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Comparing Delay Minimization and Emissions Minimization in the Network Design Problem

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Abstract: *Traditionally, transportation road networks are designed for minimal congestion. Unfortunately, such approaches do not guarantee minimal vehicle emissions. To fill this apparent gap in network design research, an emissions network design problem and solution method is proposed in this article for the purposes of comparing to the traditional network design results. Three air pollutants are considered on two road networks. The model is formulated as a bi-level optimization problem and a solution is approximated using a genetic algorithm. The influence of demand uncertainty is also incorporated into the model. Designing for minimal congestion tends to increase emissions of criteria air pollutants. However, not adding capacity to a road network also increases emissions of pollutants. Therefore, an optimization problem and solution method, such as the emissions network design problem and solution method presented here, is useful for identifying capacity additions that reduce vehicle emissions. It is also useful for understanding the tradeoffs between designing a network for minimal congestion versus minimal vehicle emissions.*

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1 INTRODUCTION

The purpose of this research is to develop a methodology for incorporating emissions into road network design. The objectives of this article are as follows: (1) demonstrate the need to incorporate air quality considerations into network design problems; (2) present and apply a method for incorporating vehicle emissions into network design problems; and (3) present results from exploring the differences and similarities between designing a network for minimal congestion (i.e., total travel time) versus minimal total vehicle emissions, while considering uncertain travel demand. The following paragraphs motivate the consideration of air quality in the network design process.

The Environmental Protection Agency (EPA) is the federal government entity responsible for recommending air quality standards to lawmakers and enforcing the resulting National Ambient Air Quality Standards (NAAQS) set by Congress under the Clean Air Act. The NAAQS comprises primary and secondary ambient air concentration limits for six pollutants; these pollutants are: (1) carbon monoxide (CO); (2) nitrogen dioxide (a compound within the nitrogen oxides family); (3) ground-level ozone; (4) particulate matter; (5) lead (an air toxin); and (6) sulfur dioxide (primary sources are power plants and other industrial facilities) (EPA, 2009). Primary standards (i.e., limits) are set to protect public health and secondary standards are set to protect public welfare including crops, vegetation, and animals (EPA, 2009). Metropolitan areas are required to comply with the standards for the six criteria pollutants. If they do not comply with the standards, regions fall into non-attainment for whichever pollutant whose limit was exceeded.

Consequences of non-attainment can be burdensome to the metropolitan planning organizations (MPOs), public transportation agencies, private developers, prospective employers, and residents in the non-attainment region. Falling into non-attainment results in: (1) a loss of federal highway and transit funding; (2) mandatory boutique fuels (i.e., cleaner burning, more expensive fuels); (3) restrictive permitting requirements; (4) mandatory emissions offsetting; and (5) loss of economic development opportunities (USCC, 2009). One of the more significant consequences for transportation agencies in non-attainment regions is the additional analysis and project screening work they must do to remain eligible for federal funds. To be eligible for federal funds, transportation agencies in non-attainment regions must be able to demonstrate that a proposed project will not increase emissions (USCC, 2009). As a result, regions at-risk for non-attainment or those already in non-attainment need planning tools and information to help them identify infrastructure improvements that do not increase system emissions relative to a do-nothing or no-build scenario.

We propose a methodology for incorporating emissions considerations into planning for road network improvements. The proposed formulation is a bi-level optimization problem where the upper level minimizes system emissions of a specific pollutant and the lower level enforces user-equilibrium (UE) route choice. The resulting problem solutions are a set of capacity improvements to a given network, for a given demand, subject to user-specified budget constraints and resulting in minimal network emissions. The problem is solved using a genetic algorithm (GA). We consider three key pollutants: CO, hydrocarbons also known as volatile organic compounds (VOC), and nitrogen oxides (NOx). These three pollutants were chosen because of their respective and combined significant impacts on human health and the environment. Furthermore, CO, VOC, and NOx in the presence of sunlight react to form detrimental air toxins and greenhouse gases.

The methodology presented in this article is applied to two different road networks in the United States: one relatively small network, Sioux Falls, ND, and the other of moderate size, Anaheim, CA. We also investigate the influence of demand uncertainty on the type of improvements identified to obtain minimal road network emissions. The proposed methodology and application fill a current gap in research related to network design problems. Based on our literature review, there is minimal to no research investigating: (1) how capacity additions to a network, made to minimize congestion, influence system emissions; and (2) how striving to minimize system emissions influences which capacity additions are made to a road network. Traditionally, road network design problems have focused on minimizing system travel time (or travel cost) rather than system emissions.

The rest of the article is outlined as follows. Section 2 discusses traditional road network design problems and how emissions have been integrated into those as well as other related network optimization problems (e.g., traffic assignment), the consideration of demand uncertainty in road network design problems, and background on the emissions model. Section 3 presents the model formulation. Section 4 presents the GA-based solution method. Section 5 outlines the experimental analysis on two test networks and Section 6 presents the corresponding results. The article concludes with a discussion of key contributions in Section 7.

2 BACKGROUND

2.1 Literature review

Traditionally, network design problems have focused on finding the optimal set of network improvements to minimize total system travel time or cost either through adding new links (discrete network design problems) or by increasing capacity on existing links (continuous network design problems) (see LeBlanc, 1975; Poorzahedy and Turnquist, 1982; LeBlanc and Boyce, 1986; Friesz et al., 1992; Suh and Kim, 1992; Solanki et al., 1998; Cho and Lo, 1999). Network design related research in the 1960s through the 1990s tended to explore ways to formulate network design problems to reasonably approximate practical planning applications as well as develop more efficient solution algorithms (see Magnanti and Wong, 1984; Yang and Bell, 1998). In the late 1990s and 2000s, researchers increased the complexity and robustness of network design problems by formulating them as multi-criteria and multimodal problems (see Cantarella and Vitetta, 2006; Kim and Kim, 2006). However, throughout this evolution, the primary focus of most network design problems has remained minimizing total system travel time (or cost) without a thorough understanding of what this means to total system emissions.

Consideration for emissions has been integrated into research regarding network topology and performance in the form of alternatives analyses, before and after empirical studies, and traffic signal timing considerations (see Lozano et al., 2008; O'Donoghue et al., 2007; Unal et al., 2003; Li et al., 2004; Yunpeng et al., 2008; Spall and Chin, 1997). In the specific context of network design, there have been some formulations focused on setting traffic signal timing along corridors to minimize emissions (see Medina et al., 2007; Stevanovic et al., 2009; Sharma and Mathew, 2007). Also, in some instances, the multi-criteria network design formulations create opportunities to incorporate emissions into a larger societal cost function (see Cantarella and Vitetta, 2006; Kim and Kim, 2006). However, these formulations contain limitations in how they consider and calculate pollutant emissions. Examples of limitations in previous research include fixed pollutant emissions that do not vary with vehicle speed or vehicle type, restricting consideration to a single pollutant without considering the tradeoffs, and/or characterizing environmental impacts via an ill-defined monetary cost. Furthermore, the structure of the multi-criteria formulations makes the models difficult to transfer to practical applications and challenging to infer informative trends related to emissions and system performance. For example, it is not clear how results from the multi-criteria objective problem differ compared to minimizing only total system travel time (i.e., congestion) or only system emissions or another attribute of societal cost.

System emissions have been more thoroughly explored in traffic assignment and network pricing literature in contrast to the network design literature. Results from the traffic assignment and network pricing literature generally indicate routing vehicles to minimize emissions on the network (either through information dissemination or through pricing) tends to result in different link flows, higher total system travel time, higher individual travel time, and lower system emissions than when vehicles are routed to minimize individual travel time or total system travel time (see Johansson, 1997; Benedek and Rilett, 1998; Yin and Lawphongpanich, 2006; Sugwara and Niemier, 2002; Ahn and Rakha, 2008). Pertinent research incorporating emissions into traffic assignment and network pricing problems is discussed below.

Earlier research incorporating emissions into the traffic assignment problem includes work by Tzeng and Chen (1993), Rilett and Benedek (1994), and Benedek and Rilett (1998). These works tend to focus on developing a base methodology for incorporating emissions by considering a single pollutant. Tzeng and Chen (1993) created a multiobjective traffic assignment method in which they incorporated CO emissions through a fixed emission factor. Rilett and Benedek (1994) and Benedek and Rilett (1998) developed a formulation considering equitable traffic assignment with environmental cost functions. Initial findings indicated the objectives of minimizing total system travel time and system emissions via traffic assignment are conflicting (Rilett and Benedek, 1994). Subsequently, Benedek and Rilett (1998) found routing vehicles to minimize CO emissions under congested conditions resulted in an approximately 7% emissions reduction compared to UE and system optimal (SO) assignment. Benedek and Rilett (1998) noted the potential benefit could increase for networks with more route choices and networks not at or near saturation.

In more recent research, Sugawara and Niemeier (2002) formulated an emissions optimized (EO) assignment to route vehicles to minimize system CO emissions. They compared system travel time and emissions performance to system emissions experienced under UE and SO assignments. Sugawara and Niemeier (2002) found the EO assignment effectively reduced emissions but increased system travel time 3.3% to 5% compared to UE and SO assignments. They also found route assignment varied depending on the level of congestion in the network. At lower levels of congestion, EO assignment results in vehicles assigned to only surface streets rather than freeways and results in 23.9% to 26.0% reduction in CO emissions compared to UE and SO assignment (Sugawara and Niemeier, 2002). As congestion increased, EO assignment still favored surface streets but inevitably became more similar to UE and SO assignments as route choices decreased; however, even under more congested conditions, EO assignment still provided 7% reduction in CO emissions compared to UE and SO assignment (Sugawara and Niemeier, 2002). These findings support the results discovered by Benedek and Rilett (1998). Sugawara and Niemeier (2002) results are also consistent with those found by Yin and Lawphongpanich (2006) in their research on network pricing to reduce emissions as well as research by Ahn and Rakha (2008).

While little research has examined the impact of considering uncertainty in the road network design problem, this is not the first. Duthie et al. (2010) assigned probability distributions to baseline employment and household regional control totals, and pairs of road improvements to find the one that worked best in terms of future traffic on average. Lam and Tam (1998) used Monte Carlo simulation methods to study the impact of uncertainty in traffic and revenue forecasts for road investment projects. They assumed normal distributions for each of several uncertain parameters, including population and demand elasticity. Waller et al. (2001) assigned independent distributions for each origin–destination pair's future year demand in three test networks (ranging from 2 to 100 origin–destination pairs) and demonstrated how assignment models relying on expected values of all inputs will tend to underestimate future congestion and may (in 14% of cases studied) lead to selecting projects with higher average future travel costs (i.e., lower net benefits) than ideal, and higher variance in such costs (which implies more risk). Ukkusuri et al. (2007) also treat the origin–destination trip matrix as uncertain in a formulation that aims to find the best overall network design, in terms of minimizing a weighted sum of average and standard deviation of total system travel time. As in this article, a GA is used as the solution method. GAs have proven successful in many other transportation applications including forecasting accident duration times (Lee and Wei, 2010), traffic flow forecasting (Vlahogianni et al., 2007), highway alignment optimization (Kang et al., 2009), traffic signal optimization (Teklu et al., 2007), traffic management (Karoonsoontawong and Lin, 2011), highway network optimization (Karoonsoontawong and Waller, 2006), bus network optimization (Yang et al., 2007), and infrastructure maintenance (Ng et al., 2009). GAs have also been used successfully in the broader area of civil engineering for many applications including structural optimization and control (Adeli and Cheng, 1994a, b; Adeli and Kumar, 1995; Sarma and Adeli, 2000, 2001; Mathakari et al., 2007; Jiang and Adeli, 2008; Marano et al., 2011), cost optimization (Kim and Adeli, 2001), and staffing allocation (Al-Bazi and Dawood, 2010).

Findings from this literature review on traffic assignment and network pricing problems incorporating emissions indicate a consistent trend in results even with the varying levels of sophistication in modeling emissions. The more sophisticated emissions models (e.g., research considering multiple pollutants, allowing emission rates to vary with vehicle speed) provide more valuable and potentially useful information for policy and decision making. However, the general results of the traffic assignment and pricing research consistently indicate operating a network to minimize total system travel time or individual user travel time does not guarantee minimal system emissions. This is a key reason for incorporating emissions into network design problems; it seems plausible that designing a network to minimize total system travel time (i.e., congestion) does not guarantee minimal system emissions (i.e., minimal vehicle air pollution). Section 3 describes a formulation to test this hypothesis.

2.2 Emission factors

Each pollutant considered in this research has its own unique stepwise function that was created from emission factors developed using the EPA's software program MOBILE6.2. This software program estimates emission factors as grams per mile per vehicle for fuel and diesel highway vehicles. MOBILE6.2 has been used widely in practice and research for such things as EPA's evaluation of mobile emissions source control strategies and state, local, and MPO-level planning to control or reduce vehicle emissions for a region (EPA, 2003). The program has the ability to calculate emissions rates for 28 different types of vehicles that span the calendar year from 1952 forward to 2050. MOBILE6.2 calculates emission factors for the following air pollutants: VOCs, CO, NOx, particulate matter, sulfur dioxide, ammonia, six hazardous air toxins, and carbon dioxide.

To calculate emission factors, MOBILE6.2 works from a basic emission rate and applies correction factors determined by analysts' inputs regarding vehicle operating conditions. The basic emission rates and the correction factors are based on the research conducted by the EPA (see the technical articles posted at http://www.epa.gov/otaq/models.htm for the specific calculation procedures embedded within MOBILE6.2). Basic emission rates are developed from emission tests conducted under a standard set of conditions with regard to temperature, fuel, driving cycle, and other related operating conditions. Correction factors are applied when conditions differ from the standard set under which the basic emission rates were developed.

There are 27 different input parameters for which analysts are responsible for providing data or values (in the absence of data, default values are used; default values are based on EPA's national data). The input parameters address context-specific characteristics (e.g., calendar year, month, minimum and maximum temperature, altitude), vehicle or vehicle fleet related characteristics (e.g., fuel type, vehicle type, vehicle inspection/maintenance programs), and operating characteristics (e.g., average vehicle speed, road facility type). Adjustments to the basic emission factors are made depending on which (if any) of the characteristics vary from the standard testing conditions. For the research presented in this article, the most significant of these characteristics are average vehicle speed, facility type, temperature, and humidity. For more in-depth information on MOBILE6.2's structure and how to use it, please refer to the EPA's *User's Guide to MOBILE6.1 and MOBILE6.2* (see EPA, 2003).

From the date of the completion of the analysis mentioned in this article, the EPA has released an update to MOBILE6.2 called MOVES2010 (Motor Vehicle Emission Simulator 2010) (EPA, 2010). The most substantial differences between MOBILE6.2 and MOVES2010 do not influence the methodology presented in this article, nor do they influence the results and trends discussed in the following sections. The most significant gain made with the MOVES2010 software in modeling emissions (as compared to MOBILE6.2) is the ability to use acceleration and deceleration data to calculate emissions more precisely (as opposed to using average vehicle speed) (EPA, 2009). However, the research presented here is at the macroscopic model level, therefore the most refined speed data available are average speed, so MOBILE6.2 remains an appropriate emissions modeling tool. The ability of MOVES2010 to model the effects of acceleration and deceleration on emissions will be beneficial for future planned research expanding the emissions network design problem discussed in this article to a dynamic context.

3 FORMULATION

In this research, the traditional network design problem (i.e., minimizing total system travel time) is solved alongside of the emissions network design problem. Therefore, each is applied to the same test networks, under the same conditions, and solved simultaneously using the same solution method. More specifically, the bi-level problem is solved simultaneously for four upper-level objectives: minimizing total system travel time, minimizing VOC emissions, minimizing CO emissions, and minimizing NOx emissions. The purpose of this approach is to compare and contrast the results of designing for minimal system travel time (i.e., congestion) versus designing to minimize each of the three air pollutants. The formulation for the problem is given below.

The traditional general form of the upper level objective function when system congestion is minimized (i.e., total system travel time) is shown in Equation (1).

$$Minimize\ f_{TSTT}(v.y) = \sum_{i \in I} v_i\ t_i\ (v_{i,y_i}) \tag{1}$$

where i is the link index, I is the set of all links, v is vehicle flow (vehicles per hour), and t is travel time per vehicle as a function of flow and added capacity, y.

The general form of the upper level objective function for minimizing system emissions is given in equation (2). System emissions for each pollutant is calculated by multiplying the vehicle flow on each link by the length of the link and an emissions factor per link (the emissions factor is specific to a pollutant and varies with average vehicle speed) and then summing across links in the network.

$$Minimize\ f_{SE,a}(v, y) = \sum_{i \in I} v_i(y)\, k_{a,i} \tag{2}$$

where a is the index specific to an air pollutant, l is link length, and k is the link emissions (grams).

The emission factor function is a stepwise function defined by Equations (3i) through (3iii).

$$k_{a,i} = l \sum_{b \in B} \sum_{r \in R} \gamma_{r,a,b}\, s_r(s_i)\, L_b(i) \tag{3i}$$

$$S_r(s_i) = \{1\ if\ s_i\ \in\ r, 0\ \ otherwise\} \tag{3ii}$$

$$L_b(i) = \{1\ \ if\ type(i) = b, 0\ otherwise\} \tag{3iii}$$

where γ is an emission factor corresponding to speed increment r, air pollutant a, and facility type b; S_r is the indicator function for the stepwise function; R is a set of speed increments (set to 1 mile-per-hour); L_b is the indicator function for whether or not link i is of type b (i.e., type(i) = b); and B is the set of all link types. The stepwise function adds to the computational complexity of the model by requiring several function look-ups at each model iteration.

Equation (4) illustrates the relationship between average speed, s, vehicle flow, v, and added capacity, y.

$$s_i(v_i, y_i) = \left\{ \frac{l}{t_i(v_i, y_i)} \right\} \tag{4}$$

where t is the travel time (minutes). Speed is assumed to be uniform across each link and delays due to intersections are assumed to be approximated via the volume-delay function in Equation (10). It is assumed that the links are short enough that the average value is representative of conditions regardless of the level of congestion. A dynamic model, however, would better capture speed variations due to shockwaves.

Demand uncertainty was incorporated into some instances of the problem by modifying the upper-level objective function to minimize the expected value of total system travel time, VOC system emissions, NOx system emissions, and CO system emissions. Alternative upper-level objective functions could be considered, such as minimizing pollution in the worst case scenario. Demand is randomly sampled over the range of a pre-specified uncertainty (e.g., $\pm$ 15%). Since data are not available on the shape of the probability distribution, the simplest—uniform distribution—is assumed. The sample demand values are then used to solve the lower level objective function (i.e., UE) and then calculate the network performance measures (i.e., total travel time, total VOC emissions, total NOx emissions, and total CO emissions). A sample average is then calculated from the upper level objective function values resulting from each realization of demand, and this sample average approximates the true expected value.

The expected value for total travel time is defined in Equation (5).

$$E\ f_{TSTT}(y, \tilde{d}) = \overline{f_{TSTT}(y) + \varepsilon} \tag{5}$$

where $E\, f_{TSTT}(y, \tilde{d})$ is the expected value of total system travel time, $\overline{f_{TSTT}(y)}$ is the sample average, $\tilde{d}$ is a matrix of uncertain demands, and ε is sampling error.

The general form of the expected value for total VOC, NOx, and CO system emissions is defined in Equation (6).

$$E\, f_{SE,a}(y, \tilde{d}) = \overline{f_{SE,a}(y)} + \varepsilon \tag{6}$$

where $E\, f_{SE,a}(y, \tilde{d})$ is the expected value of total system emissions for pollutant a, $\overline{f_{SE,a}(y)}$ is the sample average for pollutant a, $\tilde{d}$ is a matrix of uncertain demands, y is added capacity, and ε is sampling error.

Therefore, when incorporating demand uncertainty and designing for minimal system travel time, the upper-level objective function is to minimize Equation (5). Similarly, when incorporating demand uncertainty and designing for minimal air pollution, the upper-level objective function is to minimize Equation (6).

The upper level problem contains constraints for the budget (see Equation 7), and non-negativity (see Equation 8). The budget constraint limits the amount of capacity (vehicles per hour) that can be added to the network. This constraint can be modified and additional related constraints can be added to reflect more complex fiscal constraints depending on an agency's needs.

$$\sum_{i \in I} w_i\, y_i \;\le\; \Psi \tag{7}$$

where w is the weight applied for each link (e.g., this could be set to link length) and ψ is the available capacity budget. The left-hand side of the equation could be weighted depending on the units used or, for example, if the money spent depended on link length. Equation (8) ensures that the capacity is added in discrete and non-negative increments.

$$y_i \;\in\; \{0, 1, 2...\}\ \forall\, i \in I \tag{8}$$

where y is the added capacity and i is the link index.

The lower level objective function is shown in Equation (9). It enforces UE route choice. UE was first stated by Wardrop (1952) and is paraphrased in the following two sentences. UE route choice assigns vehicles to routes such that users experience minimal and equivalent travel time per origin–destination pair. As a result, no user can unilaterally switch routes and reduce his or her travel time.

$$Minimize\;\; f_{UE}(v, y) = \sum_{i \in I} \int_{x=0}^{v_i} t_i(x_i, y_i)\, dx \tag{9}$$

where t is travel time (minutes), v is vehicle flow (vehicles per hour), y is added capacity (vehicles per hour), and i is the link index. While alternatives exist to UE (e.g., stochastic UE which considers the uncertainty in user perceptions of travel time), the alternatives are used infrequently in practice and are more complicated and time-consuming to solve.

Equations (3) and (4) connect the upper level objective function with the lower level objective function through the travel time on each link, which is determined by link flow and added capacity per link. Travel time is defined by the U.S. Bureau of Public Roads link performance function, shown as Equation (10).

$$t_i(v_i, y_i) = t_i^0 \left[1 + a_i \left(\frac{v_i}{c_i + y_i} \right)^{\beta_i} \right] \tag{10}$$

where t^0 is free flow travel time (minutes), c is original capacity (vehicles per hour), y is added capacity (vehicles per hour), α and β are link-specific parameters that can vary based on facility type, and i is the link index. We assume adding capacity to a link will influence the travel time on the link, but will not influence the link's free flow travel time.

The lower level problem is subject to flow conservation between vehicle link flows, vehicle path flows, and the origin–destination demand. The flow conservation constraints ensure vehicles are not randomly created or lost within the network. These, as well as the non-negativity constraint for vehicle flow, are included in Equation (11).

$$V = \{v | v = Ph, d = Gh, v \ge 0\} \tag{11}$$

where V is the set of feasible vectors of vehicle link flows, P is a link-path incidence matrix, h is the vector of the vehicle flow per path, d is the vehicle flow per origin-destination pair, and G is an origin–destination trip-path incidence matrix.

4 SOLUTION METHOD

A GA was chosen to solve the proposed emissions network design problem; this decision was based on four related factors. First, the network design problem with UE subproblem cannot be solved analytically. This instance of the problem is especially difficult to solve due to the stepwise emission factors. Second, GA takes advantage of existing neighborhood effects when searching for a solution, which in this problem means considering link improvements (i.e., capacity additions) similar to those that have been shown to perform well in previous iterations. Second, research by Karoonsoontawong and Waller (2006) found GA to outperform simulated annealing (SA) and random search (RS) solution algorithms in solving continuous network design problems. GA outperformed SA and RS in terms of solution quality, convergence, speed, and process time. Duthie and Waller (2008) also found GA to work well for a variant on the network design problem. Finally, there are plans to expand this research to consider the emissions network design problem in a dynamic context, which is the context in which Karoonsoontawong and Waller (2006) conducted their research.

Below are the steps of the GA as applied to solve the emissions network design problem formulation presented in Section 3. See Holland (1975) and Goldberg (1989) for a comprehensive discussion of GA. Each chromosome corresponds to an improvement scenario. The genes that make up each chromosome take binary values depending on whether or not the candidate link is selected for improvement.

Step 1: Initialize population: Set the index for the current generation to $n = 1$. Randomly set each gene in each of the chromosomes to 0 or 1. This first set of chromosomes represents the initial population, pop_n.

Step 2: Demand sampling (to account for demand uncertainty): Randomly sample demand values based on a specified uncertainty. Solve UE and calculate performance measures (i.e., total system travel time, VOC system emissions, NOx system emissions, and CO system emissions) for each chromosome and each realization of demand.

Step 3: Calculate objective functions: Calculate the expected value per performance measure for each chromosome in pop_n. If reached, stop. Else, go to Step 4.

Step 4: S-tournament selection: For each group (i.e., tournament) of s chromosomes, keep the best chromosome as a parent for generation $n+1$.

Step 5: Crossover: Let $n = n+1$. Generate K uniform (0,1) random numbers for each pair of "parent" chromosomes. If the kth random number is less than the probability of crossover, p_c, perform a uniform crossover operation on the kth sub-strings in the pair to create two new "child" chromosomes. The set of children chromosomes is pop_n.

Step 6: Mutation: Mutate each gene of each chromosome in pop_n with probability pm.

Step 7: Check stopping criterion: If reached, stop. Else, go to Step 2.

Initial runs were conducted to determine an appropriate value for n_{max}, i.e., n_{max} is set such that the objective function was no longer improving in each scenario.

5 EXPERIMENTAL DESIGN

This section describes the scenarios that were analyzed on each of the two test networks (Sioux Falls, ND and Anaheim, CA) as well as the parameters selected for use in the GA. The Sioux Falls network has 76 links and 576 origin-destination (OD) pairs. The Anaheim network has 916 links and 1,406 OD pairs. See Bar-Gera (2011) for illustrations and more information on both networks. All emission factors were obtained from MOBILE6.2 (EPA, 2010).

5.1 Analysis scenarios

A number of analysis scenarios were run to investigate the influence of: (1) adding smaller increments of capacity versus larger increments of capacity to a network; (2) increasing demand (i.e., congestion) on the network; (3) increasing the available budget; (4) increasing the number of road links eligible for improvement; and (5) increasing demand uncertainty. The scenarios tested on the Sioux Falls and Anaheim networks are summarized in Table 1. Demand uncertainty was only considered on the Sioux Falls network due to the computational effort involved.

In total, 18 analysis scenarios were run for the Sioux Falls network with fixed demand, 11 analysis scenarios were run for the Anaheim network with fixed demand, and 7 analysis scenarios were run for the Sioux Falls network with demand uncertainty (in each case, 50 realizations of demand were used). The following paragraphs discuss the reasoning for the attribute (e.g., budget, eligible links) values that define the scenarios in Table 1.

The base (100%) demand level was chosen so that it provided a medium level of congestion. This choice allowed higher levels of demand to congest the network without over-congesting it (e.g., volume to capacity ratios greater than one throughout the network) and lower levels of demand to still provide interesting results (e.g., not all links in free-flow). The percentage values for the OD demand loaded on the Anaheim network are higher than the Sioux Falls network, because the original base OD demand table for Anaheim has a lower level of congestion than the Sioux Falls base OD demand table.

The capacity increment was initially set to 1,800 vehicles per hour on each link because this approximates adding one lane. Some variation was then added to a few scenarios to allow for operational improvements that could lead to smaller increments in capacity improvements such as a signal timing change. The budget constraint provides an upper bound on the amount of capacity that can be added. The percent of links in the network eligible for improvement are based primarily on network size and corresponding run time to execute the solution method. Larger networks such as Anaheim take considerably longer to run due to the increased number of possible solutions; therefore, the percent of

Table 1
Analysis scenarios

Scenario attributes	*Sioux Falls with fixed demand*			*Sioux Falls with demand uncertainty*
	Vary budget, small arterial increments	*Vary budget, large arterial increments*	*Vary congestion*	*Vary uncertainty*
% Of OD table on network (base congestion)	100%	100%	25%, 50%, 75%, 100%, 125%, 150%, 175%, 200%	100%
Budget constraint (100 veh/hour)	3, 6, 9, 18, 27, 36	3, 6, 9, 18, 27, 36	18	18
Capacity increments added to				
Arterial roadways (veh/hour)	300	1,800	1,800	
Freeways (veh/hour)	1,800	1,800	1,800	1,800
% Network eligible for improvement	94.7%	94.7%	94.7%	94.7%
Demand uncertainty	0.00%	0.00%	0.00%	10%, 15%, 20%, 25%, 30%, 35%, 40%

Scenario attributes	*Anaheim with fixed demand*		
	Vary budget	*Vary congestion*	*Increase # eligible links*
% Of OD table on network (base congestion)	200%	150%, 175%, 200%, 225%, 250%, 275%	200%
Budget constraint (100 veh/hour)	18, 36, 54, 72	72	72
Capacity increments added to arterial roadways (veh/hour)	1,800	1,800	1,800
Capacity increments added to freeways (veh/hour)	1,800	1,800	1,800
% Network eligible for improvement	4.36%	4.36%	10.92%
Demand uncertainty	0.00%	0.00%	0.00%

eligible links was kept smaller to keep the run time manageable.

The effect of adding smaller increments of capacity was explored using 300 vehicle/hour increments for arterial roadways; this value was selected as a means to approximate additional capacity due to improved signal timing. The larger increment of capacity (1,800 vehicles/hour) is a conservative value for approximating the capacity gained by adding a travel lane to a road link. The purpose of this analysis was to consider if adding smaller increments of capacity enabled the model to better optimize system performance measures than adding larger increments of capacity. For example, it considers the question: is it more advantageous to add smaller amounts of capacity throughout many links on the network or add larger amounts of capacity to only a few links on the network?

5.2 Calculating emission factors

Emission factors were developed for the two test network cities: Sioux Falls, ND and Anaheim, CA. Data were not available regarding vehicle or vehicle fleet characteristics specific to these two cities; therefore the EPA default values based on national data were used for inputs such as fuel type, vehicle fleet mix, and inspection/maintenance programs. Data and information were available to provide context (i.e., environment) and operating characteristics specific to each city. Table 2 summarizes the characteristics modified to fit each city and the corresponding input values used.

Using the inputs in Table 2, emission factors were calculated for average vehicle speed of 2.5 mph up to 65 mph (these are the limits of MOBILE6.2) at 1 mph increments for vehicles operating on arterial roadways

Table 2
Key inputs used to develop emission factors

Input parameter	*Sioux Falls*	*Anaheim*
Calendar year	2030	2030
Month	July	July
Minimum temperature (°F)	60	62
Maximum temperature (°F)	86	84
Absolute humidity (grains water/lb of dry air)	95	114
Altitude (low or high)	Low	Low

and freeways. The resulting composite vehicle emission factors form the functions used in the upper-level objective function of the formulation in Section 3 to capture system emissions. There are two sets of functions, one for arterial roadways and one for freeways, for each pollutant type (six functions per city). The calendar year was set to 2030 to mirror a 20-year planning horizon (this influences the vehicle fleet mix that MOBILE6.2 uses in its calculations). The minimum and maximum temperatures per city and absolute humidity values are based on historic averages for each city in the month of July; such information is available online at: http://www.weather.com.

Figure 1 illustrates relationship between emissions and average vehicle speed for VOC, CO, and NOx.

The hydrocarbons (VOC) curve shows decreasing emissions as average vehicle speed increases. Since higher speeds are equated with lower travel times, it is reasonable to expect emissions of these types to be near their minimal amount when system travel time is minimized.

The CO and NOx curves are convex and bowl-shaped where the lowest emission rate for the case illustrated occurs around 33 mph and 37 mph, respectively. This shape compared to the average travel time curve supports the findings from the traffic assignment and network pricing with emissions research: travel time and emissions have different relationships to traffic flow characteristics such as average vehicle speed. From a network design perspective, to minimize CO emissions one would not want to design the network such that vehicles are traveling as fast as possible to their destinations. Instead a certain amount of congestion or slower speed facilities appear desirable to minimize CO emissions.

5.3 Solution method parameters and effectiveness

In applying a GA to solve the emissions network design model, the cross-over probability was set to 0.8, the cross-over type was uniform cross-over, the mutation probability was 0.01, and the population was set to 100. These parameters were found to work well in other similar problem instances (Karoonsoontawong and Waller 2006; Duthie and Waller, 2008). The number of generations used for the analysis scenarios with fixed demand was 35, 40, 45, or 60 and the number of generations used for the scenarios including demand uncertainty was 30. The number of generations used for the scenarios with fixed demand changed based on the scenario's attributes and the corresponding convergence of the fitness values (i.e., objective values). A sufficient level of convergence was defined as when the change in each objective value over the last 10 generations is less than 0.25%. Analysis scenarios that were run with more generations were those at the higher end of the available budget range, the higher end of the demand range (i.e., base congestion range), and/or had a higher number of links eligible for improvement. This was done to ensure solution convergence for scenarios likely to encounter more feasible solutions due to relaxed constraints (e.g., increasing the available budget, increasing the number of links eligible for improvement). Overall, the GA solution method employed for the emissions network design problem appeared to be efficient, as objective values tended to stop improving in 20 to 45 generations.

6 RESULTS

From the analysis scenarios conducted, emerging trends were identified and organized into two categories: (1) general findings and (2) the effect designing to minimize each objective has on system performance (i.e., total travel time and system emissions). Subsections 6.1 and 6.2 discuss the trends within each of these categories.

6.1 General findings

Two interesting and important general findings emerged from the analysis results. The first finding: across all 36 analysis scenarios, a system change or set of changes to the road network could always be made to reduce each of the three air pollutants. Since CO and NOx emissions are a nonlinear function of speed, this is not necessarily intuitive. Figure 2 illustrates this result on the Anaheim network for a fixed budget. (The *y*-axis on the figure represents the percent improvement relative to the do-nothing scenario for each of the performance measures shown in the legend.) Each line represents the results for optimizing only one performance measure. As expected, the potential for improvement in system travel time increases as demand (and therefore congestion) on the network increases. This increasing trend was still apparent, though less

Fig. 1. The relationship between emissions rate (grams/mile/vehicle) and average vehicle speed for each of the three emissions types considered. The curve is specific to arterial facilities located in Anaheim, CA in July, but the functional form is the same for each.

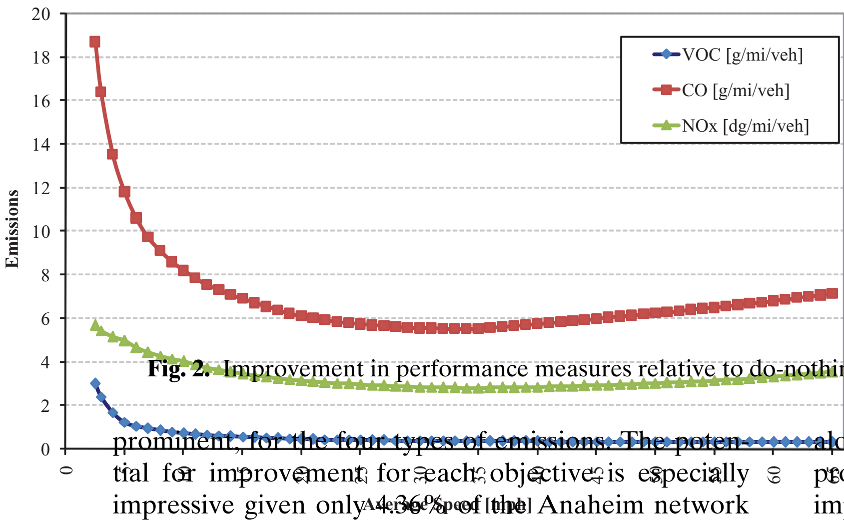
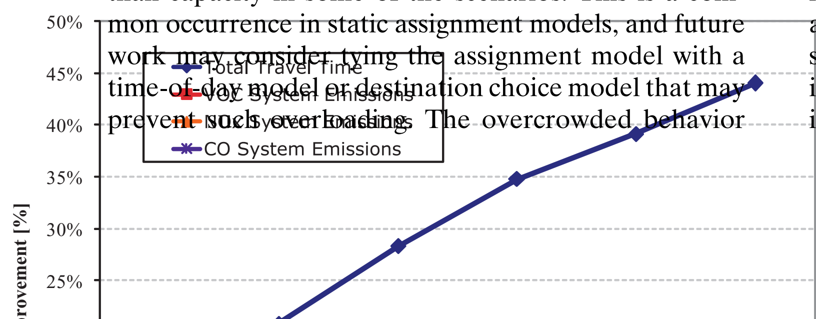


Fig. 2. Improvement in performance measures relative to do-nothing scenarios as demand increases on Anaheim network.



prominent, for the four types of emissions. The potential for improvement for each objective is especially impressive given only 4.36% of the Anaheim network was eligible for improvement. Results were similar for other budget levels and for the Sioux Falls network. Some links in the network do have volumes greater than capacity in some of the scenarios. This is a common occurrence in static assignment models, and future work may consider tying the assignment model with a time-of-day model or destination choice model that may prevent such overloading. The overcrowded behavior along with the limited number of links available for improvement may be the cause of the stabilization of the improvements in emissions as demand gets very large.

The second general finding: reducing the increments of capacity added to the network had a limited effect on model results. Adding smaller increments of capacity resulted in a marginal additional decrease in NOx and CO system emissions (when the network was designed to minimize each). Conversely, adding smaller increments of capacity resulted in a marginal increase in total travel time (when the network was designed to minimize total travel time). Travel time decreases monotonically as speed increases, therefore larger increments of capacity added to a link translate to faster speeds and lower travel time. These results were found with the analysis on the Sioux Falls network, a relatively small network. Similar analysis on larger networks is expected to indicate adding smaller increments of capacity across a network is more effective at reducing NOx and CO emissions than adding larger increments of capacity. Further tests are needed to verify this hypothesis.

6.2 Effects on system performance

In this research, system performance is characterized by four different measures: (1) total travel time; (2) total VOC emissions; (3) total NOx emissions; and (4) total CO emissions. When one measure is minimized, the tradeoffs with the other measures become evident.

In the emissions network design model, total system travel time and VOC system emissions behave similarly (i.e., when one is minimized the other also tends to be minimized). Also, NOx and CO system emissions tend to behave similarly, but usually in contrast to total system travel time and VOC system emissions. Analysis results also indicate the differences between designing for minimal total travel time or VOC system emissions versus designing for minimal NOx or CO system emissions tend to increase as the number of links eligible for improvement increases and as the base congestion for a network increases (i.e., demand for travel on the network increases). Interestingly, the differences tend to vary little for a given demand level (i.e., base congestion level) despite increasing the available budget.

The following figures illustrate three key trends in effects on system performance found in the analysis results. Figure 3 has one curve showing the percent increase in CO when total system travel time (TSTT) is minimized versus when CO is minimized, and a second curve showing the percent increase in TSTT when CO is minimized versus when TSTT is minimized. The objective is to assess the adverse impact as demand (i.e., congestion) on the Sioux Falls network increases on CO (or TSTT) when TSTT (or CO) is minimized. Demand was assumed to be fixed in these analyses. The difference in CO system emissions went from approximately 1% increase over minimal CO system emissions to nearly a 6% increase over minimal CO system emissions when the network is designed for minimal total travel time. Similarly, the difference between minimal total travel time and total travel time when the network is designed for minimal CO system emissions increases considerably as demand on the network increases. However, the percent difference in TSTT when CO is minimized versus when TSTT is minimized decreases from more than 16% to approximately 13% when the percent of OD demand increases from 175% to 200% of the base demand. More numerical analysis is needed to explore this trend further. The Anaheim network showed similar results, however, the increasing trend was less apparent due to the small percent (4.36%) of links available for improvement.

It is apparent from the above results that there are tradeoffs between designing a network for minimal total travel time and designing it to minimize a specific pollutant, especially minimal NOx or CO system emissions. An example of this competing relationship is shown in the pareto-optimal curve in Figure 4. Total travel time and CO system emissions objectives behave in contrast to each other, which is similar to the relationship between total travel time and NOx system emissions. When travel time increases or decreases, CO and NOx system emissions tend to do the opposite. Tests where multiple objectives are considered simultaneously were conducted by using a modified version of the nondominated sorting algorithm (NSGA-II) (Deb et al., 2002). In each generation, solutions are labeled with the rank of their efficient front as well as the density of surrounding solutions. More details on NSGA-II are given by Deb et al. (2002).

Results from incorporating demand uncertainty into the Sioux Falls network indicate that accounting for demand uncertainty when it exists results in better system performance for each objective (i.e., designs achieve lower total travel time and lower emissions). Figure 5 illustrates the expected value of CO emissions when the problem was solved to minimize this value considering demand uncertainty. These expected values are then compared to the expected values calculated with the solutions found under the fixed demand analysis scenarios (using the mean demand from the distribution) evaluated against the numerous uncertain demand scenarios. Results are similar for all four objective functions, both networks, and different capacity increments and budget levels.

Due to the relationship between NOx emissions and average vehicle speed as well as CO emissions and average vehicle speed, accounting for demand uncertainty is particularly critical for these performance measures. Designs that create too high or too low of average vehicle speeds can be detrimental to minimizing NOx and CO system emissions; therefore, finding the right balance, the most robust solutions for long-term variations in demand (i.e., demand uncertainty) is paramount.

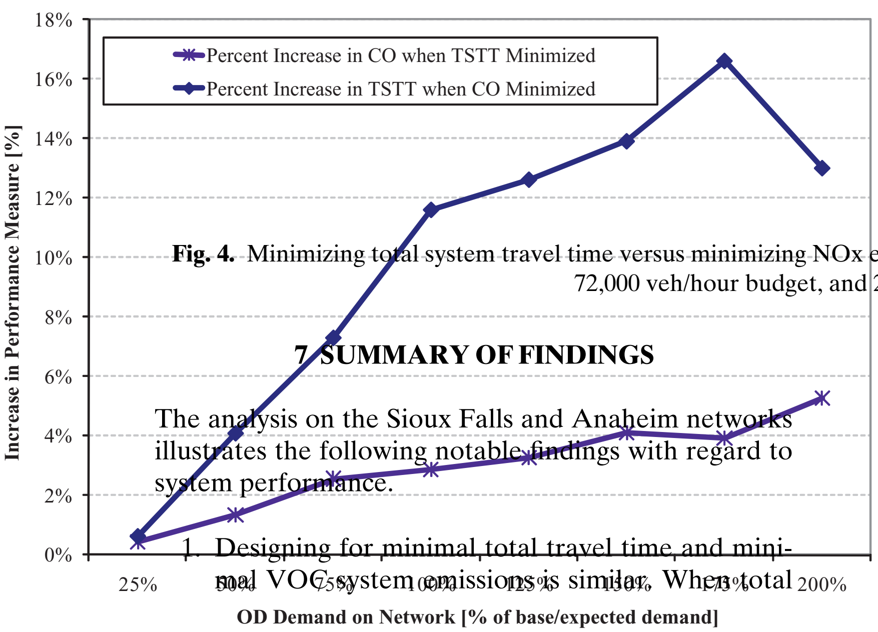


Fig. 3. Increase in CO emissions and total system travel time (TSTT) as demand increases on Sioux Falls network.

Fig. 4. Minimizing total system travel time versus minimizing NOx emissions, non-dominated solutions for Anaheim network, 72,000 veh/hour budget, and 200% OD demand.

7 SUMMARY OF FINDINGS

The analysis on the Sioux Falls and Anaheim networks illustrates the following notable findings with regard to system performance.

1. Designing for minimal total travel time and minimal VOC system emissions is similar. When total travel time is minimal, VOC system emissions also tend to be minimal and vice versa.
2. Designing for minimal NOx system emissions and minimal CO system emissions is similar; when one is minimized, the other also tends to be minimized.
3. When a network is designed for minimal total travel time or minimal VOC system emissions, NOx and CO system emissions tend to increase

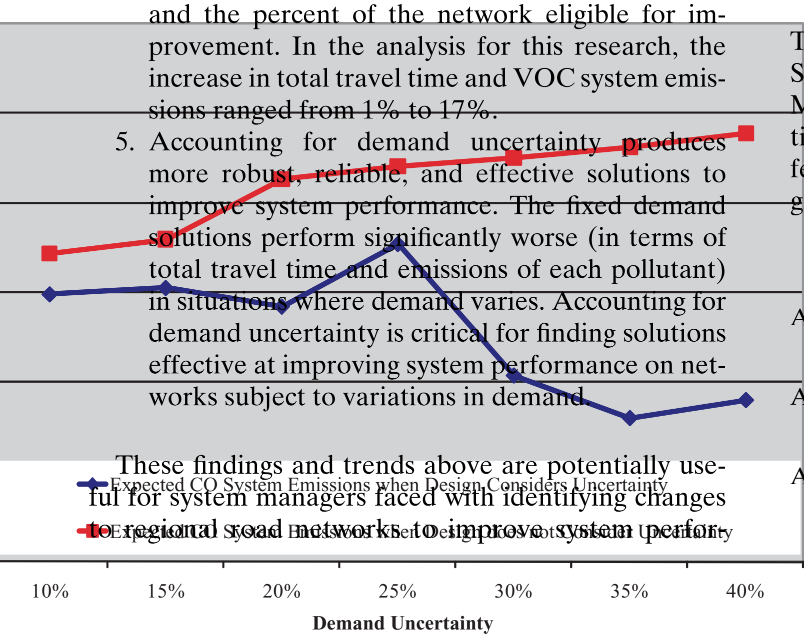


Fig. 5. Expected CO emissions when network is designed with fixed demand and evaluated against uncertain demand versus expected CO emissions when network is designed with uncertain demand—Sioux Falls network.

relative to their respective minimal values. The magnitude of the increase depends on the level of base congestion on the network and the percent of the network eligible for improvement. In the analysis for this research, the increase in NOx and CO system emissions ranged from approximately 1% to 6%.

4. When a network is designed for minimal NOx system emissions or minimal CO system emissions, total travel time and VOC system emissions tend to increase relative to their respective minimal values. Again, the magnitude of the increase depends on the level of base congestion on the network and the percent of the network eligible for improvement. In the analysis for this research, the increase in total travel time and VOC system emissions ranged from 1% to 17%.
5. Accounting for demand uncertainty produces more robust, reliable, and effective solutions to improve system performance. The fixed demand solutions perform significantly worse (in terms of total travel time and emissions of each pollutant) in situations where demand varies. Accounting for demand uncertainty is critical for finding solutions effective at improving system performance on networks subject to variations in demand.

These findings and trends above are potentially useful for system managers faced with identifying changes to regional road networks to improve system performance under an emissions constrained environment. Each finding provides insight into tradeoffs in system performance between designing a network for minimal total travel time versus a specific pollutant. These insights can be valuable in informing planning policies and the general approach taken to planning road network modifications. It is clear from the above findings that minimizing network congestion does not produce minimal emissions of critical criteria pollutants such as NOx or CO.

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REFERENCES

Adeli, H. & Cheng, N.-T. (1994a), Augmented Lagrangian genetic algorithm for structural optimization, *Journal of Aerospace Engineering, ASCE*, **7**(1), 104–18.

Adeli, H. & Cheng, N.-T. (1994b), Concurrent genetic algorithms for optimization of large structures, *Journal of Aerospace Engineering, ASCE*, **7**(3), 276–96.

Adeli, H. & Kumar, S. (1995), Distributed genetic algorithms for structural optimization, *Journal of Aerospace Engineering*, **8**(3), 156–63.

Ahn, K. & Rakha, H. (2008), The effects of route choice decisions on vehicle energy consumption and emissions, *Transportation Research*, **13D**(3), 151–167.

Al-Bazi, A. & Dawood, N. (2010), Developing crew allocation system for precast industry using genetic algorithms, *Computer-Aided Civil and Infrastructure Engineering*, **25**(8), 581–95.

Bar-Gera, H. (2011). Transportation Network Test Problems. Last updated on January 12, 2011. Available at: http://www.bgu.ac.il/~bargera/tntp/, accessed March 31, 2011.

Benedek, C. M. & Rilett, L. R. (1998), Equitable traffic assignment with environmental cost function, *Journal of Transportation Engineering*, **124**(1), 16–22.

Cantarella, G. E. & Vitetta. A. (2006), The multi-criteria road network design problem in an urban area, *Transportation*, **33**, 567–88.

Cheng, T. M. & Yan, R. Z. (2009), Integrating messy genetic algorithms and simulation to optimize resource utilization, *Computer-Aided Civil and Infrastructure Engineering*, **24**(6), 401–15.

Cho, H. & Lo, S. (1999), Solving bilevel network design problem using a linear reaction function without nondegeneracy assumption, *Transportation Research Record*, **1667**, 96–106.

Deb, K. D., Pratap, A., Agarwal, S. & T. Meyarivan. (2002), A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, **6**(2), 182–97.

Duthie, J., Voruganti, A., Kockelman, K.M. & Waller, S.T. (2010), Highway improvement project rankings due to uncertain model inputs: application of traditional transportation and land use models, *Journal of Urban Planning and Development*, **136**(4), 294–302.

Duthie, J. & Waller, S.T. (2008), Incorporating environmental justice measures into equilibrium-based network design, *Transportation Research Record*, **2089**, 58–65.

EPA (Environmental Protection Agency). (2003). User's Guide to MOBILE6. 1 and MOBILE6.2: Mobile Source Emission Factor Model. Assessment and Standards Division Office of Transportation and Air Quality U.S. Environmental Protection Agency. EPA420-R-03–010.

EPA (Environmental Protection Agency). (2009). National Ambient Air Quality Standards (NAAQS). Available at: http://www.epa.gov/air/criteria.html, accessed December 13, 2009.

EPA (Environmental Protection Agency). (2010). Mobile 6 Vehicle Emission Modeling Software. Available at: http://www.epa.gov/ oms/m6.htm, accessed February 20, 2010.

Friesz, T. L., Cho, H. J., Mehta, N. J., Nam, K., Shah, S.J. & Tobin, R. L. (1992), A simulated annealing approach to the network design problem with variational inequality constraints, *Transportation Science*, **26**(1), 12–26.

Goldberg, D. E. (1989), *Genetic Algorithms in Search Optimization and Machine Learning*, Addison-Wesley, Boston.

Holland, J.H. (1975), *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor.

Jiang, X. & Adeli, H. (2008), Neuro-genetic algorithm for nonlinear active control of high rise buildings, *International Journal for Numerical Methods in Engineering*, **75**(8), 770–86.

Johansson, O. (1997), Optimal road-pricing: simultaneous treatment of time losses, increased fuel consumption, and emissions, *Transportation Research*, **2D**(2), 77–87.

Kang, M.W., Schonfeld, P. & Yang, N. (2009), Prescreening and repairing in a genetic algorithm for highway alignment optimization, *Computer-Aided Civil and Infrastructure Engineering*, **24**(2), 109–119.

Karoonsoontawong, A. & Lin, D.-Y. (2011), Time-varying lane-based capacity reversibility for traffic management, *Computer-Aided Civil and Infrastructure Engineering*, **26**(8), 632–46.

Karoonsoontawong, A. & Waller, S.T. (2006), Dynamic continuous network design problem linear bilevel programming and metaheuristic approaches, *Transportation Research Record*, **1964**, 104–77.

Kim, B. J. & Kim, W. (2006), An equilibrium network design model with a social cost function for multimodal networks, *The Annals of Regional Science*, **40**(3), 473–91.

Kim, H. & Adeli, H. (2001), Discrete cost optimization of composite floors using a floating point genetic algorithm, *Engineering Optimization*, **33**(4), 485–501.

Lam, W. H. K. & Tam, M. L. (1998), Risk analysis of traffic and revenue forecasts for road investment projects, *Journal of Infrastructure Systems*, **4**(1), 19–27.

LeBlanc, L. J. (1975), An algorithm for the discrete network design problem, *Transportation Science*, **9**(2), 183–99.

LeBlanc, L. J. & Boyce, D. E. (1986), A bilevel programming algorithm for exact solution of the network design problem with user-optimal flows, *Transportation Research*, **20B**(3), 259–65.

Lee, Y. & Wei, C.H. (2010), A computerized feature selection using genetic algorithms to forecast freeway accident duration times, *Computer-Aided Civil and Infrastructure Engineering*, **25**(2), 132–48.

Li, X., Li, G., Pang, S., Yang, X. & Tian, J. (2004), Signal timing of intersections using integrated optimization of traffic quality, emissions and fuel consumption: a note, *Transportation Research*, **9D**(5), 401–7.

Lozano, A., Granados, F. & Antun, J. P. (2008), Estimation of vehicle flows and emissions for various scenarios of street network modifications in Mexico City, *American Journal of Environmental Science*, **4**(3), 198–203.

Magnanti, T. L. & Wong, R. T. (1984), Network design and transportation planning: models and algorithms, *Transportation Science*, **18**(1), 1–55.

Marano, G. C., Quaranta, G. & Monti, G. (2011), Modified genetic algorithm for the dynamic identification of structural systems using incomplete measurements, *Computer-Aided Civil and Infrastructure Engineering*, **26**(2), 92–110.

Mathakari, S., Gardoni, P., Agarwal, P., Raich, A. & Haukaas, T. (2007), Reliability-based optimal design of electrical transmission towers using multi-objective genetic algorithms, *Computer-Aided Civil and Infrastructure Engineering*, **22**(4), 282–92.

Medina, J. S., Moreno, M. G. & Royo, E. R. (2007), Study of correlation among several traffic parameters using evolutionary algorithms: traffic flow, greenhouse emissions and network occupancy, *Lecture Notes in Computer Science*, **4739**, 1134–41.

Ng, M., Lin, D.-Y. & Waller, S.T. (2009) Optimal long-term infrastructure maintenance planning accounting for traffic dynamics, *Computer-Aided Civil and Infrastructure Engineering*, **24**(7), 459–69.

O'Donoghue, R. T., Broderick, B. M. & Delaney, K. (2007), Assessing the impacts of infrastructural road changes on air quality: a case study, *Transportation Research*, **12D**(8), 529–36.

Poorzahedy, H. & Turnquist, M. A. (1982), Approximate algorithm for the discrete network design problem, *Transportation Research*, **16B**(1), 45–55.

Rilett, L. R. & Benedek, C. M. (1994), Traffic assignment under environmental and equity objective, *Transportation Research Record*, **1443**, 92–9.

Sarma, K. & Adeli, H. (2000), Fuzzy genetic algorithm for optimization of steel structures, *Journal of Structural Engineering, ASCE*, **126**(5), 596–604.

Sarma, K. C. & Adeli, H. (2001), Bi-level parallel genetic algorithms for optimization of large steel structures, *Computer-Aided Civil and Infrastructure Engineering*, **16**(5), 295–304.

Sharma, S. & Mathew, T. V. (2007), Transportation network design with emission pricing as a bi-level optimization problem, *Transportation Research Board 86th Annual Meeting Compendium*, Report number 07–2143, 17 pp. Available at: http://trid.trb.org/view.aspx?id=802056, accessed December 2011.

Solanki, R. S., Gorti, J. K. & Southworth, F. (1998), Using decomposition in a large-scale highway network design with a quasi-optimization heuristics, *Transportation Research*, **32B**(2), 127–40.

Spall, J. C. & Chin, D. C. (1997), Traffic-response signal timing for system-wide traffic control, *Transportation Research*, **5C**(3/4), 153–63.

Stevanovic, A., Stevanovic, J., Zhang, K. & Batterman, S. (2009), Optimizing traffic control to reduce fuel consumption and vehicular emissions: integrated approach with VISSIM, CMEM, and VISGAOST, *Transportation Research Record*, **2128**, 105–13.

Sugawara, S. & Niemeier, D. A. (2002), How much can vehicle emissions be reduced? Exploratory analysis of an upper boundary using an emissions-optimized trip assignment, *Transportation Research Record*, **1815**, 29–37.

Suh, S. & Kim, T. J. (1992), Solving nonlinear bilevel programming models of the equilibrium network design problem: a comparative review, *Annuals of Operations Research*, **34**(1), 203–18.

Teklu, F., Sumalee, A. & Watling, D. (2007), A genetic algorithm for optimizing traffic control signals considering routing, *Computer-Aided Civil and Infrastructure Engineering*, **22**(1), 31–43.

Tzeng, G. H. & Chen, C. H. (1993), Multiobjective decision-making for traffic assignment, *IEEE Transactions on Engineering Management*, **40**, 180–7.

Ukkusuri, S. V., Mathew, V. T. & Waller, S. T. (2007), Robust transportation network design under demand uncertainty, *Computer-Aided Civil and Infrastructure Engineering*, **22**, 6–18.

Unal, A., Rouphail, N. M. & Frey, H. C. (2003), Effect of arterial signalization and level of service on measured vehicle emissions, *Transportation Research Record*, **1842**, 47–56.

USCC (United States Chamber of Commerce). (2009). Consequences of non-attainment. Available at: http://www.uschamber.com/issues/index/environment/nonattainmentconseq.htm, accessed November 16, 2009.

Vlahogianni, E. I., Karlaftis, M. G. & Golias, J. C. (2007), Spatio-temporal short-term urban traffic flow forecasting using genetically-optimized modular networks, *Computer-Aided Civil and Infrastructure Engineering*, **22**(5), 317–25.

Waller, S. T., Schofer, J. L. & Ziliaskopoulos, A. K. (2001), Evaluation with traffic assignment under demand uncertainty, *Transportation Research Record*, **1771**, 69–75.

Wardrop, J. G. (1952), Some theoretical aspects of road traffic research, *Proceedings Institution of Civil Engineers II*, 325–78.

Yang, H. & Bell, M. G. H. (1998), Models and algorithms for road network design: a review and some new developments, *Transport Reviews*, **18**(3), 257–78.

Yang, Z., Yu, B. & Cheng, C. (2007), A parallel ant colony algorithm for bus network optimization, *Computer-Aided Civil and Infrastructure Engineering*, **22**(1), 44–55.

Yin, Y. & Lawphongpanich, S. (2006), Internalizing emission externality on road networks, *Transportation Research*, **11D**(4), 292–301.

Yunpeng, W., Dong, G., Shiwu, L., Yu, W. & Li, Z. (2008), Signal timing optimization simulation on urban road intersection based on vehicle emissions, in *Proceedings from The Eighth International Conference of Chinese Logistics and Transportation Professionals*, American Society of Civil Engineers, 4762–67.