Multi-Objective Traffic Network Design Accounting for Plug-in Electric Vehicle Energy Consumption

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Abstract

In order to exploit the potential of plug-in electric vehicles (PEVs) as a sustainable form of transport, this novel technology must be integrated into the traditional transport system planning process. This work takes a step in that direction by incorporating PEV energy consumption rates into network design decisions. Not only is energy consumption a proxy for emissions in traditional vehicles, it will also become an essential issue for regional energy providers who will need to adapt to the additional electricity demand created as PEVs become a more ubiquitous form of transport. This work addresses the network design problem (NDP) to minimize both system level energy consumption and total system travel time, independently and as a multi-objective problem. The NDP is formulated and solved for a road network with a high penetration of PEVs using a heuristic approach. For certain design scenarios, minimizing total system travel time and minimizing energy consumption are demonstrated to be conflicting objectives. The tradeoff in terms of each system performance measure is quantified. Based on the results it is evident that both objectives must be considered when planning for future networks that will be comprised of some portion of PEVs.

1. INTRODUCTION

Electric vehicles are experiencing a surge in popularity due to advancements in technology, their potential to reduce harmful emissions originating from traditional petroleum-fuelled 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 PEVs introduce a closer tie between the road network and the electric power system that will require new collaborations and modeling tools to effectively exploit. Traditionally electric power systems operators have needed to predict energy demand that results from static sources (e.g., households, buildings, industries). However, when PEVs 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, PEV energy use, PEV market locations, and spatiotemporal charging behavior.

The transport problem of interest in this work is the well-known network design problem (NDP), which identifies the capacity enhancements for a network to achieve a stated objective. The traditional NDP objective is minimizing total system travel time (TSTT). In this work an additional objective is considered – minimizing total system energy consumption (TSEC) – where the energy is generated by PEV mobile activity in a network. Both single and multi-objective NDPs are evaluated. The sub-problem of the road network design problem is user equilibrium (UE) assignment. As part of the UE sub-problem the proposed model tracks the two classes of vehicles (PEVs and traditional internal combustion engine vehicles (ICEVs)) through the network in order to quantify their energy consumption. The energy consumption of vehicles is calculated using a speed-variable model that is established on real data from reputable sources in industry. Based on the UE vehicular trajectories and calculated energy consumption rates, this work implements a heuristic method, a genetic algorithm, to solve the various network design problems. The tradeoff between TSTT and TSEC is compared under different design objectives and different budget constraints.

Hence, the motivation for this work is twofold: to explore the effects of an additional performance measure (energy consumption by PEVs) 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 PEVs in their region (*1*), (*2*). 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 PEV technology, these forecasts are generally based on annual vehicle travel estimates and static energy consumption estimates, or estimated battery capacities. This work addresses the issue of additional demand, and provides a more accurate estimation by exploiting each driver's disaggregate travel patterns as revealed by the UE assignment model, computing the respective energy consumption, and aggregating across vehicles in the network. This type of analysis is integral for power systems tasked with predicting regional demands. In many situations, 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 in Section 2, while Section 3 introduces the mathematical model for the problem. Section 4 discusses the solution methodologies employed in this research, Section 5 presents the computational results, and Section 6 concludes this work with remarks about future directions for research.

2. LITERATURE REVIEW

This work focuses on the NDP with added element of tracking the energy consumption of vehicles through the network. Formulations and solution algorithms for the traditional traffic network design problem exist in many variations and applications; however, to the authors' knowledge this is the first work that examines the energy consumption of PEVs. Most generally, network design is conceptually simple: the problem of finding the optimal location(s) to enhance a network given limited "budget." Such enhancements are generally capacity improvements that can have a variety of interpretations, from the discrete additions (e.g., lanes, roads) to project that may have a more continuous nature (e.g., optimized signal timing plans, other projects like widening of shoulders, 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 (*3*).

Early work on the NDP concentrated on formulating the problem to approximate planning applications and developing efficient algorithms to solve these formulations. Leblanc pioneered the use of the branch and bound method to solve the single-objective discrete NDP (*4*). A convex, system-optimal formulation was introduced by Danzig et al and solved using a decomposition algorithm *(5)*. Chen and Alfa also attempted the discrete NDP, in which they minimized travel cost and combined trip assignment and distribution (*6*). Chen and Alfa proposed a discrete stochastic UE NDP using an incremental traffic assignment approach (*7*). Davis later solved this formulation using a heuristic algorithm (*8*). While a few works have been highlighted here, a more comprehensive evaluation can be found in (*9*) or (*2*).

Some of the more recent work in the field is concerned with more complex multi-objective formulations and applications. The multi-objective network design problem (MNDP) uses a weighted combination of different objectives. This is a more realistic approach to modeling a complex transport system, but it also results in a more difficult mathematical problem to solve. Friesz et al first proposed a multi-objective network design and solved it through a simulated annealing inspired heuristic *(10)*, which was extended by (*11*). Additionally, 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 (*12*), accounting for demand uncertainty (*13*), optimal toll pricing strategies (*14*), examining the impact of environmental justice considerations (*15*), and minimizing emissions (*16-17*).

While the authors are unaware of previous works attempting to combine the NDP and PEVs, researchers have begun to incorporate the impact of PEVs into other traditional transport models. Artmeier et al introduced a vehicle routing problem where PEVs can use regenerative braking to regain battery power and extend their range (*18*). Jiang et al also formulated a constrained shortest path problem, and apply it in a traffic assignment model that is solved using a Frank-Wolfe based algorithm (*19*). Most notably, (*20*) introduced a model that tracks vehicle energy consumption, similar to the one employed in the lower level problem in this work. However, the previous work is concerned with the impact of travel demand variability on PEV energy consumption, while this one uses a heuristic approach to solve the discrete NDP and examines the tradeoffs between minimizing for different objectives.

3. MATHEMATICAL MODEL

The formal mathematical formulation of the NDP, UE assignment model, and system performance measures are presented in this section. Consider a transportation network $G = (N, A, \mathbf{D}, \mathbf{W}, \mathbf{T})$ consisting of a set of nodes N; a set of directed arcs A; a demand matrix $\mathbf{D}$ with $|N|$ rows and columns, mapping the demand for travel from every node to every other node; the |*N*|x|*N*| matrix $\boldsymbol{W}$ representing the percentage of each origin-destination demand consisting of PEVs; and $\boldsymbol{T}$, a vector of link cost functions for all links in the network.

The multi-objective network design problem is formulated as a bi-level problem. The upper level seeks to minimize total system energy consumption, E, or total system travel time, Z, by adding the capacity on some number of links subjected to a total budgetary constraint. The lower level problem is the user equilibrium model with PEVs that will be further discussed in Section 4.2.Users react to the capacity changes that are implemented by the system operators in the "upper level", which lends itself to the bi-level formulation. The formulation for the upper level problem is shown below for the objective of energy minimization (the same formulation holds for the objective of minimizing TSTT, with E replaced by Z in the objective function):

$$Minimize\ \mathrm{E} \tag{1}$$

s.t.

$$E = \sum_{a \in A} [EC_{ICEV}(s_a) v_a^{ICEV} + EC_{PEV}(s_a) v_a^{PEV}] \tag{2}$$

$$\mathrm{Z} = \sum_{a} v_a t_a(v_a, \delta_a) \tag{3}$$

$$\sum_{\forall a} g_a(\delta_a) \leq B \tag{4}$$

$$\delta_a \geq 0 \qquad \forall a \in A \tag{5}$$

Where δ_a is the capacity added to link a, $g_a(\delta_a)$ is the function that represents the cost of adding that amount of capacity to link a, and B is the total budgetary constraint. The lower level problem outputs the ICEV and PEV link level flows, $v_a^{ICEV}$and v_a^{PEV} respectively, and link travel times t_a (and thus link average speed, s_a). Therefore Z represents the total system travel time, and E represents total system energy consumption, computed by summing the energy consumption for all vehicles on a link, for all links in the network, based on the speed-variable equation that will be presented in Table I.

The lower level problem represents the users' reaction to the network changes. The formulation of this model requires some additional notation: the demand matrix **D** represents the aggregate demand for both ICEVs and PEVs. Let R and S represent the set of all origins and destinations respectively, while $r \in R$ and $s \in S$ are indexes representing one particular origin and destination respectively and d_{rs} denotes the demand between origin $r \in R$ and destination $s \in S$. The percentage of each origin-destination demand realization that are PEVs is z_{rs}, ($0 \leq z_{rs} \leq 1$), which is specified a priori. Let $k \in K_{rs}$ represent the set of paths connecting origin $r \in R$ and destination $s \in S$, f_k^{rs} represent the total (ICEV and PEV) flow on path k connecting origin r and destination s, and δ_{ak}^{rs} be the link path incidence variable. The mathematical programming formulation for the lower level problem is then (based on (*21*)):

$$Minimize \sum_{\forall a} \int_0^{v_a} t_a(y) dy \tag{6}$$

s.t.

$$\sum_k f_k^{rs} = z_{rs} d_{rs} + (1 - z_{rs}) d_{rs} \qquad \forall r \in R, \forall s \in S \tag{7}$$

$$f_k^{rs}, v_a \geq 0 \qquad \forall k \in K_{rs}, \forall r \in R, \forall s \in S \tag{8}$$

$$v_a = \sum_r \sum_s \sum_k f_k^{rs} \delta_{ak}^{rs} \qquad \forall a \in A \qquad (9)$$

$$v_a^{ICEV} + v_a^{PEV} = v_a \qquad \forall a \in A \qquad (10)$$

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 (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, and was used in this work:

$$t = t_0 \left(1 + \alpha \left(\frac{v}{C + \delta}\right)^{\beta}\right) \qquad (11)$$

Where t is link travel time, t_0 is free-flow travel time (miles per hour), v is hourly volume (vehicles), C is hourly capacity (vehicles per hour (vph)), and α and β are parameters that depend on link geometry. The UE problem in the lower level was solved used a Frank-Wolfe based linearization method. The next section describes the genetic algorithm that was used to solve the upper level design problem.

4. SOLUTION METHODOLOGY

The following section describes the solution methodology implemented for the above problem. Three main components of the methodology are described: the upper level network design problem, the lower level user equilibrium assignment problem, and the energy consumption model used to compute TSEC.

4.1 Network Design Problem

The network design problem as formulated in the above section cannot be solved to a guaranteed global optimal value using known optimization techniques because of the non-convex cost function. Therefore heuristic solution methods are necessary. This research applied a genetic algorithm (GA), a technique inspired by principles of natural evolution. GAs provide a flexible, rigorous, scalable framework to solve challenging optimization problems, and are a relatively common research method to solve the bi-level traffic network design problem. Additionally, (*22*) showed that in terms of heuristic approaches to solve the continuous NDP, GAs perform better than simulated annealing or random search algorithms. Because GAs are a heuristic method, they correctly identify local extrema that are not guaranteed to be the global optimal value.

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, and over time, the population evolves according to a “natural selection” process, where the best individuals are identified and combined using a crossover technique to form new populations of individuals. A basic genetic algorithm is outlined below:

1. Begin by randomly generating a population of *n* chromosomes;
2. Evaluate the fitness *f(x)* of each chromosome *x* in the population;
3. Create a new population by iterating the following steps until the new population is filled:
    a. Select two parent chromosomes (with fitter individuals having a higher likelihood of being chosen)
    b. Using a crossover probability, form a new offspring from the two parents; without crossover, child will be exact copy of a parent.
    c. Mutate new offspring using a mutation probability;

   d. Accept and place offspring into new generation of population.
4. Check to see if convergence criteria is met; if yes, stop. Else, return to Step 2 using the new generation.

Both single- and multi-objective variations of the nondominant sorting genetic algorithm II (NSGA-II) by (*23*) were used in this work. NSGA-II is a well-known algorithm that has proven to be the best GA tool for solving multi-objective optimization problems (*23*). This algorithm utilizes several techniques that provide superior performance. The feasibility of solutions is handled by penalizing infeasible individuals in such a way that ensures that feasible solutions are ranked higher than infeasible solutions, which are ranked higher than infeasible solutions with greater constraint violations. Additionally, solutions are labeled according to their efficiency front and the density of surrounding solutions, which makes the selection process more efficient and preserves the diversity of solutions within a population (*23*). See ((*12*)-(*17*)) for other examples that utilize NSGA II for various applications of the traffic network design problem.

In this application of a GA, discrete variables were used to represent the additional capacity on a link, represented in binary form, with one bit allocated to each link such that a '1' identified the link for improvement and a '0' meant the link would stay the same. Thus an individual chromosome represented the capacity changes for all links in the network, and a population carried the different possibilities for discretely adding capacity to some number of links. During the crossover operation, two new capacities are generated for a link by combining the first part of the binary capacity representation from one "parent" with the second part of the binary capacity representation of the other "parent". An important factor in the performance of the NSGA II (and all GAs) are the input parameters, which are case specific to any problem. As such, input settings were determined using sensitivity analysis and are further discussed for each of the test cases in section 5.

4.2 Traffic Assignment Model

The design problem presented here uses the traffic assignment formulation based on the well-known Wardropian equilibrium for the lower level problem to represent traveler behavior (*24*). In this formulation, users will choose a path to minimize their own travel; collectively, resulting in a state of network equilibrium, where no user can independently change paths for a shorter travel time. This model is straightforward, flexible, and appropriate for this application, which employs a heuristic solution method based on iteration in which the UE model must be computed many times. However, this model is static so it does not capture the effects of acceleration or gradient (which could be important for PEVs in a regenerative braking scenario).

The UE model distinguishes between two "classes" of vehicles, PEV and internal combustion engine vehicles (ICEVs). The model assumes that these two vehicles types do not differ in terms of user behavior; thus, all drivers will make decisions based on minimizing their travel time, not accounting for potential charging incentives at the destination or range anxiety, either of which might change route choice decisions from a PEV driver. Additionally, the model assumes there are no charging opportunities available from public infrastructure, therefore all vehicles charge at home and begin each trip with a fully charged battery. PEVs and ICEVs differ based on the former's limited all-electric range. This model only applies to the energy consumption of all-electric vehicles, although with a different energy consumption model, plug-in hybrid electric vehicles could also be represented. The next section discusses how the traffic assignment model is combined with an energy consumption model to find the total energy use of PEVs in the traffic network.

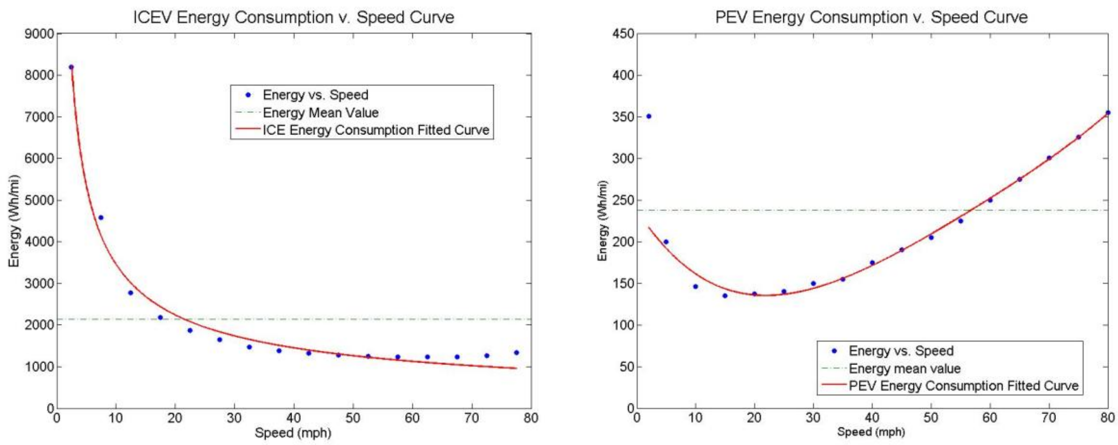
4.3 Energy Consumption Evaluation

The energy consumption of PEVs is a particularly important issue for regional electricity providers, who will need to know about the electricity demand created by the use of PEVs. In particular, electric power systems managers will be interested in knowing where and when PEVs will plug in, how much electricity they will need, 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 PEVs. A traffic assignment model is exploited to answer this question by providing individual user travel patterns and average speeds, from which energy consumption can be closely approximated.

However, vehicle energy consumption rates are difficult to quantify, even for ICEVs which have a longer history in both practice and research. 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 of the vehicles (which are not always a representative of real-world driving, see (*25*), and the software itself can be prohibitively expensive.

Few empirical results exist for the energy consumption of PEVs (*26*), although this dataset is expanding rapidly. A great deal of research has focused on the long-term impact of the energy consumption of PEVs (*27*), but 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 use of vehicle energy consumption. Future versions of this model will account for more complex factors such as the impact of congestion and gradient effects like acceleration and braking.

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 (*28*). This software finds energy consumption and emissions production from vehicles based on a variety of factors including meteorology, vehicle fleet composition (vehicle miles travelled (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 1a show the energy consumption for an average ICEV depending on speed obtained (in during 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.



(a) (b)

FIGURE 1 (a) the energy consumption model for ICEVs based on MOVES2010a and (b) the energy consumption model for PEVs based on data from Tesla.

Based on the powertrain configuration, PEVs consume energy in a different manner from ICEVs. At lower speeds (like what might result from congestion effects), PEVs actually consume relatively *less* energy than their ICEV counterparts. The energy consumption model used in this project was based on the data obtained from (*29*) describing the energy use of a Tesla electric vehicle in terms of ancillary, tires, aerodynamics, and drivetrain. Figure 1b shows the approximated points and the polynomial regression curve fitted to the data using Matlab. The two functions used for energy consumption for ICEVs and PEVs respectively are shown in Table I. The average speed on each link is then multiplied by the length of the link to calculate the energy consumption of the vehicle on that individual link. The total energy consumption is found by aggregating over all vehicles and links in the network. Also in Table I are the adjusted R squared values for both regression models. Values near one indicate that these curves are a reasonably good fit to the data.

TABLE 1 Energy consumption functions for ICEVs and PEVs

Energy Consumption (TEC) [kWh/mi]	Adjusted R^2 Value
$EC_{ICEV}(s) = 14.58s^{-0.6253}$	0.9846
$EC_{PEV}(s) = 1.79\text{e-}8s^4 - 4.073\text{e-}6s^3 + 3.654\text{e-}4s^2 - 0.0109s + 0.2372$	0.9651

While the curves in Figure 1 capture the fundamental differences between vehicle technologies, the scale between the two models is significantly different; this data implies that PEVs are about ten times more efficient than ICEVs, which is not accurate. However, for the purposes of this work, it is the difference between the behavior of these two curves that is important. Additionally, these models compare an "average" ICEV with a highly efficient PEV. 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 PEVs will likely decrease, particularly in the long-term future period this work is interested in. However, the different efficiency curves will remain a vital factor.

5. COMPUTATIONAL RESULTS

This section presents the computational results to the NDP model defined in Section 3. Numerical analysis is provided for the Nguyen–Dupius network. This analysis considers two objective functions, minimizing TSEC and minimizing TSTT. Results are presented for each, and the tradeoff between energy consumption and travel time in regards to network design decisions are discussed. In order to isolate the impact of PEV energy consumption, the computation assumed 100% PEV presence$\{z_{rs} = 1.0 \quad \forall r \in R, \forall s \in S\}$, unless explicitly stated otherwise.

5.1 Nguyen-Dupius Network

The Nguyen-Dupius network (Figure 2) is a small 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 and 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 have an initial capacity of 2,200 vehicles per hour (vph) except links 3, 4, 6, and 7 which have a capacity of 1,800, all links have a free flow speed of 50 mph, and BPR design parameters, α and β, of 0.15 and 4, respectively.

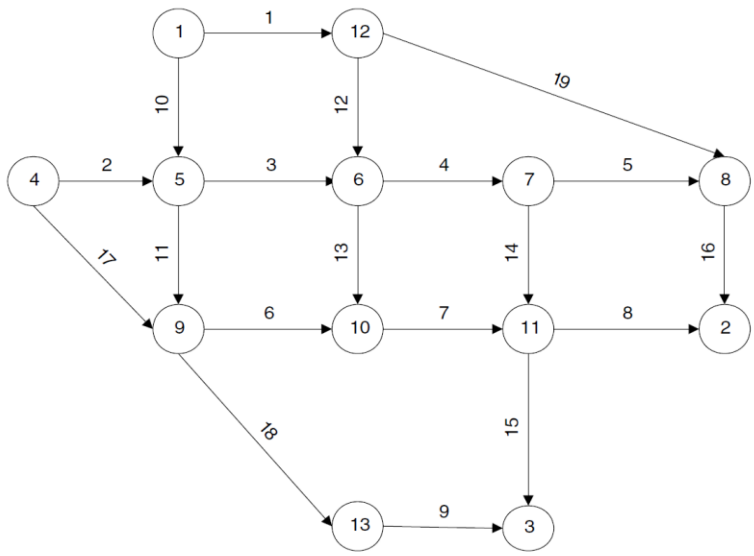


FIGURE 2 The Nguyen-Dupius test network

The problem is defined as follows: the network planner desires to improve network performance (i.e., TSEC, TSTT, both) by increasing the capacity on individual links. Different design scenarios were explored, defined by the number of links that could be improved, and the amount of capacity to be added. Combinations evaluated include capacity enhancements of 500, 1000, 1500 and 2000 vph, for either 2, 3, 4 or 5 links, for a total of 16 scenarios. The NDP, that is identifying the optimal links to improve, for each of these scenarios was solved using the GA to minimize either TSTT or TSEC for a total of 32 different cases. A large population size of 100, crossover probability of 0.9, and mutation probability of 0.01 were utilized as the GA inputs. Note that the GA was run for a large number of generations (about 500) to allow the GA time to "evolve" to the best solution.

For each case the performance measure is the percentage improvement in TSEC or TSTT (dependent on the specified objective) relative to the base case. This is equal to the percentage decrease in travel time or energy consumption after adding capacity . The base case is defined as the network performance prior to any link improvements.

Table 2 illustrates the results of each experiment for the Nguyen–Dupius network. The number of allowed link improvements is listed on the far left. For each evaluated number of link improvements the specified objective function, capacity allotment per link, performance measure, and set of links identified for expansion for the given scenario are provided from left to right along a row. The total capacity added to the network in each case is the capacity enhancement per link times the number of link improvements allowed. For a given scenario the set of links identified for expansion are highlighted with an ‘X’ in the column. Note that links 2, 3, 13, 18, and 19 were not identified as optimal locations for improvement in any scenario and therefore are included in the table. The presentation style provides a means to compare results by objective and scenario relatively easily. As illustrated, the results reinforce the complex behavior of the NDP, as well as the expected sensitivity to the specified objective function.

TABLE 2 Results for discrete design scenario selection on Nguyen-Dupius network

		Capacity Enhancement per lane	% Performance Measure Improvement	Link Number													
				1	4	5	6	7	8	9	10	11	12	14	15	16	17
2 Links Improved	TSTT	500	3.6%	X								X					
		1000	9.4%										X	X			
		1500	12.0%										X	X			
		2000	13.5%										X	X			
	TSEC	500	4.2%					X						X			
		1000	3.5%					X					X				
		1500	3.0%			X		X									
		2000	2.7%			X		X									
3 Links Improved	TSTT	500	7.6%									X	X	X			
		1000	12.3%										X	X		X	
		1500	15.3%										X	X		X	
		2000	18.2%	X									X	X			
	TSEC	500	5.3%			X		X						X			
		1000	5.2%	X		X		X									
		1500	4.7%	X		X		X									
		2000	3.7%	X				X					X				
4 Links Improved	TSTT	500	9.7%									X	X	X		X	
		1000	12.6%				X						X	X		X	
		1500	18.2%	X									X	X		X	
		2000	21.7%	X									X	X		X	
	TSEC	500	7.0%	X		X		X						X			
		1000	8.1%	X		X		X					X				
		1500	5.2%	X		X		X					X				
		2000	3.7%	X				X			X		X				
5 Links Improved	TSTT	500	10.2%					X				X	X	X		X	
		1000	15.3%					X				X	X	X		X	
		1500	19.9%	X				X					X	X		X	
		2000	23.4%	X	X								X	X		X	
	TSEC	500	8.5%	X		X		X		X				X			
		1000	8.1%	X		X		X					X		X		
		1500	5.2%	X		X		X					X				X
		2000	3.7%	X				X	X		X		X				

For discussion purposes, focus will be on the two performance measures of interest in this research, TSTT and TSEC. When fewer, smaller total improvements were desired (which in some cases may be the more economical option), the two objectives almost always chose different links to improve. This indicates that TSTT and TSEC do not have a positive correlation, i.e., minimizing one objective will not necessarily result in improved network performance for the opposing objective. This implication is further analyzed, and the conflicting behavior is confirmed in Figure 3.

Figure 3 displays the same results that were included in Table 2, with the addition of the corresponding change in the opposite performance measure, where each point is one of the design scenarios presented in Table 2. Figure (3a) shows the results from the design scenarios based on minimizing TSEC and Figure (3b) shows the results for scenarios based on minimizing TSTT. In a number of potential improvement scenarios, the performance measure that was not considered in the optimization problem actually demonstrates *poorer* performance than in the base case. This behavior is more prevalent when the objective of the

NDP is to minimize TSTT, especially in the scenarios that added a greater amount of capacity. It is therefore likely the selected set of link improvements that minimize TSTT will actually result in an increase in TSEC. This outcome can be explained by the energy consumption curves provided in Figure 1. In terms of energy consumption, PEVs are more efficient at lower speeds than ICEVs. Under this assumption a congested network, which results in slower speeds on average, will actually result in lower energy consumption than an uncongested network with a high penetration of PEVs. Because capacity expansion projects often reduce congestion on a link, therefore reducing travel times, the solution which minimizes TSTT can be expected to potentially increase TSEC. In addition, because of the different functional form of PEVs as compared to traditional ICEVs, this conflicting behaviour may not appear in networks comprised totally of traditional vehicles. However the observed the negative correlation does not always hold true when the NDP objective is to minimize TSEC. Under the TSEC objective, multiple scenarios resulted in an optimal solution that improved both TSTT and TSEC, although the TSTT performance measure improvement was significantly less than when TSTT was directly minimized.

When the objective was to minimize TSEC, multiple scenarios resulted in the same performance measure, even though additional capacity was added. For example, when 2000 vph were added to 3, 4, or 5 links, 3.7% improvement in TSEC resulted in each case. The same behavior was observed for an additional capacity of 1000 vph to either 4 or 5 links, which actually resulted in a 8.1% improvement in TSEC. This is because after adding three links to the network, improving another link will result in a suboptimal solution, and so the GA arbitrarily chose a link that did not impact the final system performance. This indicates that performing additional projects will not necessarily be beneficial for TSEC, whereas additional projects always provide an improvement in TSTT. Moreover, these results highlight another contribution of this work, a means for quantitatively evaluating and ranking potential design projects. Such a ranking will help identify the most cost effective options for achieving a given objective.

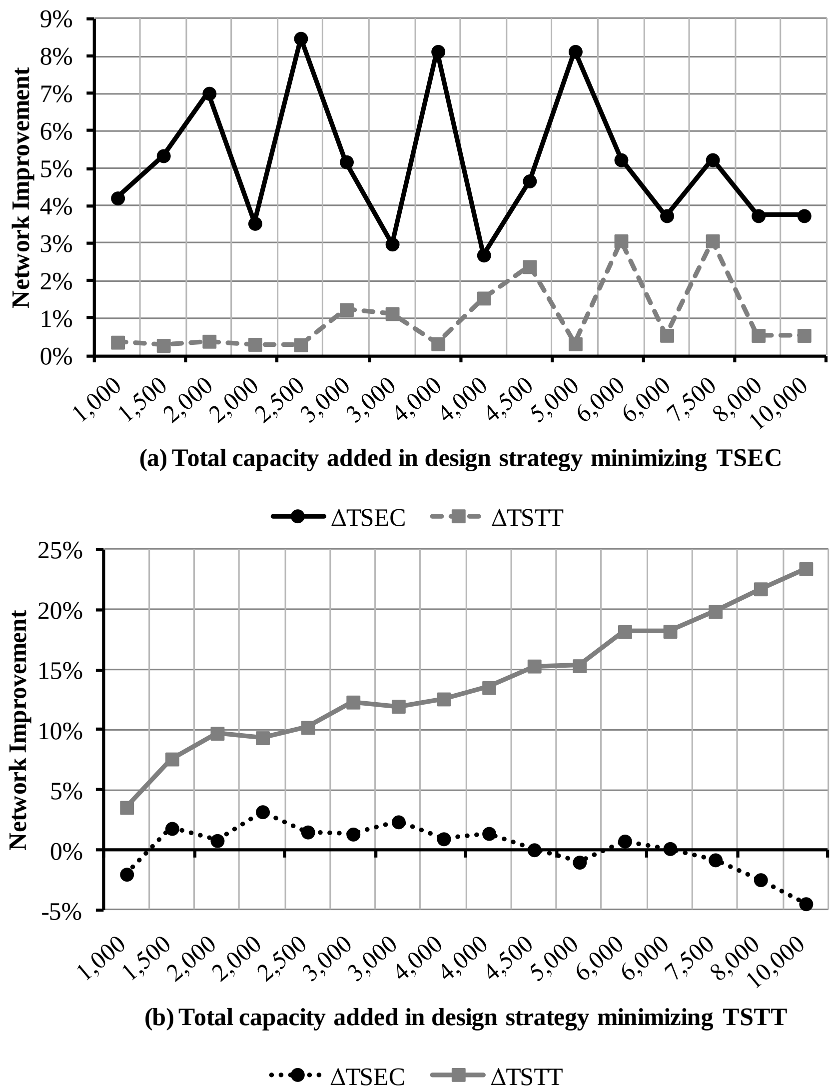


FIGURE 3 (a) Performance measures for design scenarios minimizing TSEC and (b) performance measures for design scenarios minimizing TSTT

Furthermore, this work employs a modified multi-objective version of the NSGA II to explore potential tradeoffs between TSTT and TSEC. One of the benefits of a multi-objective GA is its ability to find many Pareto-optimal solutions in a single run, and this diversity of solutions confirmed the findings from computations using a single-objective. Alternative options for two cases can be seen in Figure 3(b), adding 1,500 to 4 links or 2,000 to 4 links, and these results are presented in Table 3. When minimizing solely the objective of TSTT, these cases resulted in poor network performance or even an overall increase for TSEC. When these scenarios were optimized considering both TSEC and TSTT, the GA identified multiple options that improved TSEC as well as TSTT. However, there is a clear trade-off between the behavior of the two opposing objectives. Table 3 displays two options for each scenario, one option favoring TSTT and one option favoring TSEC. These results support the conclusion that one objective does not need to be optimized at the expense of another. Solutions that are beneficial for TSEC and TSTT exist.

TABLE 3 Results for multi-objective design scenarios

# Links Improved	Capacity added per link	ΔTSTT	ΔTSEC
4	1500	5.7%	4.0%
4	1500	14.8%	3.1%
4	2000	13.6%	1.5%
4	2000	5.1%	2.9%

Finally, design solutions were tested on a network made up of varying levels of PEVs. For a network comprised of 100% ICEVs, it was observed that TSTT and TSEC behave in a similar manner. Minimizing one objective will also result in favorable performance from the other, and when a multi-objective GA is implemented, there are cases that find the same solution as the single-objective variation. This behavior is predictable based on the similarity between the functional form of the ICEV energy consumption curve (Figure 1.a) and the BPR cost function. These findings highlight the fundamental differences between a traditional network comprised of ICEVs and a network of the future that could potentially contain a significant proportion of PEVs.

6. CONCLUSION

In this work the network design problem (NDP) is implemented to minimize both TSEC and TSTT, independently and as a multi-objective. The problem was modeled using a bi-level formulation where the upper level was solved using a genetic algorithm and the lower level was a multiclass user equilibrium traffic assignment model. Vehicle energy consumption was computed based on industry data for PEVs and ICEVs. A number of discrete design scenarios were examined, and the results revealed the two performance measures to often be conflicting objectives.

Specifically, when the NDP objective was to minimize only TSTT (the traditional planning objective), the solution often resulted in an increased TSEC relative to the base case. Similarly, when the objective was to minimize only TSEC multiple solutions resulted in an increased TSTT, however there were also solutions which improved both performance measures, especially for higher capacity scenarios. These results motivated the need for considering a multi-objective NDP, which was implemented and identified solutions that improved both TSEC and TSTT. In particular, this works highlights the following findings:

- If multiple objectives are not explicitly considered, it is possible that a design decision intended to improve the network performance of one objective (i.e., TSTT) will do so at the expense of another (i.e., TSEC).
- Design strategies that result in a superior performance for both TSEC and TSTT exist. A multi-objective NDP identifies these potential options.
- PEV energy consumption behaves in a fundamentally different manner from the energy consumption of traditional vehicles and must be explicitly accounted for by network planners.

As PEVs become more prominent, transport network planners will require new research tools that account for the impact of this novel technology. Planned future research will address demand and capacity uncertainty, as well as incorporating dynamic traffic assignment into the sub-problem. These extensions will provide a more accurate appraisal of energy consumption, particularly by accounting for the dynamics of vehicle flow and energy use. Additionally, forthcoming data on the expected penetration rates of PEVs by region can be incorporated into the model to quantify the spatiotemporal energy demands generated for a realistic mix of PEVs and ICEVs, an essential component for regional energy providers.

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