) propose an alternate equilibrium-based approach where recharging time, energy consumption, and enhanced solution algorithms are also considered (although network design is not), and Agrawal et al. (2015) account for a range of heterogeneous population of EV drivers in terms of their range anxiety. However, this work applies the constrained routing algorithm of Jiang (2012) because it captures the behavior of users at question and due to its straightforward implementation, it allows for the exploration of numerous scenarios for policy implications.

Previous work by Gardner, Duell, and Waller (2013) identified the need to incorporate EVs into the transport planning process, and highlighted the importance of considering variability in system performance that may result from uncertain travel demand. Gardner et al. also emphasized the difference in system performance resulting from the technological differences between EVs and traditional ICEVs, however they assumed that EV drivers would recharge at home, and ignored any behavioral effects of range anxiety, or constrained routing. This work builds on the previous work by Gardner, Duell, and Waller (2013) with two main contributions. Firstly, we consider a novel distance constrained routing algorithm (with and without recharging) within the UE Assignment model to account for the differences in route choice behavior of EV drivers. Secondly, we use a heuristic approach to solve the discrete NDP under the assumption of EV users, accounting for both system travel time and system energy consumption.

Problem formulation

The DIMEND problem is formulated using a bi-level model. The upper level problem is the road NDP, which will be described in detail in the section on solution methodology. The lower level problem is the traditional UE traffic assignment problem with an added distance constraint and en-route recharging, which relies on the well-known principle of Wardropian UE (Wardrop 1952). Under UE, drivers will unilaterally choose a path to minimize their own travel cost. When all users behave in this manner, the network reaches a state of equilibrium, where no user can independently change paths for a shorter travel time. The output of the UE problem is a set of link flows, typically based on a deterministic forecasted travel demand and origin–destination matrix.

The proposed DIMEND model is straightforward, flexible, and appropriate for the proposed application, which employs an iterative heuristic solution method (a genetic algorithm (GA)). Within the DIMEND model, the two vehicle technologies, EV and ICEV, are treated as different vehicle classes. The underlying distance constrained UE model is able to incorporate different route choice models for EV drivers and ICEV drivers simultaneously, and can be implemented to estimate vehicle travel time and energy consumption for a system composed of both ICEVs and EVs. In other words, the distance constrained UE model implemented is able to capture the impact EV driver's constrained route choice has on the system, as well as all other users (including ICEV drivers). In the next two sections, we present the mathematical formulations for each of two constrained route choice models, where the first doesn't include the presence of charging stations and the second allows for en-route recharging.

Distance constrained traffic assignment problem

As stated previously, EV drivers may behave differently than ICEV drivers due to imposed distance constraints. Therefore, novel route choice models are better able to capture the behavior of the new vehicle technology considered in this work. In this section and the next section, the two novel route choice models first proposed by Jiang (2012) are described. The novel route choice models are implemented instead of the traditional shortest path problem within the UE framework, in order to capture the effect of the imposed distance constraint on EV driver behavior. The UE model forms the lower level subproblem of the DIMEND, and produces the travel patterns which correspond to a given network design. From these travel patterns, the total system travel time and energy consumption are computed. In the next section, the models used to estimate system level energy consumption for each vehicle technology are presented.

In the first variation of the traditional shortest path assignment introduced by Jiang (2012), EV drivers are constrained by a distance limitation. This is represented using a distance constrained shortest path algorithm. Under distance constrained traffic assignment problem (DCTAP) conditions, charging is assumed to only be available at home or at the destination, or recharging time may be prohibitively long. The distance limitation may represent constraints based on the capacity of the battery, or the range anxiety of EV drivers. While the actual limitation on range of an EV is a complex interaction of speed, acceleration, road grade, energy consumption, driving behavior, and driving conditions, the range anxiety may be perceived by the driver as a simple distance. If a vehicle is constrained by distance, the set of path options available in a feasible route set contains fewer options than that of a vehicle with a greater distance available. As a result, an EV driver may select a route that is shorter by distance but more congested, and therefore has a higher travel time than other routes.

In order to present the formulation of the DCTAP problem, consider a directed graph $G = (N, A)$, where N is the set of nodes (vertices) and A is the set of arcs (edges), in which (i, j) indicates an arc connecting nodes i and j. Let W be the set of origin–destination pairs connecting origins b with destination c, and let K_{bc} be the set of paths connecting origin b and destination c. Assume there are M vehicle classes indexed by $m \in M$. Travel demand between an origin b and destination c for the vehicle class m is indexed using g_m^{bc}. Assume $t_{ij}(x)$ is the travel cost function for arc (i, j) which is dependent on the flow of that arc x_{ij}, the decision variable of this problem. Each $m \in M$ class of vehicles is constrained by a distance limitation D_m. $\delta_{ij,k}^{bc}$ is the arc-path incidence matrix, equal to 1 if link (i, j) is contained in path k from origin b to destination c and 0 otherwise. The mathematical programming formulation for the DCTAP is presented in Equations (1-5).

$$\text{Minimize} \sum_{(i,j)\in A} \int_0^{x_{ij}} t_{ij}(\omega)d\omega \tag{1}$$

s.t.

$$\sum_{k\in K_{bc}} f_{k,m}^{rs} = g_m^{bc} \quad \forall rs \in W, m \in M \tag{2}$$

$$f_{k,m}^{bc} \geq 0 \quad \forall k \in K_{bc}, bc \in W, m \in M \tag{3}$$

$$\left(D_m - l_k^{bc}\right) f_{k,m}^{bc} \geq 0 \quad \forall k \in K_{bc}, bc \in W, m \in M \tag{4}$$

$$x_{ij} = \sum_{bc\in W} \sum_{k\in K_{rs}} \sum_{m\in M} f_{k,m}^{rs} \delta_{ij,k}^{rs} \quad \forall (i,j) \in A \tag{5}$$

The equilibrium objective function (1) remains the same as traditional UE because users still intend to minimize their travel cost. Constraints (2), (3), and (5) are also the same as traditional multiclass equilibrium. Constraint (4) represents the distance limitation of vehicles, where l_k^{bc} is the length of path k from origin b to destination c and equal to $\sum_{(i,j)} d_{ij}\delta_{ij,k}^{bc}$, where d_{ij} indicates the length of arc (i, j).

Traffic assignment problem with en-route recharging

In the second variation, EV drivers can recharge en route to their destination at any node where a charging station exists. Jiang (2012) proposed the traffic assignment problem with en-route recharging (TAPER) formulation to describe a second possible future scenario for EVs. The TAPER conditions may represent a future in which there are a limited number of fast charging stations available, or a situation that includes trips of longer distances, thus necessitating the ability to recharge the EV battery during the trip. Again, the equilibrium principle applies, but there is an additional constraint because the distance traveled between two consecutive charging stations cannot exceed the range limitation of the vehicle. The TAPER subproblem differs from the DCTAP due to the presence of charging stations and the distance limitation of a vehicle class; in DCTAP if the distance constraint is too small, vehicles cannot travel through the network, but in TAPER, the vehicle can recharge but must travel through a specific node to do so. As the distance constraint becomes larger, the TAPER problem becomes equivalent to the DCTAP problem which becomes equivalent to an unconstrained shortest path problem.

Building upon the notation previously introduced, let V be the set of charging station pairs indexed by (p, q), where V_k^{bc} is the set of charging station pairs on path k connecting origin b and destination c. Let Q be a sufficiently large constant value. The parameter d denotes distance, where d_{ij} is the length of link (i, j) and $d_k^{bc,pq}$ represents the distance of the subpath between changing station pq on path k between origin r and destination s. Additionally, the link subpath incidence parameter $\delta_{ij,k}^{bc,pq}$ is equal to 1 if the link (i, j) is contained in the subpath between charging station pair pq on path k connecting origin b and destination c, and otherwise is 0.

Additionally, two 'pseudo path flow' variables are introduced, each representing the addition of a unit of flow added to a path with positive traffic flow. The binary variable y_k^{bc} is equal to 1 if the flow of the path $f_k^{bc} > 0$, and otherwise equal to 0. Finally, $y_{k,m}^{bc,pq}$ represents the pseudo subpath flow between any two charging stations. Let $y_k^{bc,pq} = 0$ if $y_k^{rs} = 0$ and p and q are two charging stations on path k between b and c; otherwise $y_k^{bc,pq} = 0$. The nonlinear integer programming formulation for the TAPER follows:

$$\text{Minimize} \sum_{(i,j)\in A} \int_0^{x_{ij}} t_{ij}(\omega)d\omega \tag{6}$$

s.t.

$$\sum_{k\in K_{rs}} f^{bd}_{k,m} = g^{bc}_m \quad \forall rs \in W, m \in M \tag{7}$$

$$f^{rs}_{k,m} \geq 0 \quad \forall k \in K_{bc}, bc \in W, m \in M \tag{8}$$

$$Qy^{rs}_{k,m} \geq f^{bc}_{k,m} \quad \forall k \in K_{bc}, bc \in W, m \in M \tag{9}$$

$$y^{bc}_{k,m}\delta^{bc}_{ij,k} = \sum_{p,q\in V^{rs}_k} y^{bc,pq}_{k,m}\delta^{bc,pq}_{ij,k} \quad \forall k \in K_{rs}, \forall rs \in W, \forall(i,j) \in A, m \in M \tag{10}$$

$$d^{bc,pq}_k y^{bc,pq}_{k,m} \leq D_m \quad \forall bc \in W, \forall k \in K_{rs}, pq \in V^{bc}_k, m \in M \tag{11}$$

$$y^{rs}_{k,m} \in \{0,1\} \quad \forall rs \in W, k \in K_{rs}, m \in M \tag{12}$$

$$y^{rs,pq}_{k,m} \in \{0,1\} \quad \forall rs \in W, k \in K_{rs}, pq \in V^{rs}_k, m \in M \tag{13}$$

where

$$x_{ij} = \sum_{rs\in W}\sum_{k\in K_{rs}}\sum_{m\in M} f^{rs}_{k,m}\delta^{rs}_{ij,k} \quad \forall(i,j) \in A, m \in M \tag{14}$$

$$d^{rs,pq}_k = \sum_{(i,j)\in A} d_{ij}\delta^{rs,pq}_{ij,k} \quad \forall rs \in W, k \in K_{rs}, pq \in V^{rs}_k \tag{15}$$

Constraints (7), (8), and (14) are the same as the traditional Beckmann formulation for UE. Constraint (11) ensures that the distance traveled by a vehicle (i.e. unit of pseudo-flow) between charging stations will be less than the distance limitation of the vehicle class. Note that this formulation does not include the time it will take to recharge the vehicle at a charging station. While adding this consideration is reasonably trivial (Jiang 2012), for the purposes of this work, we assume that the disutility of charging time will have a negligible effect on EV drivers, or cause them to not recharge at all. The TAPER scenario may be assumed to be applied in a future technologically advanced enough that charging time is inconsequential and does not add to the disutility experienced by EV drivers.

Energy consumption evaluation

The energy consumption of EVs is a particularly important issue for regional electricity providers, who will need to be able to predict the electricity demand resulting from the use of EVs. In particular, electric power systems managers will be interested in knowing where and when EVs will plug in, how much electricity they will consume, and the power management scheme that will be utilized (i.e. smart charging). The proposed model takes a first step in answering these questions by quantifying *how much* energy will be consumed by the EVs. A traffic assignment model is exploited to answer this question using individual user travel patterns and average speeds to approximate energy consumption rates.

However, vehicle energy consumption rates and environmental impacts are difficult to quantify, even for ICEVs which have a longer history in both practice and research (Aziz and Ukkusuri 2012; Mindali, Raveh, and Salomon 2004; Poudenx 2008). Existing commercial software often uses a dynamic simulation method that was developed based on extensive testing and data. However, such a method can be computationally cumbersome, depends on driving cycles to predict the mobility patterns of the vehicles (which are not always a representative of real-world driving, see Joumard et al. (2000)), and the software itself can be prohibitively expensive. Alternatively, simulation-based traffic modeling-based approaches can make estimations of vehicle energy consumption, but the data and computational requirements may present significant barriers for many applications (Ahn et al. 2002).

Fewer empirical results exist for the energy consumption of EVs (Graver, Frey, and Choi 2011; Howey et al. 2011), although this data-set is expanding rapidly. While previous research has focused on the long-term impact of the energy consumption of EVs (Ford et al. 2011), it is usually based on average driving distances, driving cycles, and average per mile estimates. This work is an improvement over past models because it is able to capture the speed-varying energy consumption rates of vehicles, although there are still limitations. Future versions of this model will account for more complex factors such as the impact of congestion, gradient effects like acceleration and braking, and vehicle weight, which may have a significant impact for heavy vehicles.

The energy consumption model for ICEVs in this work was based on data from the Environmental Protection Agency's MOVES 2010a (Motor Vehicle Emissions

Simulator) software package (USEPA 2009). This software finds energy consumption and emissions production from vehicles based on a variety of factors including meteorology, vehicle fleet composition (vehicle miles traveled (VMT) estimates, vehicle age distribution, vehicle populations, sales and VMT growth rates), vehicle activity, fuel characteristics, and emission control program data. The points in Figure 1(a) show the energy consumption for an average ICEV depending on speed obtained (using default data for the summer AM peak hour in Travis County) from MOVES. The curve was fitted to the data using the power regression tool in Matlab. This regression model is less accurate at higher speeds, when the efficiency of ICEVs in reality begins to decrease. Therefore, for this model to be applied to networks where speeds above 75 mph are present, an adjusted energy consumption curve would be necessary. However, this inaccuracy does not impact the analysis presented in this study.

Based on the powertrain configuration, EVs consume energy in a different manner from ICEVs. At lower speeds (like what might result from congestion effects), EVs actually consume relatively *less* energy than their ICEV counterparts. The energy consumption model used in this project was based on the data obtained from (Tesla 2012) describing the energy use of a Tesla EV in terms of ancillary, tires, aerodynamics, and drivetrain. Figure 1(b) depicts the approximated points and the polynomial regression curve fitted to the data using Matlab. The two functions used for energy consumption for ICEVs and EVs, respectively, are shown in Equations (16) and (17), where EC indicates energy consumption and v is the average vehicle speed on a link (calculated based on the link length and UE travel time). The average speed on each link is then multiplied by the length of the link to calculate the energy consumption of a single vehicle on the link. The total energy consumption is found by aggregating over all vehicles and links in the network.

$$EC_{ICEV}(v) = 14.58v^{-0.6258} \tag{16}$$

$$EC_{EV}(y) = 1.79\times10^{-8}v^4 - 4.073\times10^{-6}v^3 + 3.654 \times 10^{-4}v^2 - 0.0109v + 0.2372 \tag{17}$$

While the curves in Figure 1 capture the fundamental differences between vehicle technologies, the scale between the two models is significantly different; these data imply that EVs are about 10 times more efficient than ICEVs, which is not accurate. This is a result of comparing an 'average' ICEV with a highly efficient EV. However, for the purposes of this work, it is the difference between the behaviors of these two curves that is of interest. Finally, these models reflect mobile vehicle energy use only; they do not account for the upstream energy use in terms of the production or transmission of electricity, refining petroleum or transporting products, or other inefficiencies in either process. As technology advances, the energy consumption of both ICEVs and EVs will likely decrease, particularly in the long-term future which is the time frame of interest in this study. However, even in the future, the difference in efficiency curves will remain a vital factor. Lastly, this model only applies to the energy consumption of all-EVs, although with a different energy consumption model, plug-in hybrid EVs could also be represented.

Network design problem and scenario evaluation

The DIMEND model is formulated as a bi-level nonlinear mathematical programming problem. The upper level seeks to minimize a given objective, for example,

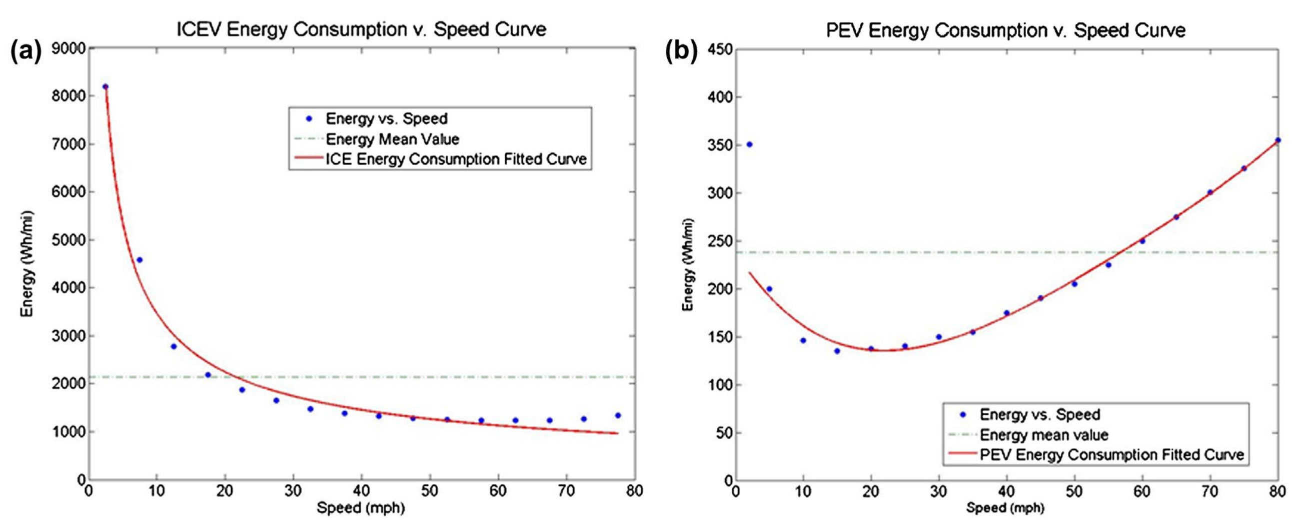

Figure 1. (a) The energy consumption model for ICEVs based on MOVES2010a and (b) the energy consumption model for EVs based on data from Tesla.

total system energy consumption E or total system travel time T, both of which are a function of the link flow patterns and capacity changes in the transportation network. The lower level problem represents drivers' reactions to changes in the road network, represented by the DCTAP and TAPER subproblems.

This work focuses on ranking and evaluating design projects in a traffic network, although principles similar to those discussed here would apply to other NDP applications. Let S be a predetermined set of possible network design scenarios indexed by s, each of which is defined by the amount of capacity p from a set of possible capacity additions P_s to add to each of n links from a set of possibilities N_s (i.e. project $s_{1000,3}$ indicates the addition of 1000 vph to 3 links) in order to minimize objective $w \in \Omega$. δ_{ij}^s is a binary decision variable equal to 1 if link (i, j) is an optimal location to add capacity in project scenario s. Note that links which are not available to be improved by the amount $p \in P_S$ will be constrained such that $\delta_{ij}^s = 0$. This approach does not consider an explicit budget because such a decision is highly network dependent, but the combination of adding p capacity to n links may be considered an informative proxy.

The upper level problem represents the 'planner's' perspective, who seeks the optimal links to which to add capacity for each design scenario in order to minimize an objective $s_{p,n}^w$. The upper level decision variables also impact the lower level problem, which is the multiclass UE model accounting for distance limitation and recharging, using the DCTAP or TAPER problems. For each design scenario $s_{p,n}^w$, the formulation to minimize the objective w follows:

$$\text{Minimize } w = \sum_{m \in M} E_s^m(x, s) \text{ or } T_s(x, \delta^s) \tag{18}$$

s.t.

$$\sum_{(i,j) \in A} \delta_{ij}^s = N_s \tag{19}$$

$$\delta_{ij}^s \in \{0, 1\} \quad \forall (i, j) \in A \tag{20}$$

s.t.

$$\text{Minimize } z(x, \delta^s) = \sum_{\forall (i,j) \in A} \int_0^{x_{ij}} t_{ij}(\omega, \delta^s) d\omega \tag{21}$$

s.t.

$$\text{DCTAP constraints or TAPER constraints} \tag{22}$$

For the purposes of this analysis, it is assumed that EVs begin each trip fully charged with the same specified all-electric range D_{EV}.

The link cost function t_{ij} may be any function that defines the relationship between the number of users traveling a particular link and the cost to travel that link (e.g. travel time, money, emissions, etc.). The Bureau of Public Records (BPR) function is a common choice in both transportation literature and in practice. The link cost function in this work when considering a design scenario $s_{p,n}^w \in S$ is:

$$t_{ij}^s(x, \delta^s) = t_{ij}^0 \left(1 + \alpha_{ij} \left(\frac{x_{ij}^s}{c_{ij} + \delta_{ij}^s p_s} \right)^{\beta_{ij}} \right), \forall s \in S \tag{23}$$

Where for arc (i, j), t_{ij}^s is the travel cost in demand scenario s, t_{ij}^0 is free-flow travel time (distance per time), x_{ij} is hourly volume (vehicles), c_{ij} is hourly capacity (vehicles per hour (vph)), α and β are parameters that depend on link geometry, p_s is the capacity in vph to be added in project scenario $s_{p,n}^w$, and δ_{ij}^s is an indicator equal to 1 if link (i, j) has been identified as an optimal location to add capacity in project scenario $s_{p,n}^w$. Although ICEV and EV drivers make different route choices on account of their different range considerations, they still experience travel cost in the same way, and therefore this function applies to both ICEVs and EVs. The total system travel time, $T_s(x_{ij})$ is then the sum of travel cost function on each link multiplied by the flow on that link.

The total system energy consumption is the second metric of interest in this work. The energy consumption for a class of vehicles m, in a particular design scenario E_s^m is a function of the speed vehicles travel on each link, v_{ij}, which is a function of network link flows. E_s^m is found by multiplying the energy consumption on link (i, j) (defined by the appropriate equation in Table 1 in kWh/mile) by the length of the link (i, j) in miles by the number of vehicles of that class on the link. The total energy consumption in the network is a sum of the energy consumption of all vehicle classes.

$$E_s\left(x_{ij}, v_{ij}\right) = \sum_{m \in M} \sum_{(i,j) \in A} \text{EC}^m(v) \times d_{ij} \times x_{ij}^{m,s} \tag{24}$$

Table 1. Travel time and energy system performance metrics disaggregated by vehicle class, and presented for a single design scenarios (2000,2) and range of EV penetration levels.

Objective	ε (%)	$\Delta T_{2000,2}$ (%)	$\Delta E_{2000,2}$ (%)	ΔT_{ICEV} (%)	ΔT_{EV} (%)	ΔE_{ICEV} (%)	ΔE_{EV} (%)
T	10	11.2	7.0	11.2	11.4	7.1	0.4
	50	10.9	3.0	10.9	10.9	3.2	0.8
	80	14.0	−0.2	13.0	14.3	0.8	−2.3
E	10	8.5	7.2	8.5	8.6	7.4	−8.6
	50	8.6	5.9	8.7	8.6	7.6	−8.1
	80	8.8	3.0	8.6	8.8	8.7	−8.9

Finally, system performance metrics are introduced to rigorously evaluate the design scenarios examined in the DIMEND problem. The performance metrics are chosen to capture the impact of the design scenario on system-wide network conditions and to enable comparison between different design scenarios. The performance metrics capture the improvement in total system travel time or total system energy consumption for each design scenario, relative to the base case network, where there are no capacity additions to any link. The performance metrics ΔT_s and ΔE_s are presented in Equations (25) and (26).

$$\Delta T_s = 1 - \frac{T_s}{T_0} \tag{25}$$

$$\Delta E_s = 1 - \frac{E_s}{E_0} \tag{26}$$

The output for each design scenario $s^w_{p,n}$ are the performance metrics ΔT_s and ΔE_s, and the matrix δ^s that identifies the optimal links for capacity additions. The UE problem in the lower level is solved using a Frank–Wolfe-based linearization method. The next section describes the enumeration algorithm to solve the DIMEND problem, including the GA that was used to solve the for the optimal project selection in each individual design scenario.

Solution methodology

The section describes the solution methodology implemented for the discrete multi-objective equilibrium NDP. The solution methodology includes a heuristic solution method to solve the bi-level network design formulated in (18)–(22) and (1)–(15) and the simple enumeration algorithm to construct and test the set of design scenarios S. The lower level employs a Frank–Wolfe solution method to solve for the equilibrium flows, T_s and E_s. The solution method for the upper level model uses a GA to find the optimal set of link improvements for a design scenario δ_s. The output of the GA is the chromosome ϕ_s. The Frank–Wolfe method and the GA are detailed in the following sections. Thus, the output for each design scenario $s^w_{p,n}$ is the optimal set of n links (contained within the best chromosome ϕ^*_s), and the performance metrics ΔT_s and ΔE_s. Figure 2 outlines the DIMEND enumeration algorithm. The advantage of this method lies in its straightforward implementation and evaluation, although it should be noted that a high number of objective function evaluations will be necessary.

The Frank–Wolfe linearization method is a commonly employed solution approach to the traffic equilibrium problem. The Frank–Wolfe approach was selected here for its ease of implementation. Figure 3 outlines the Frank-Wolfe method in the context of this work. The modifications include accounting for the impact of the design scenario chromosome ϕ_s.

```
Algorithm 1 DIMEND Pseudocode
Input: Ω, P_S, N_S
procedure MAIN
    for ∀w ∈ Ω do
        T_0, E_0 ←Frank Wolfe(s^w_{0,0}, φ_0)
        for ∀p ∈ P_S do
            for ∀n ∈ N_S do
                construct design scenario s^w_{p,n}
                φ*_s ←GA(s^w_{p,n})
                T_s, E_s ←Frank Wolfe(s^w_{p,n}, φ_s)
                calculate ΔT_s, ΔE_s
            end for
        end for
    end for
end procedure
Output: ∀s ∈ S : φ*_s, ΔT, ΔE
```

Figure 2. DIMEND scenario evaluation pseudo-algorithm.

```
Algorithm 1 Frank Wolfe Pseudocode
Input: G, W, V, M, D
procedure FRANK WOLFE(s^w_{p,n}, φ_s)
    for i ∈ φ_s do
        c_i ← c_i + p
    end for
    while gap > 0.001 do
        find SP: DCTAP/TAPER
        find stepsize λ to min z((1 − λ)X + λX′), 0 ≤ λ ≤ 1
        update flows and gap
    end while
    return T_s, E_s
end procedure
```

Figure 3. Outline of Frank–Wolfe solution procedure.

The NDP as formulated in the previous section cannot be solved to a guaranteed global optimal value using standard optimization techniques because of the non-convex cost function (Equation (11)). Therefore, heuristic solution methods are necessary. This research applied a GA, an optimization technique inspired by principles of natural evolution. GAs provide a flexible, rigorous framework to solve challenging optimization problems, and are widely applied in a variety of real-world settings, particularly design problems such as water distribution systems and urban transit networks (Chakroborty 2003), stopping patterns in passenger rail, traffic management, and numerous other civil infrastructure management problems.

GAs are also a well-established research method to solve the bi-level traffic NDP (Ferguson, Duthie, and Waller 2012; Sun, Benekohal, and Waller 2006; Unnikrishnan and Lin 2012). Karoonsoontawong and Waller (2006) showed that in terms of heuristic approaches to solve the continuous NDP, GAs perform better than simulated annealing or random search algorithms. A GA will correctly identify local extrema, but as is the case with all heuristics, the solution is not guaranteed to be the global optimal value.

In this approach, steps taken to ensure that the GA had converged on the best solution.

A GA locates an optimal solution by searching for promising regions in which there are a high proportion of 'good' solutions. It begins with a randomly generated initial population of individuals that represent potential solutions (called chromosomes). Over 'time,' the population evolves according to a natural selection process, in which the best individuals are selected and combined using a crossover technique to form new populations of individuals. The basic GA in the context of this work is outlined in Figure 4.

This work utilized both single- and multi-objective variations of the nondominant sorting genetic algorithm II (NSGA-II) by Deb et al. (2002), using the binary encoding approach. NSGA-II is a well-known algorithm that has proven to be the best GA tool for solving multi-objective optimization problems, and utilizes several techniques that provide superior performance. See Sun, Benekohal, and Waller (2003), Duthie and Waller (2008), Sharma and Mathew (2011), and Ferguson, Duthie, and Waller (2012) for other examples that utilize NSGA II for various applications of the traffic NDP.

The current application utilizes the GA in a manner to avoid over-complication, primarily by eliminating issues of feasibility. Discrete variables were used to represent p, the capacity to be added to a link, which is an input to the GA. In order to avoid infeasible regions, GA variables were integer values that represented the link to which p was to be added. A chromosome ϕ_s contains n GA variables, each of which represents a link number to which to add capacity. The memory allocated to a GA variable was limited to the number of bits required to represent all links in the network $(i,j) \in A$ in binary form, and there were no infeasible solutions. However, this does enable the GA to select the same link for multiple projects, i.e. the solution to $s_{500,2}^{\mathrm{TSTT}} = \{2,2\}$, resulting in the equivalent of 1000 vph capacity added to link 2. Constraints could be introduced to eliminate this possibility, but for the sake of simplicity, were not used here. While numerous other GA variable representations are possible, the approach here was selected for its superior performance. Another important factor in the performance of the NSGAII (and all GAs) is the input parameters, which are case specific to any problem. As such, input settings were determined using sensitivity analysis and are further discussed in the following section.

Algorithm 2 Genetic Algorithm Pseudocode

Input: PS (population size), crossover probability, mutation probability, I (number of generations), RS (random seed);

procedure GA($s_{p,n}^{w}$)
  initialize(RS, PS) $Population(\phi)$
  while generation $i < I$ **do**
    for $\forall \phi \in Population$ **do**
      $T_{\phi_s}, E_{\phi_s} \leftarrow$Frank Wolfe($s_{p,n}^{w}, \phi_s$)
    end for
    rank chromosome fitness by objective w
    crossover procedure(crossover probability)
    mutation procedure(mutation probability)
  end while
  return ϕ_s^*
end procedure

Figure 4. GA pseudocode.

Demonstration and analysis

This section presents the computational results and discussion regarding the DIMEND model and the solution method presented in previous sections. Numerical analysis is provided for a variant of the Nguyen–Dupius network (Nguyen and Dupius 1984). First, this section explore the implications of the TAPER routing problem and the DCTAP routing problem for evaluation and ranking of design scenarios in networks of EVs. Next, this section examines the policy implications of optimal project selection in a mixed network comprised of both ICEVs and EVs. Of interest in this work are the *planning and policy* implications of different vehicle technologies on the ranking and evaluation of network design scenarios under the presence of EVs.

The DIMEND problem is contextualized as follows: the network planner wishes to determine the optimal design scenario to improve system performance by adding capacity to links in the network. A design scenario is defined by the design objective w, the number of links to which to add capacity n, and the amount of capacity to be added to each link p. For this demonstration, a design scenario $s_{p,n}^{w} \in S$ is defined by the objective $w \in \Omega{:}\{T, E\}$, the capacity to be added to each link $p \in P_s{:}\{500, 1000, 1500, 2000\}$ (vph), and the number of projects allowed $n \in N_s{:}\{1, 2, 3, 4, 5\}$, resulting in a total of 40 possible scenarios for each fixed network state.

Additionally, there are four sets of model parameters that influence the optimal design scenario: the vehicle travel demand matrix W, EV market penetration level defined by the percentage of EV class vehicles in the network, ε, the locations of charging stations V, and the distance constraint D_m, primarily D_{EV}. The feasible solution space for δ_{ij}^{s} includes only links that have been pre-identified by the planner as being available for the specified capacity addition. A large population size of 100, crossover probability of 0.9, and mutation probability of 0.01 were set as the GA inputs. The GA was run for a large number of generations and tested with multiple random seeds in order to ensure that the best solution had been found.

The Nguyen–Dupius network (Figure 5) is a test network consisting of 13 nodes, 19 links, and 4 OD pairs. There are two origins (1 and 4) and two destinations (2 and 3), with a demand between OD pair (1,2) of 1,528, (1,3) of 1,840, (4,2) of 1,680, and (4,3) of 1,360. All links

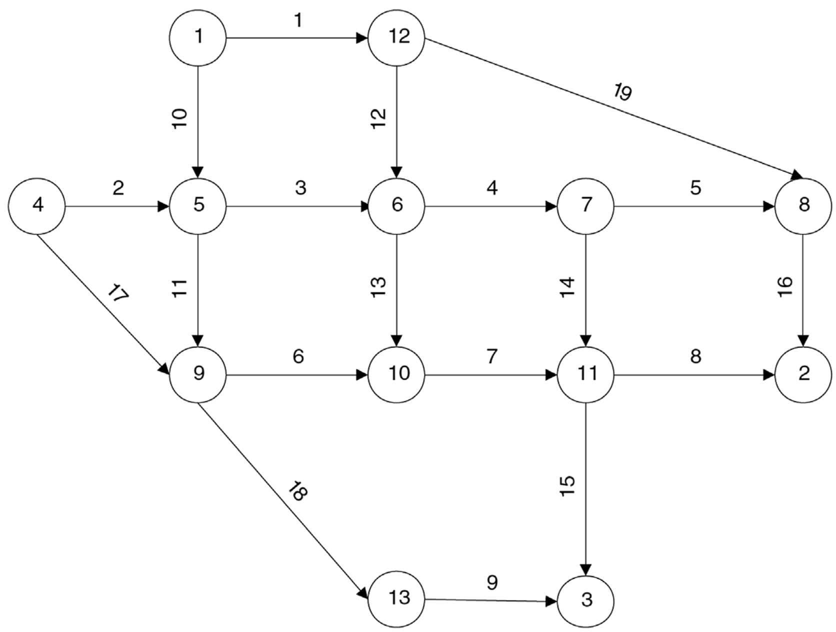

Figure 5. The Nguyen–Dupius test network with link and node indices shown.

have an initial capacity of 2,200 vehicles per hour (vph), a free flow speed of 50 mph, and BPR design parameters α and β of 0.15 and 4, respectively.

Impact of the TAPER routing on the DIMEND problem

In the TAPER routing subproblem, there are charging stations in the network in which EVs will recharge en route. When D_{EV} is limited, the feasible path set for EVs will be determined by the locations of the charging stations.

Figure 6 illustrates the results for the 20 design scenarios $s^{T}_{n,p}$, where the objective $w = T$, $D_{\mathrm{EV}} = 19$, and $V = (6, 10)$ (where charging stations imply the TAPER subproblem). In order to illustrate the behavioral differences in travel time and EV energy consumption for EVs and ICEVs, the results in Figure 6(a) correspond to the network composed of solely ICEVs, $\varepsilon = 0$ and the results in Figure 6(b) correspond to a network composed of solely EVs, $\varepsilon = 100$. These extreme cases help isolate the relationship between EV driver behavior and energy consumption as predicted by the DIMEND model. The horizontal axis identifies the design scenario by p and n. The vertical axis corresponds to ΔT and ΔE as a percentage. The lightly shaded columns correspond to the energy performance metric, ΔE and the more darkly shaded columns correspond to the travel time metric ΔT.

Figure 6 shows that due to the fundamentally different behavior of EV drivers and technology, T_s and E_s are fundamentally conflicting in nature in EV networks (Figure 6(b)); whereas traditionally, the relationship between T and E has been very predictable (Figure 6(a)). In a network composed of ICEVs, energy consumption is highly correlated with travel time. This is due to the complementary nature of the BPR travel time function and the $\mathrm{EC}_{\mathrm{ICEV}}$ function, presented in Equation (16). However, the BPR travel time function and $\mathrm{EV}_{\mathrm{EV}}$ function in Equation (17) are conflicting. In Figure 6(b), as total travel time decreases, the total energy consumption increases. It is important that planners recognize this novel impact of EV driver behavior.

Impact of DCTAP routing on the DIMEND problem

In the DCTAP conditions, there are *no* charging stations available in the network. The feasible path set for EVs is determined by the length of the paths between their origin and destination (with no option of recharging). Figure 7 presents the performance metrics for a set of design scenarios where D_{EV} varies from 22, 23, or 24 miles. Five design scenarios are examined, where $s^{T}_{1500,n}$ and the number of projects n is varied between 1 and 5 with only EVs in the network ($\varepsilon = 100$). The horizontal axis identifies the specific design scenario and the vertical axis corresponds to the performance metrics ΔT_s and ΔE_s. The solid columns illustrate results for ΔT_s and the lined columns represent ΔE_s.

Figure 7 illustrates three main points: (i) the marginal improvements gained from adding an additional project, (ii) the relationship between that marginal improvement and the distance constraint D_{EV} (and therefore technological advances), and (iii) the contradictory behavior of the two performance metrics, energy and travel time improvement. A greater number of projects may be reflective of a larger budget and thus, the difference between each project reflects the marginal return for a greater investment.

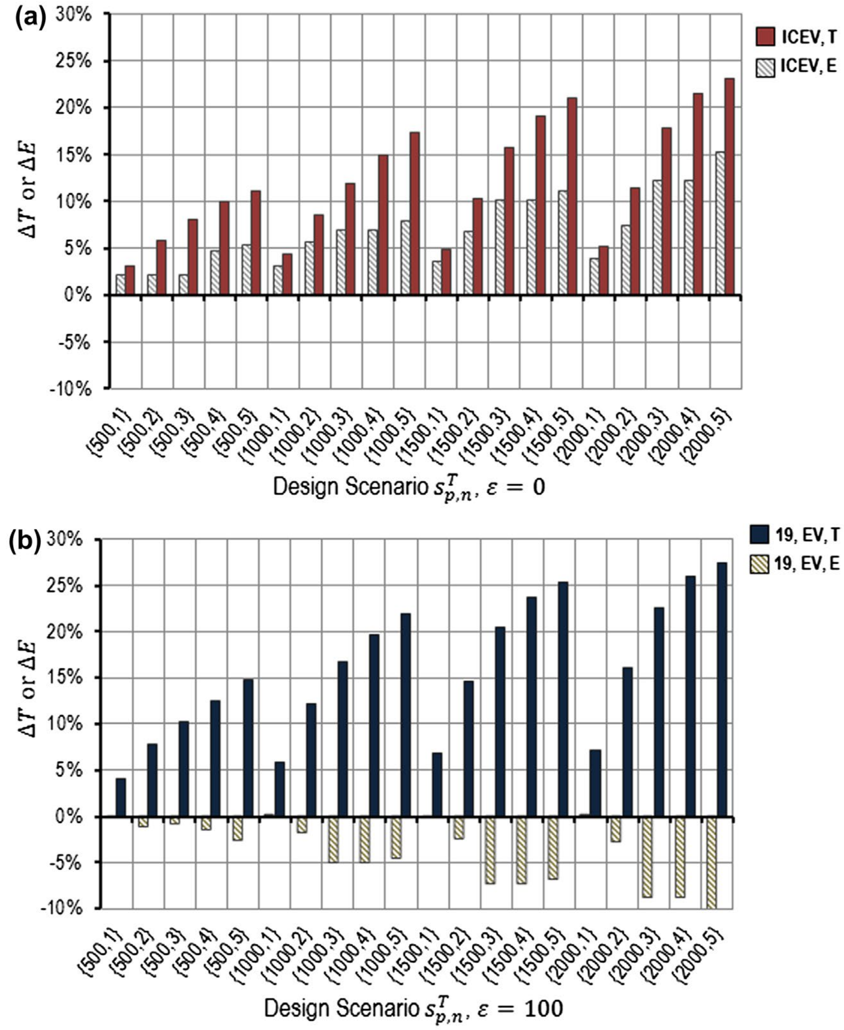

Figure 6. Illustration of system level behavioral differences for energy consumption and travel time improvements under an (a) ICEV network and (b) EV network.

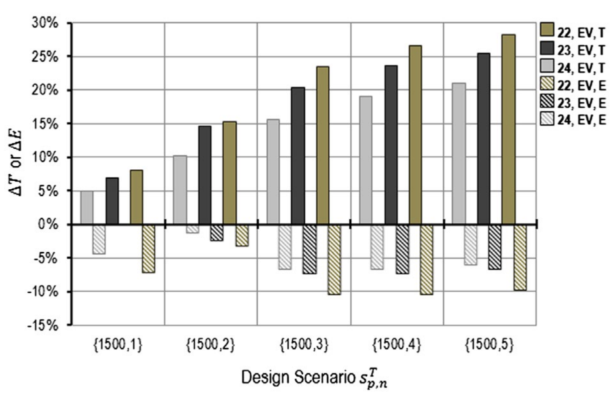

Figure 7. Illustration of travel time and energy system level performance metrics for a combination of distance constraints and design scenarios under the DCTAP subproblem.

When $n = 4$ and $n = 5$, the network is nearing free flow conditions and so the difference between ΔT_s is small, indicating a smaller marginal return. In the same scenarios, ΔE_s displays the same or worse performance, which implies that investment will not impact or increase total energy consumption.

Additionally, ΔT_s and ΔE_s are higher in networks where $D_{\mathrm{EV}} = 22$. However, investigation shows that T_0 and E_0 are also greater in a network where $D_{\mathrm{EV}} = 22$, as compared to networks where $D_{\mathrm{EV}} = 23$ or 24. Due to the more limited distance constraint, EVs have a smaller set of feasible path options, which results in high congestion and T_0. As a result, more EVs are on the same path, so the same investment will have a greater impact in this situation as compared to the situation where EVs have a range of 23 or 24. Additionally, the results illustrated in Figure 7 show that optimal project selection is dependent on the perceived distance limitation of EV drivers.

Equity issues in a mixed vehicle network

Until this point, the focus has been on extreme cases of vehicle class composition in order to isolate different network behavioral implications. However, this section considers a range of market penetration levels and highlights the impact of optimal design scenarios on each user class individually. This analysis provides a means to reveal any possible inequities which may arise from a particular design scenario. For example, one design option may benefit some user group more than another, or in an extreme case, one user group may benefit while another group incurs a loss.

Figure 8 illustrates the results for the 20 design scenarios in a TAPER network where $\varepsilon = 60$, $D_{\mathrm{EV}} = 14$, and $V = (6, 11)$. Again, the NDP objective is to minimize system travel time, T. In Figure 8, the results have been separated by the individual vehicle classes. The results presented in Figure 8 are consistent with those shown in previous figures regarding the trends of the performance metrics. However, Figure 8 also highlights the difference in these performance metrics across the two vehicle classes, specifically certain equity issues which can arise. For example, in terms of travel time, ICEV users may experience a similar travel time savings compared with the EV users. On the other hand, if the NDP objective is to minimize energy consumption, the EV users may end up with increased energy demands, while the energy consumption is reduced by over 25% for ICEV users. The reasoning for these results is the same as discussed in the section on the problem formulation, and is an outcome of the difference between the ICEV and the EV energy models.

Finally, this subsection explores a case study and potential paradox for several different levels of EV market penetration. For the purposes of illustrating an important policy observation, we isolate the design scenario where $p = 2000$ and $n = 2$, and compare the two objectives, T and E, at penetration levels $\varepsilon = 10, 50, 80$. The set of charging stations for this TAPER experiment is $V = (6, 10, 11)$, opening up routes to EV drivers that were not available in the previously results in Figure 8. Note that E was not

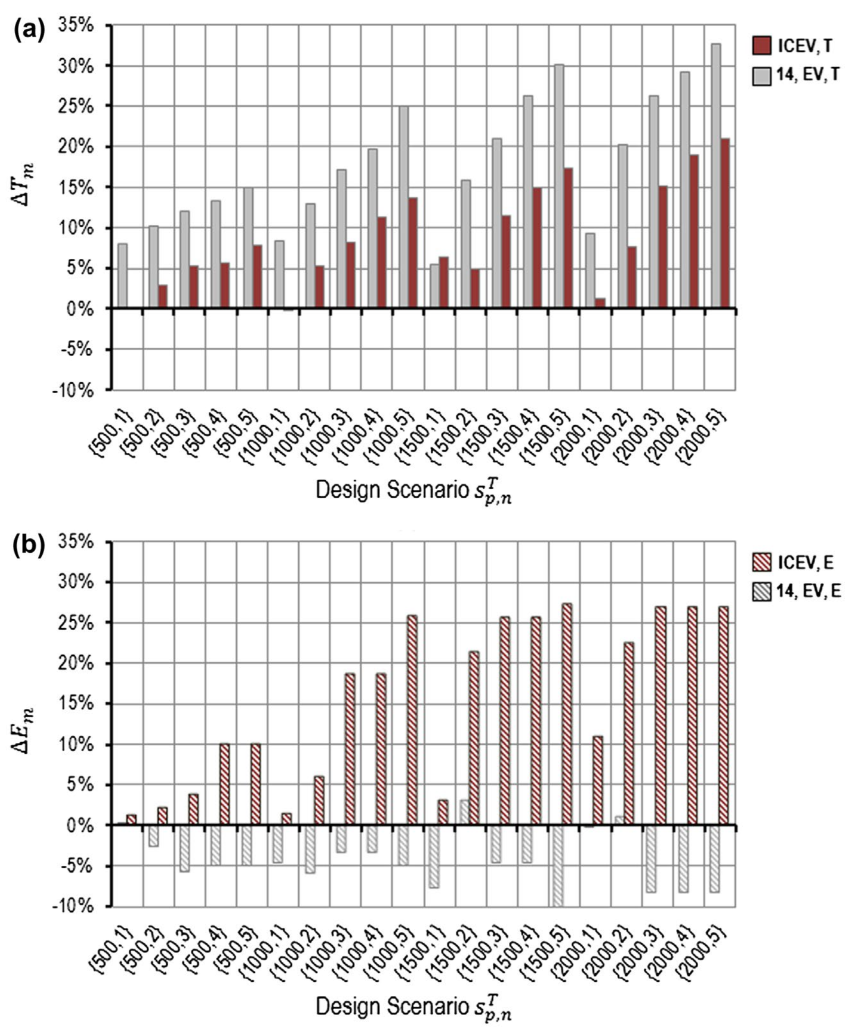

Figure 8. System level performance metrics for (a) travel time and (b) energy, separated by each vehicle class and presented for various design scenarios when $\varepsilon = 60$.

the objective of interest in previous cases where $\varepsilon = 100$ because due to the conflicting nature of travel time and EV energy consumption, no design scenarios benefiting energy consumption were available. However, ICEV energy consumption is closely correlated with travel time and dominates EV energy consumption. Therefore, design strategies targeting ΔE will be possible in the mixed network case; however, they will have an unequal impact on different user classes.

Table 1 presents the results for the paradox experiment in terms of the entire system (ΔT and ΔE) and also separated by vehicle class (ΔT_m and ΔE_m). The results for T are approximately equal for all users in the system. However, Table 1 reveals an important insight: in a mixed network, EVs almost always consume more energy due to capacity additions, which corresponds to a higher fuel cost that may impact both users and electric power companies. This inequality results even when the system metric ΔE indicates that the design scenario is beneficial on a network level. Counterintuitively, this result is magnified when the targeted objective is minimizing energy. This outcome results because the total energy consumed by ICEVs dominates the energy consumed by EVs, even when ε is high. However, planners concerned about network equity should be aware of this possible paradox.

Discussion and conclusion

This work implemented the DIMEND problem using EVs and traditional ICEV to examine the policy implications of different strategies of network design scenarios. The problem was modeled using a bi-level formulation where the upper level was solved using a GA and the lower level was a multiclass UE traffic assignment model. Vehicle energy consumption was computed based on industry data for EVs and ICEVs. A number of discrete capacity enhancement scenarios were evaluated, and the results revealed the two performance measures to often be conflicting objectives.

As mentioned, there are two important policy issues with regard to design scenarios: project selection and project performance. Project performance is estimated based on the model outputs. Project selection is influenced by the relative rankings between different design scenarios, based on each individual project performance. Both of these criteria are dependent on assumed behavior of drivers, particularly of EV drivers, and on parameters such as the perceived distance constraint of EVs, the network travel demand, and the profile of vehicle classes in the network. This work highlights the need carefully consider each of these aspects and highlights the new effects created by the constrained routing of EVs in order to properly evaluate projects.

In regard to the modeling approach proposed here, results from the analysis reveal that design scenarios can impact network travel patterns in one of two ways. First, an improvement can lower the cost of a path such that it becomes more attractive to drivers, who then change routes, thereby causing nonlinear, unpredictable variations in system travel time. Secondly, a design scenario can lower the travel time on a particular path but not cause any route choice changes. In the second scenario, the impact on system travel time will change according to the travel cost function. In the case of this study, the marginal improvement of adding more projects decreased, but remained proportional between different design scenarios (i.e. implementing 5 projects vs. 4 projects will simply lower the travel time on the links). Because adding capacity to transport networks is expensive, it is important to identify the marginal returns of an additional project, and more importantly, the point at which adding capacity does not produce sufficient returns to warrant the expenditure. The impact of the design scenarios on network energy consumption is less clear, although results presented in the previous section suggest that E_{EV} is fundamentally conflicting with T.

Another interesting outcome of this study highlights equity issues which can arise in networks comprised of mixed vehicle classes. Based on the behavioral difference displayed by different user classes, it follows that user groups experience the impact of a given design scenario differently. Therefore, if planners do not model the individual vehicle classes explicitly, the variable impacts on each user group will likely go unaddressed.

In conclusion, this works highlights the following findings:

- EV energy consumption behaves in a different manner from the energy consumption of traditional ICEVs, and must be explicitly accounted for by network planners.
- Depending on driver perceptions (i.e. imposed distance constraints based on range anxiety) and charging infrastructure location, different design scenarios rankings may result.
- In a network comprised of both ICEVs and EVs, particular attention must be paid to the impact of design scenarios on individual user classes; examples presented here showed capacity additions can increase energy consumption for EVs, but significantly lower energy consumption (and therefore fuel costs) for ICEVs.

As EVs become more prominent, transport network planners will require new research tools that account for the impact of this novel technology. Future research will expand on this study to address integral issues such as demand and capacity uncertainty. In addition dynamic traffic assignment will be incorporated into the subproblem to provide a more accurate appraisal of energy consumption, particularly by accounting for the dynamics of vehicle flow and energy use. Lastly, forthcoming data on the expected penetration rates of EVs by region can be incorporated into the model to quantify the spatio-temporal energy demands generated for a realistic mix of EVs and ICEVs, an essential component for regional energy providers.

Disclosure statement

No potential conflict of interest was reported by the authors.

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