A Simulation-Optimization–Based Decision Support Tool for Mitigating Traffic Congestion

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UTCA

University Transportation Center for Alabama
The University of Alabama, The University of Alabama at Birmingham,
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University Transportation Center for Alabama

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16. Abstract

Traffic congestion has grown considerably in the United States over the past twenty years. In this paper, we develop a robust decision support tool based on simulation optimization to evaluate and recommend congestion-mitigation strategies to transportation-system decision-makers. A tabu-search–based optimizer determines different network design strategies on the road network while a traffic simulator evaluates the goodness of fit. The tool is tested with real traffic data.

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Executive Summary

Traffic congestion has grown considerably in the United States over the past twenty years. In this paper, we develop a robust decision support tool based on simulation optimization to evaluate and recommend congestion-mitigation strategies to transportation-system decision-makers. A tabu-search–based optimizer determines different network design strategies on the road network while a traffic simulator evaluates goodness of fit. The tool is tested with real traffic data.

Section 1
Introduction

Traffic congestion has grown considerably in the United States. The hours of delay per traveler is more than five times greater than it was 20 years ago. In 2005, the nation's drivers experienced a total of 4.2 billion hours (about 38 hours per driver) in traffic delays. Along with fuel waste, this translates to a cost of about $78.2 billion. Recent growth in manufacturing in the southern United States, especially in the automotive industry, has increased freight movement with regard to raw materials, in-process parts, and finished goods. Although this indicates economic growth for the southern states, it causes high utilization of state and federal highways and potential congestion in the region's urban areas.

The investigation of transportation networks is typically studied using a network design or stand-alone simulation. A network design is useful for identifying problem areas on a network and suggesting improvements, but it fails to capture the stochastic, dynamic nature of the traffic flow, thereby giving a false sense of the congestion. Stand-alone simulation provides a better representation of the traffic flow by guessing the resource settings and strategies that would allow the system to perform at its best. This is difficult due to the large number of possible combinations of mitigation strategies and problem parameters, as well as constraints on budgets, personnel, and other resources. To remedy the issues of these common solution approaches, we employ a simulation-optimization approach that efficiently searches for the best combination using smart search techniques.

In this report, we aim to assist transportation-system designers and decision-makers in dealing with the root causes of urban traffic congestion (e.g. capacity bottlenecks, traffic incidents, work zones) by developing a decision support tool based on simulation optimization that evaluates, analyzes, and recommends mitigation strategies to lessen the congestion. To investigate and evaluate potential mitigation strategies, we examine the incorporation of an optimization technique, in the form of a tabu-search meta-heuristic, with an existing traffic-simulation model created using TRANPLAN traffic simulation software. TRANPLAN is an integrated suite of programs for forecasting the impacts of alternative land-use scenarios or transportation networks on highway and public-transit systems (The Urban Analysis Group, 1998).

In this problem, our goal, given a congested traffic network, is to minimize the total time traveled on the network by determining the optimal set of congestion mitigation strategies to implement. Typical mitigation strategies include, but are not limited to, additional capacity, reversible lanes, dedicated lanes, variable toll schedule, and new roads. The implementation of these types of strategies are restricted by operational constraints such as manning capacity and budget limitations. In our investigation, we concentrate on additional capacity strategies while adhering to budgetary constraints.

This research effort explores new areas of study with respect to mitigating traffic congestion in an urban environment. The task of determining the types of mitigation strategies to employ and the location of their implementation typically falls on regional planning commissions (RPCs) or metropolitan planning organizations (MPOs). This is a challenging and cost-prohibitive task given the large number of possible strategy combinations and potential locations. Thus, the purpose of this research is to develop a decision support tool to aid transportation planners in determining the best options without the need for exhaustive alanlysis of alternatives. The decision support tool helps identify the congestion points and potential mitigation strategies to alleviate congestion as well as evaluate the impact of the strategy alternatives on the traffic network. Furthermore, a sensitivity analysis may be performed regarding the robustness of the suggested solution due to different resource levels, traffic scenarios, and freight-movement expectations.

The remainder of the paper is organized as follows. In the next section, we briefly review the traffic-mitigation and simulation-optimization literature and summarize the work related to the problem under consideration. In Section 3, we discuss the general framework of our simulation-optimization approach. Next, we explain the details of the metaheuristic-optimization and simulation components in Sections 4 and 5. In Section 6, we describe a scenario based on a real traffic network, demonstrate the performance of the simulation-optimization methodology, and illustrate the potential of the solution approach. Finally, in Section 7, we summarize our findings and conclude the paper by discussing the potential impact of this work.

Section 2
Literature Review

Metropolitan areas worldwide are experiencing an increase in traffic congestion. In many cases, the congestion-mitigation alternatives of constructing new routes and increasing roadway capacity have become limiting and often cost prohibitive. Therefore, means to improve the planning and operational aspects of transportation networks to maximize the utility of the existing transportation network are the focus of transportation research and current practices. Our problem borrows from and contributes to three main areas of research: network design, congestion-mitigation simulation modeling, and simulation optimization. We review work from these areas most related to our paper.

2.1 Network Design/Redesign

The network design problem (NDP) has long been recognized as one of the most difficult and challenging in transportation. It involves choosing the best from a set of projects and making decisions that optimize an objective (e.g., minimizing total travel time) while keeping resource consumption (e.g. budget) within its limits. This problem is difficult to solve because of its combinatorial nature and non-convexity of the objective function (Yang and Bell, 1998). Historically, this problem has been posed in three forms: a discrete form dealing with the addition of new links to an existing road network, a continuous form dealing with the optimal capacity expansion of existing links, and the mixed NDP in which the enhancement and addition of road segments to an existing transport network is treated jointly rather than separately. For rural environments, or networks, that have the capability to change the capacity of their edges, researchers shift their focus to, but do not always solely rely on, capacity expansion. Regardless of form, the objective is to optimize a given system-performance measure (e.g. reducing congestion time or minimizing total cost of transportation) while accounting for the route choices of the network users and system constraints such as budget and other resource limitations.

Over the last few decades, significant attention has been given to the transportation-network design problem and to reducing traffic congestion and travel costs. There are several approaches to solve the NDP. Steenbrink (1974), Wong (1984), and Magnanti and Wong (1984) survey earlier algorithms for solving this problem. Yang and Bell (1998) present a recent endeavor in the review of NDP models and algorithms. One of the earlier exact optimization approaches—a branch-and-bound algorithm—is presented by LeBlanc (1975). Merchant and Nemhauser (1978) modeled a directed network where traffic flows move toward a single destination as a linear programming formulation and solved it using decomposition algorithms. Other exact-optimization solutions for the NDP involve branch-and-cut algorithms (Gunluk, 1999), cutting-plane algorithms (Pesenti, et al., 2004), stochastic programming models (Riis and Andersen, 2002; Riis and Lodahl, 2002), joint optimization following Wardrop's principles (Chiou, 2005), and using different types of modeling programs (Athanasenas, 1997; Maze and Kamayab, 1998; Ukkusuri and Waller, 2008). However, the precision of the optimization algorithms in solving the problem makes the solutions computationally expensive when the solution space exceeds even twenty alternatives, which is a fairly small number. Heuristic approaches provide a remedy, as they encompass a wide range of alternatives to search. Among the heuristic approaches, simulated annealing (Lee and Yang, 1994), ant-colony-based metaheuristic (Poorzahedy and Abulghasemi, 2005), genetic algorithm (Yin, 2000), and particle swarm optimization (Zhang and Gao, 2007) have been successfully implemented to solve larger instances of the NDP. With this motivation, our work focuses on capacity expansion of existing roads with a subset of selected strategies using local-search and tabu-search heuristics for the link selection. Both local and tabu-search heuristics have been used in the literature to solve combinatorial optimization problems. In addition to their solution quality, their ease of implementation makes them favorable choices.

2.2 Traffic Simulations

As transportation systems have become more complex and increasingly congested, simulation modeling has gained recognition as an effective approach for quantifying traffic operations. Simulation models are designed to model any combination of surface street and freeway facilities, including most signal control and other operational strategies. Thus, to cope with complex transportation-planning tasks, traffic engineers are increasingly using traffic simulation as a means for evaluating the effectiveness of new road designs.

Traffic-simulation models are often separated into three classes according to level of detail (Erlemann and Hartmann, 2005): macroscopic, mesoscopic, and microscopic. Macroscopic models are most common where traffic flow is emulated as a stream of particles subject to the laws of fluid dynamics (Daganzo, 1995; Helbing, et al., 2002; Kotsialos and Papageorgiou, 2004; Papageorgiou, 1990). On the other extreme, microscopic models focus on individual vehicles and driving behavior. Macroscopic models typically simulate large road networks, and as a result use fewer computational resources. However, macroscopic models usually provide less detail compared to microscopic models. In this research, we contribute to the work involving macroscopic simulation models by utilizing a model of this type and taking advantage of the speed and high-level representation in the model.

Microscopic traffic simulation is a modeling approach and analytical tool increasingly used to support planning and operational decisions. A number of microscopic models have been developed for motorway networks, urban networks, and mixed corridors (van Aerde, et al., 1997; Yang and Koutsopoulos, 1996). Microscopic models provide a better representation of time dynamics, congestion build-up, and the interrelation between operations and impacts. For instance, in urban networks with little or no room for road expansion, researchers turn their focus to changing the timing of light signals (Cantarella, et al., 2006; Chiou, 2007; Wen, 2008), lane changing and merging (Hidas, 2002), or the construction of intersections (Doniec, et al., 2006). While solving for changes in signal timings, Wen (2008) combined the use of a simulation model with a basic algorithm that determined how long the light would remain a certain color and when that countdown would start. Chiou (2007) addressed the concept of reserved capacities in signal-controlled networks. Cantarella, et al. (2006) created a solution that considered both the coordination of the signal settings on adjacent intersections and the influence of the new system on the path choice of drivers. Hidas (2002), on the other hand, focused on lane-changing and merging algorithms within a massive multi-agent simulation system in which driver-vehicle objects were modeled as autonomous agents. For low levels of congestion, changing the timing of traffic lights on a network is a reasonable approach to congestion mitigation. However, it is not a reasonable approach for large networks since building a large-scale microscopic simulation model is costly and demanding in terms of data inputs, calibration efforts, and computational resources (Balakrishna, et al., 2007).

Mesoscopic models, in contrast, bridge the gap between macroscopic and microscopic simulation by using individual vehicles actuated through macroscopic control variables. Mesoscopic models (Chiu, 2009; Yang, 1997) consider packets of vehicles with similar characteristics (e.g. same origin and destination) as autonomous entities and move them inside the network according to macroscopic traffic-flow dynamics and specific route choice patterns. The intent of this type of modeling is to take advantage of the strengths associated with microscopic and macroscopic modeling. However, for this research, a macroscopic approach is still most appropriate since we are dealing with mitigation strategies at a lower fidelity level.

2.3 Simulation Optimization

As we discussed in the previous section, even though simulation models are capable of capturing complex system behaviors of transportation traffic networks (Helbing, et al., 2002; Herty and Klar, 2003; Hidas, 2002; Owen, et al., 2000), they may require lots of development and time to run, which typically makes them inadequate for solving optimization problems. Proposed operational improvements for these networks are difficult to evaluate or to simulate accurately because of the increased effect of vehicle interactions and impact of design elements on traffic flow, which occur under congestion. This situation is remedied by the simulation-optimization approach in that it efficiently searches for the best combination of problem parameters using smart search techniques.

A more formal definition of simulation optimization is provided by Law and McComas (2000) as “the orchestration of the simulation of a sequence of system configurations so that a system configuration eventually is obtained that provides an optimal or near optimal solution.” The main optimization approaches utilized in simulation optimization include random search (Andradóttir, 2005); response surface methodology (Barton, 2005); gradient-based procedures (Fu, 2005); ranking and selection (Kim and Nelson, 2005); sample path optimization (Rubinstein and Shapiro, 1993); and metaheuristics (Ólaffson, 2005), including tabu search, genetic algorithms, and scatter search. Until a few years ago, the research on simulation optimization had focused on theoretical developments (Fu, 2002). As Fu (2002) pointed out, there is a need for algorithms that take advantage of the theoretical results of the literature but are still flexible and applicable to real problems. Within the transportation literature, to the best of our knowledge, there is no other research paper that takes advantage of the benefits of the simulation optimization for traffic-congestion mitigation. Our paper contributes to this gap by developing a tabu-search–based simulation-optimization approach for a road-network improvement problem.

Section 3
General Model and Solution Framework

3.1 General Model

The overall goal of this research is to minimize overall travel time on the road network by reducing congestion via determination of appropriate congestion-mitigation strategies. For this purpose, we first present a formulation of our problem, which is a generalization of the single-destination dynamic traffic assignment problem presented by Merchant and Nemhauser (1978). We represent the traffic network by a directed graph $\mathcal{G} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N} = \{1, \ldots, i, \ldots, N\}$ is the set of nodes and $\mathcal{L} = \{1, \ldots, l, \ldots, L\}$ is the set of links. To alleviate congestion, we consider a number of mitigation strategies to implement on this network, which is represented as $\mathcal{S} = \{1, \ldots, s, \ldots, S\}$. In the case of unlimited resources, one would implement the best congestion-alleviation strategy on every congested link. However, in reality, constraints—such as physical, budgetary, and environmental—exist that restrict unlimited strategy implementation. In this paper, we explicitly consider budget constraints where the implemented strategies cannot exceed a certain pre-set budget, B. To formulate the problem, we define the following additional notation:

Parameters

$\mathcal{T}$	set of time intervals during the simulation run time, $t = 1, \ldots, T$.
$I(i)$	the set of incoming links of node $i \in \mathcal{N}$.
$O(i)$	the set of outgoing links of node $i \in \mathcal{N}$.
P_{it}	number of vehicles entering at node i at time interval t, $i \in \mathcal{N}$ and $t \in \mathcal{T}$.
b_{sl}	budget requirement of strategy s on link l, $s \in \mathcal{S}$ and $l \in \mathcal{L}$.
$w_{sl}(.)$	exit link function of link l, $l \in \mathcal{L}$.

Decision Variables

x_{slt}	number of vehicles on link l at time interval t using strategy s, $s \in \mathcal{S}$, $l \in \mathcal{L}$, and $t \in \mathcal{T}$.
u_{slt}	number of incoming vehicles to link l at time interval t under strategy s, $s \in \mathcal{S}$, $l \in \mathcal{L}$, and $t \in \mathcal{T}$.
y_{sl}	1, if strategy s is implemented on link l, $s \in \mathcal{S}$ and $l \in \mathcal{L}$.

Formulation

$$\text{Min} \quad \sum_{s \in \mathcal{S}} \sum_{l \in \mathcal{L}} \sum_{t \in \mathcal{T}} C_{slt}(x_{slt}) \qquad (NDP)$$

subject to

$$x_{slt} - x_{sl,t-1} = u_{slt} - w_{sl}(x_{sl\,t-1}), \qquad \forall l \in \mathcal{L}, \forall t \in \mathcal{T}, \text{ and } \forall s \in \mathcal{S}. \tag{1}$$

$$\sum_{s\in\mathcal{S}}\sum_{l\in I(i)} u_{slt} - \sum_{s\in\mathcal{S}}\sum_{l\in O(i)} w_{sl}(x_{s,l,t-1}) = p_{it}, \qquad \forall i \in \mathcal{N}, \forall t \in \mathcal{T}, \text{ and } \forall s \in \mathcal{S}. \tag{2}$$

$$\sum_{t\in\mathcal{T}} x_{slt} \leq M y_{sl}, \qquad \forall l \in \mathcal{L}, \text{ and } \forall s \in \mathcal{S}. \tag{3}$$

$$\sum_{s\in\mathcal{S}}\sum_{l\in\mathcal{L}} b_{sl} y_{sl} \leq B. \tag{4}$$

$$x_{slt} \geq 0 \text{ and } u_{slt} \geq 0, \qquad \forall l \in \mathcal{L}, \forall t \in \mathcal{T}, \text{ and } \forall s \in \mathcal{S}. \tag{5}$$

$$y_{sl} \in \{0,1\}, \qquad \forall l \in \mathcal{L} \text{ and } \forall s \in \mathcal{S}. \tag{6}$$

In this formulation, $C_{slt}(x_{slt})$ represents the total vehicle hours due to all traffic flow on the network. $C_{slt}(.)$ is a function that represents the total vehicle hours due to strategy s on link l during time interval t. This cost function takes the decision variable x_{slt}, the number of vehicles, as an input. Since there is no closed-form expression for this function, we use simulation for the evaluation of a particular strategy s on link l during time interval t. The objective function of *NDP* aims to minimize the total vehicle hours and the total congestion in the network simultaneously. The first set of constraints (1) are state equations expressing the conservation of vehicles on a link l, $l \in \mathcal{L}$. The second set of constraints (2) are flow-balance equations at every node i, $i \in \mathcal{N}$ of the network. The third set of constraints (3) establishes the relationship between the continuous-flow variables and the binary strategy-selection variables. To establish this relationship, we use a big M-type formulation. Hence, the right-hand side of constraint set (3) is a large constant, big M, multiplied by the strategy selection variables y_{sl}. The fourth set of constraints (4) states the budget limitations. Finally, constraint sets (5) and (6) establish non-negativity and integrality. This formulation is a nonlinear, non-convex, mixed-integer programming formulation. Additionally, due to the stochastic traffic conditions and size of the network, it is difficult to solve using exact analytical approaches. Hence, we develop an approach based on simulation optimization. The next section explains the details of the solution framework.

3.2 Solution Framework

We employ a simulation-optimization approach to aid in the selection of congestion-mitigation strategies to implement on a road network to improve (lessen) travel time for the roadway users. This approach is especially useful in situations where the goal is to find a set, among many sets, of model specifications (e.g. type of mitigation strategy or location of strategy implementation) that leads to a desired (optimal or near-optimal) system performance. The methodological framework consists of two components: a simulation component and an optimization component. The components are complementary in that they exchange information during a solution execution. The simulation model depicts a complex stochastic scenario, and the optimization component provides trial solution sets for the simulation model to evaluate. Specifically, we use a macroscopic traffic simulation model to represent a roadway network consisting of primarily major thoroughfares in an urban area. Details of the simulation model are provided in Section 5.

The optimization component consists of a tabu-search–based metaheuristic that generates trial solutions for the simulation model to evaluate. Figure 1 depicts the overall framework of the solution approach.

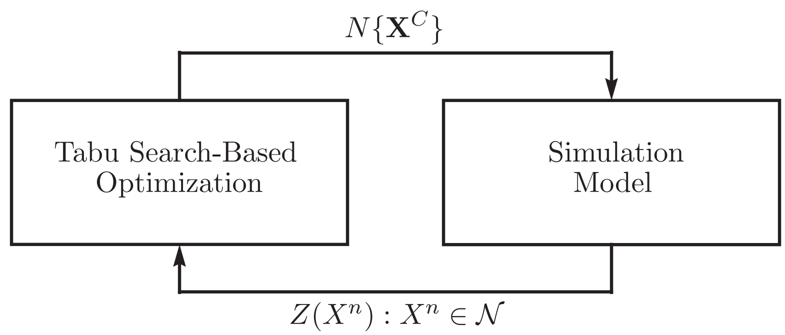

Figure 1: Simulation-optimization framework

Figure 1 shows that the simulation and optimization components work in concert by exchanging “information” throughout the duration of procedure execution. The optimization component generates trial solutions ($N\{\mathbf{X}^C\}$) that serve as inputs to the simulation model which represents the roadway network. Each trial solution is comprised of selected links of the traffic network on which to implement a type of congestion-mitigation strategy. Details of creating trial solutions are given in Section 4. The simulation model evaluates each trial solution and reports a performance measure ($Z(X^n) : X^n \in \mathcal{N}$). In this research, the performance measure is the total vehicle hours on the network over the duration of the simulation run. The optimization component uses previous evaluations from the simulation runs to determine the next set of trial solutions for the simulation to evaluate. This cycle of “information” exchange continues until an iteration limit or stopping criterion is reached (see Section 4). The successively generated input trial solutions produce varying evaluations, not necessarily all improving, but provide an efficient path to the best solution in the long run. The result of the solution procedure is the determination of a congestion-mitigation strategy that optimizes (or nearly optimizes) the traffic network performance. In other words, a solution in the form of selected road segments from the roadway network under study along with a recommended mitigation strategy for each segment is obtained that minimizes the total vehicle hours on the network while still adhering to budgetary constraints.

Section 4
Algorithmic Approach

For the optimization component, we develop two heuristic algorithms, local search and tabu search, to search the solution space. For each of these approaches, we require a starting solution to initialize the algorithms. In this effort, we use two construction heuristic methods to obtain an initial solution. In this section, we discuss the construction heuristics used for initialization, then we describe the details of the local-search and tabu-search implementations.

4.1 Construction Heuristics

Both local-search and tabu-search algorithms operate on a set of links selected for mitigation-strategy implementation. To initiate each, we investigate the performance of two construction heuristics based on greedy and random approaches, respectively. Details of the two construction heuristics follow.

4.1.1 *Greedy Initialization*

The greedy construction heuristic sorts all of the links on the network based on the level of congestion, from the highest congested link to the lowest. From this sorted list, links with a mitigation strategy implemented are added to the initial solution network until the budget limit is reached. This initial solution is then evaluated by the simulation model. Subsequent trial solutions are then generated via local search or tabu search.

4.1.2 *Random Initialization*

The random construction heuristic chooses links at random among the highly congested links. Each chosen link is then added to the initial solution until the budget limit is reached. Much like the greedy initialization, the simulation model then evaluates the initial solution, and subsequent trial solutions are generated via one of the search algorithms.

4.2 Search Algorithms

With an initial solution created via greedy or random initialization, the next step of the search procedure, both in local search and tabu search, is choosing the neighborhood of the solution for the search. In both approaches, we evaluate three neighborhoods: Random Swap, One Swap, and Two-Random Swap. In a Random Swap (RS) neighborhood, we select an add/drop link pair among the congested links at random. More specifically, we select a link to add to the current solution from the pool of congested links randomly and a link to drop from the current solution randomly. In the RS approach, we examine neighborhood sizes from one to ten. Conversely, in a One Swap (OS) neighborhood, we drop each link in the current solution one at a time and replace it with another link from the pool of congested links randomly. Hence, the size of the OS neighborhood is as large as the number of links in the current solution. That is, if there are seven links in a current solution, then seven unique neighbor solutions are generated with each link in the current solution being replaced by another congested link. The Two-Random Swap (TS) neighborhood extends RS to consider two links simultaneously. In particular, TS selects two add/drop link swaps at random and creates neighbor solutions equal to the number of links in the current solution.

4.2.1 *Local Search*

We develop a local-search procedure for each of the neighborhoods. A flowchart of the search procedure is shown in Figure 2. Our local-search implementation begins with an initial solution

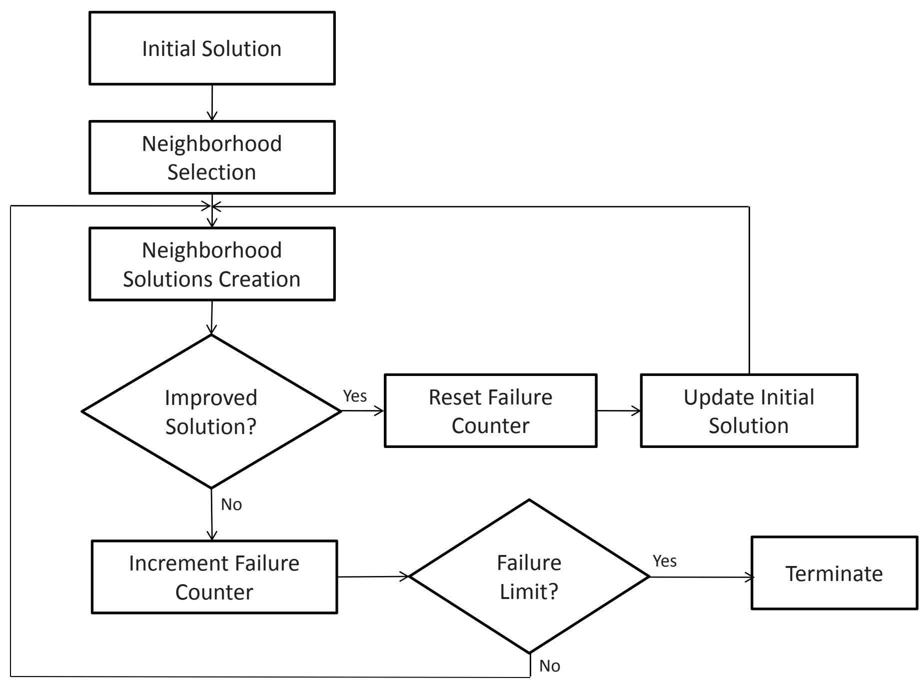

Figure 2: Local-search flowchart

returned by the construction heuristic. In local search, a neighborhood solution becomes the next current solution only if it improves upon the best solution thus far. In other words, the objective function value must be better than the current best value. Please note that given a particular solution, its objective value is returned by the simulation model. When comparing the objective value of the neighbor solutions to the current network solution, if a better neighbor solution is not found, then a failure counter is incremented and the neighbor solutions are re-selected. If the failure counter reaches a predetermined failure limit without finding a better solution, the local-search algorithm terminates. Otherwise, the failure counter is set to zero, and the current solution is updated with the newly found, better neighbor solution. Since our neighborhoods depend heavily on the random selection of links, the failure counter gives an opportunity to break free from local minima. In our experiments, we set the failure counter to five consecutive iterations without objective value improvement.

4.2.2 *Tabu Search*

As before, we represent a solution to our problem with a set of chosen congested links. Again, a move in the neighborhood of the current solution corresponds to an RS, OS, or TS neighborhood move. To prevent cycling and re-visiting prior solutions, tabu move restrictions are employed. In our implementation, we classify a dropped link from a solution as tabu for a specified number of solution procedure iterations, i.e. tabu tenure. The tabu tenure equals the number of links in the solution.

The tabu-search algorithm uses a tabu list $\mathbf{T}$, where $\mathbf{T} = (T_1, \ldots, T_L)$ with each T_l representing the tabu status of a tabu link. If $T_l > 0$ for some link $l \in \mathcal{L}$, then link l is tabu and will remain tabu for T_l iterations. Non-tabu links have a value of zero for T_l. At each iteration, when a candidate solution obtained results in dropping a link l, T_l is assigned the tabu tenure and the other positive entries in the tabu list are decreased by one. This is a type of recency-based or short-term memory since the tabu list shows how recently the solutions are visited. In this study, even without intermediate- and long-term memory components, we obtain high-quality solutions in our experiments with tabu search, as we report in Section 6.

An aspiration criterion is used to overrule the tabu restrictions so we can avoid escapes from attractive unvisited solutions. That is, even if a newly obtained solution at an iteration involves a tabu link, it is accepted as a legitimate solution if it satisfies the aspiration criterion. In our study, the aspiration criterion states that if a solution involving a tabu link has a better objective value than the best-known solution, then the tabu status is disregarded. Otherwise, if the aspiration criterion is not satisfied, we continue to the next iteration with the best non-tabu solution. The search terminates when a pre-set number of iterations is reached.

In Display 1, we describe the implementation of our tabu-search algorithm. The parameters used in tabu search are the maximum number of iterations and the tabu tenure. In the beginning of the algorithm, we initialize these parameters as well as the tabu list. Since no link is tabu in the beginning, the tabu list consists of zeros. An initial solution, $\mathbf{X}^I$, is obtained using one of the construction algorithms previously described. At each iteration, we search the neighborhood of the initial solution (based on one of the three neighborhood approaches) and pick the best solution in the neighborhood as the current solution, $\mathbf{X}^C$. To accept this solution as the best, we check the tabu status of the link that was added to create it. There are two possible outcomes of this status check. First, if the current solution, $\mathbf{X}^C$, does not contain a tabu link, we accept this solution as the current solution. Then we check if this new solution is better than the overall best solution, $\mathbf{X}^{Best}$, so far. If it is better, we update the overall best solution with $\mathbf{X}^C$. We also update the tabu list by decreasing all the positive entries by one and setting the value for the newly dropped link to the tabu tenure value. Second, if the current solution contains a tabu link, we check the aspiration criterion. If the aspiration criterion is satisfied, we accept the solution as the overall best solution,

$\mathbf{X}^{Best}$. The tabu list is also updated as before. When the aspiration criterion is not satisfied, we pick the best non-tabu solution from the neighborhood and accept it as the current solution. Again, we update the tabu list. The procedure is continued in this fashion until the preset total number of iterations is performed.

Algorithm 1 Tabu-search algorithm

Input: $\mathbf{X}^I, Z(\mathbf{X}^I)$
Output: $\mathbf{X}^{Best}, C(\mathbf{X}^{Best})$

$\mathbf{X}^{Best} \leftarrow \mathbf{X}^I; C(\mathbf{X}^{Best}) \leftarrow C(\mathbf{X}^I)$
$\mathbf{X}^C \leftarrow \mathbf{X}^I; C(\mathbf{X}^C) \leftarrow C(\mathbf{X}^I)$
maxIter $\leftarrow$ 300 ; *tabuTenure* $\leftarrow |\mathbf{X}^I|$.
iterNo $\leftarrow$ 0.
while *iterNo* $<$ *maxIter* **do**
    $\mathcal{N} \leftarrow$ *neighborhood*$(\mathbf{X}^C)$.
    $\mathbf{X}^* \leftarrow \arg\min\{Z(\mathbf{X}^n) : \mathbf{X}^n \in \mathcal{N}\}$.
    Check tabu status of $\mathbf{X}^*$.
    if $\mathbf{T}[tabu] = 0$ **then**
        $\mathbf{X}^C \leftarrow \mathbf{X}^*$; $Z(\mathbf{X}^C) \leftarrow Z(\mathbf{X}^*)$
        if $Z(\mathbf{X}^C) < Z(\mathbf{X}^{Best})$ **then**
            $Z(\mathbf{X}^{Best}) \leftarrow Z(\mathbf{X}^C)$; $\mathbf{X}^{Best} \leftarrow \mathbf{X}^C$.
        end if
        Update tabu list $\mathbf{T}$.
    else
        if $Z(\mathbf{X}^*) < Z(\mathbf{X}^{Best})$ **then**
            $Z(\mathbf{X}^{Best}) \leftarrow Z(\mathbf{X}^*)$; $\mathbf{X}^{Best} \leftarrow \mathbf{X}^C$.
            Update tabu list $\mathbf{T}$.
        else
            Let $\mathbf{X}^{**}$ be the best non-tabu solution.
            $\mathbf{X}^C \leftarrow \mathbf{X}^{**}$; $Z(\mathbf{X}^C) \leftarrow Z(\mathbf{X}^{**})$
            Update the tabu list $\mathbf{T}$.
        end if
    end if
    iterNo $\leftarrow$ *iterNo* + 1
end while

Section 5
Simulation Model

The algorithms detailed in Section 4 communicate with a deterministic simulation model representing a roadway network. The deterministic aspect of the model allows for a final model value to be obtained and used in conjunction with the optimization. If the model were stochastic, the possibility would exist to reject a potential improvement in infrastructure design. In this research, the simulation model is constructed using TRANPLAN, a transportation-planning simulation software package capable of generating macroscopic-level traffic models. The use of a macroscopic model is appropriate, as the focus is to investigate congestion-mitigation strategies and their effect on traffic flow on the entire network, not a specific roadway. The macroscopic model examines the total daily flow of vehicles on all roadways simultaneously, which allows the optimization model to analyze specific changes to roadway infrastructure. Thus, it is more appropriate to use a macroscopic model than a microscopic model in this case. A microscopic model would make evaluation and solution search difficult for the optimization component since a microscopic model would return different values throughout the day. Essentially, a final value is required for a typical day so that solutions can be compared.

TRANPLAN uses text-based input files to model the roadway structure and traffic flow on the network. A TRANPLAN model can be described as information flowing between four modules. Figure 3 shows the information exchange between the modules.

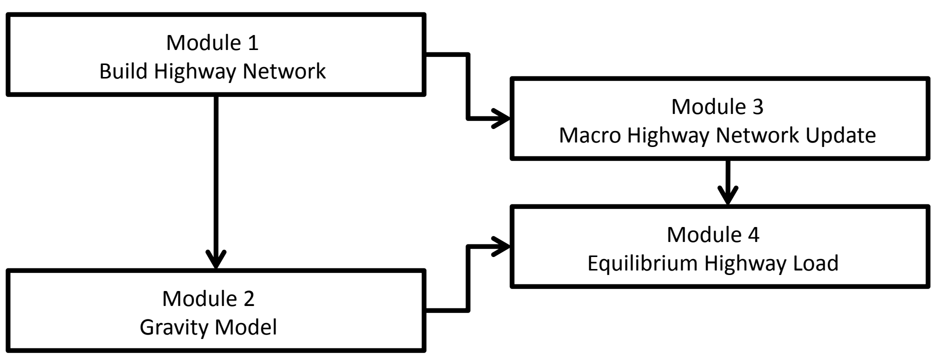

Figure 3: Simulation modules

Module 1 is invoked first in an execution. This module is responsible for constructing the roadway network by translating a text-based data file. This network configuration file contains the entire structure of all nodes and links (i.e. all roads). Additionally, each link in the network has a classification code. This code characterizes the road type (e.g. interstate highway or divided highway) of each link, the number of lanes of each road segment, and the vehicle capacity of each road segment. This module also divides the study area into zones. The movement of vehicles between these zones represents the flow of traffic on the network.

The volume of traffic flowing between any two zones is generated by module 2. In this module, a text-based production/attraction file represents the vehicle volume flowing out of and into each zone. Of course, vehicle movement between zones occurs via the roadway network. If the vehicle volume on a roadway link exceeds its capacity, that link is considered to be congested. This link may then be targeted for capacity increase in the solution procedure.

Module 3 holds a link-capacity data file that contains an exhaustive list of the link classification codes and their definitions. Thus, to change link capacities from one simulation-optimization iteration to the next, the classification code of a link must be altered in the network configuration file, which is then translated by the link-capacity data file. Specifically, the values in this file define the vehicle capacity of each road segment in the network, against which vehicle volume is measured to determine if congestion is present.

In module 4, the path for each vehicle from its origin to its destination is determined. The goal is to minimize the sum of all vehicle travel times on a particular network configuration. This is accomplished by establishing a network equilibrium that, in the context of transportation assignments, occurs when no vehicle trip can be made by an alternate path without increasing the total travel time of all vehicles in the network. More specifically, the model assigns a vehicle from origin to destination using a shortest-path algorithm adjusted for congestion. The initial assignment assigns all trips between origin and destination locations on the shortest roadway. Then the volume assigned to the roadway is compared to the capacity of the facility, and a new travel time is developed using a capacity restraint curve. A portion of the assigned model volume is then moved to an alternate path if the new travel time is greater than the original travel time. This calculation of travel time for individual roadway links is performed, and the trips are adjusted until the change of travel time between specific routes is equal. The output from module 4 (i.e. total vehicle hours on the network) is used by the optimizer to compare the effectiveness of congestion-mitigation strategies.

During the first iteration of the simulation-optimization procedure, each module is invoked. However, in subsequent iterations in which different congestion-mitigation strategies are being evaluated by the simulation model, only modules 1, 3, and 4 are invoked. This is a result of only the network configuration file being altered from one iteration to the next. The production and attraction between network zones remains constant throughout the execution of the solution procedure.

Section 6
Experimentation

In this section, we test our solution methodology using an actual traffic scenario and data set from Mobile, AL, an urban environment situated on the coast of the Gulf of Mexico. This region makes for an excellent testbed due to its expected growth over the next 25 years. Despite the recent global economic downturn, this region is experiencing economic growth, especially in the areas of manufacturing and freight movement, where the Port of Mobile is becoming a major access point to the eastern United States for global firms. This economic upturn will create more jobs in the area which, in turn, will increase the population in the region and the volume of private vehicles on the roadway network. Along with the increased commercial traffic, traffic congestion is certain to worsen over time. Figure 4 shows the current (2007) and predicted (2030) traffic congestion locations on the Mobile roadway network.

(a) Mobile network (2007) (b) Mobile network (2030)

Figure 4: Mobile, AL roadway congestion

The darkened areas on the traffic network links represent points of congestion. A thicker link indicates greater congestion. By examination of Figure 4, it is evident that a considerable increase in congestion is forecast for the roadways by 2030. Thus, we investigate the performance of our solution approach on the 2030 network in terms of solution quality (i.e. percent decrease in congestion) and computational run time.

To simplify the presentation of the experimentation, a run code was designed to describe for each outcome the solution initialization method, the type of search algorithm used, the method of link exchange in a solution vector, and the neighborhood size of a solution. In the run code, the first character is a “G” or “R” to denote if the initial solution was generated using a greedy or random technique. The second character is a “T” or “L” to designate if tabu search or local search was the solution strategy. The third and fourth characters are “RS”, “OS”, or “TS” to specify whether Random Swap, One Swap, or Two-Random Swap was used as the neighborhood-search strategy. Run codes with a fifth, sixth, and possibly seventh character represent the number of neighbor solutions in each iteration (e.g. 5N represents a neighborhood size of 5). To illustrate, a run code of GTRS5N translates to a solution run using a greedy technique for initialization, tabu search as the solution strategy, random swap for the neighborhood search, and a neighborhood size of 5. In the local-search implementation, we set the failure limit to five iterations. Finally, the termination criterion for the simulation-optimization procedure is a maximum of 300 iterations.

6.1 Traffic-Congestion Savings

In this section, we present the results of our algorithmic approaches in terms of the percent decrease in traffic congestion that would be realized with the implementation of the mitigation strategy suggested by each experimental run. After consultation with the director of the Mobile Metropolitan Planning Organization, we concentrated on the mitigation strategy of adding lanes as a means to increase capacity of roadways. Although there are other mitigation strategies available, such as the addition of high-occupancy vehicle lanes and reversible lanes, their representation as a mitigation strategy would also take the form of a roadway-capacity increase. In terms of cost, the addition of a lane (in each direction) is $5,000,000 per mile. Table 1 shows the top 20 solutions in terms of congestion savings.

This experimentation is based on the 2030 network congestion shown in Figure 4, where the predicted congestion level translates to 357,836 total vehicle hours and the non-congested level to 307,461 total vehicle hours. The values reported in Table 1 represent the savings that would be realized in 2030 if the strategy suggested by an experimental run (subject to a budgetary constraint of $25 million) were implemented. From Table 1, the maximum savings of total vehicle hours is 4.26% (i.e. 355,691 total vehicle hours).

The congestion savings are calculated with respect to the amount of congestion expected to be present on the network in 2030, which is the difference in total vehicle hours between the congested network and non-congested network. To explicitly calculate, the amount of expected congestion is 50,375 vehicle hours $(357,836 - 307,461)$. Thus, a 4.26% congestion savings is calculated as $(357,836 - 355,691)/50,375$. The total vehicle hours on the non-congested network (i.e. 307,461) is the lower bound on the network, as it is not possible to completely eliminate vehicle hours on the network. Thus, this value should be used in any congestion-savings calculation.

From a methodological viewpoint, the tabu-search strategy performs much better than the local-search strategy with 18 of the top 20 solutions based on tabu search. This is not unexpected; tabu search should generally find better solutions because it has a mechanism to avoid becoming

Table 1: Traffic-congestion savings and computational runtime performance

Run Code	Total Vehicle Hours	Congestion Savings	Run Time (sec)
GTRS9N	355,691	4.26%	5,483
GTRS10N	355,733	4.17%	6,541
RTRS6N	355,779	4.08%	5,488
RTOS	355,818	4.01%	8,872
GTRS7N	355,824	3.99%	4,103
RTRS8N	355,848	3.95%	6,812
GTTS	355,880	3.88%	6,630
GTRS6N	355,892	3.86%	3,651
RTRS10N	355,912	3.82%	7,488
GTRS8N	355,971	3.70%	5,137
GTOS	355,971	3.70%	11,540
RTRS9N	356,052	3.54%	6,979
RTRS5N	356,064	3.52%	3,798
RLRS10N	356,072	3.50%	439
GTRS5N	356,078	3.49%	3,086
RTRS4N	356,192	3.26%	2,266
GTRS4N	356,234	3.18%	2,444
RLRS9N	356,288	3.07%	861
GTRS3N	356,290	3.07%	1,714
RTTS	356,291	3.07%	5,662

trapped in local optima. Thus, the tabu-search strategy likely explores more of the solution space and finds better overall solutions. It is also of note that the better solutions tend to have larger neighborhood sizes. This is not surprising since a larger neighborhood size also allows for greater exploration of the solution space during each iteration of the solution procedure.

6.2 Methodological Comparison

In this section, we investigate the performance of our algorithmic approaches in terms of computational run time and selection of search parameters.

Table 1 shows the computational run times for the top 20 solutions in terms of congestion savings, but no obvious trends appear. Figure 5 displays the data in a scatterplot for re-examination. From

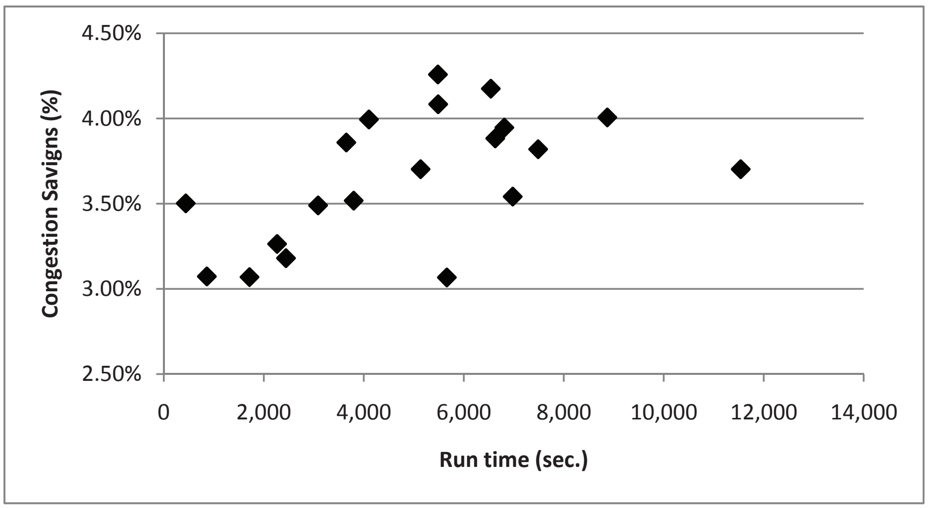

Figure 5: Congestion savings vs. run time scatterplot

the scatterplot, a general upward trend is noticeable. In other words, congestion savings increase as run times increase. This outcome makes sense, as heuristic search procedures tend to find better solutions the longer they run. The minimum run time is 439 seconds while the maximum run time is 11,540 seconds. The solution with the greatest congestion savings (i.e. 4.26%) has a run time of 5,483 seconds, but even the solution with the lowest run time shows significant congestion savings of 3.50%. This demonstrates the ability of this solution approach to generate quality solutions in a short time. This characteristic may be of great importance if the evaluation of mitigation strategies is time sensitive, such as during a disaster event. The solution approach would also be of tremendous benefit in the long-term planning of transportation networks. Typically, analysis of alternatives in transportation planning takes several months to perform. However, with a decision support tool based on simulation optimization, evaluation time can be greatly reduced even when considering the worst case result from Table 1 (i.e. 11,540 seconds, or about 3.20 hours).

Table 2 shows the effect of neighborhood size on solution search strategy (i.e. tabu search and local search) in terms of solution quality (total vehicle hours) and computational run time (in seconds).

Table 2: Neighborhood-size comparison

	Tabu Search				**Local Search**			
	Greedy Initial		**Random Initial**		**Greedy Initial**		**Random Initial**	
$\lvert\mathcal{N}\rvert$	**TVH**	**Run Time**	**TVH**	**Run Time**	**TVH**	**Run Time**	**TVH**	**Run Time**
1	356,852	539	356,883	514	357,558	53	357,567	49
2	356,709	1,125	356,412	1,228	357,145	171	357,410	138
3	356,290	1,714	356,561	1,605	356,607	198	357,202	191
4	356,234	2,444	356,192	2,266	357,003	198	356,903	253
5	356,078	3,086	356,064	3,798	356,345	539	356,790	261
6	355,892	3,651	355,779	5,488	356,881	271	356,702	342
7	355,824	4,103	356,314	4,118	356,374	507	357,204	203
8	355,971	5,137	355,848	6,812	356,366	640	356,574	507
9	355,691	5,483	356,052	6,979	356,674	382	356,288	861
10	355,733	6,541	355,912	7,488	356,976	555	356,072	439

Examining Table 2, run times increase, in general, as the neighborhood size ($\lvert\mathcal{N}\rvert$) increases. This is expected because an increase in $\lvert\mathcal{N}\rvert$ means more solutions are being evaluated by the simulation model during each iteration of the solution procedure. Furthermore, for each value of $\lvert\mathcal{N}\rvert$, the best network time (i.e. lowest total vehicle hours) is found using a strategy based on tabu search. This result is likely due to the diversity of trial solutions sent to the simulation model by the tabu-search algorithm, as opposed to the focused search employed by the local-search–based strategy. Lastly, for each value of $\lvert\mathcal{N}\rvert$, local search provides solutions in shorter times than tabu search. This outcome is likely due to the local-search procedure terminating as a result of becoming stalled at a local minimum and not providing improving solutions for several consecutive iterations (i.e. non-improving iteration limit exceeded). However, in some test instances, local search does provide a quality solution with a much shorter run time when compared to tabu search.

Section 7
Conclusions and Future Work

In this paper, we develop a simulation-optimization approach for a decision support tool to help determine the best strategies to mitigate the congestion of roadway networks. The optimization approach utilizes both tabu-search and local-search techniques to work in concert with a traffic-simulation model to explore the solution space. This approach is useful in determining the best set of roadway segments in which to implement mitigation strategies while adhering to budgetary constraints. This is especially useful for urban and regional transportation planners who have a large number of alternatives to consider. Combining the benefits of optimization and simulation, the overall solution approach provides an increased ability to investigate a large number of mitigation alternatives in a short period of time (on the order of hours) as opposed to typical alternative evaluations that take months to complete.

As a future research direction, we look to expand on the number of mitigation strategies available as well as investigate the possibility of regional transit systems to aid in the mitigation of traffic congestion. Furthermore, we plan to extend this work into the area of emergency and disaster response. During events where response time is critical, this methodology would serve as a way to examine response strategies in terms of maximizing the benefit to those affected by the disruptive event.

Section 8
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