

Network-Level Scheduling of Road Construction Projects Considering User and Business Impacts

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Abstract: *Construction projects are often associated with partial or full road closures, which result in user costs and community disruptions in terms of reduced business productivity. A number of studies have addressed the problem of scheduling construction projects based on a variety of stakeholder objectives. Yet still, there seems to exist a few gaps regarding (a) possible tradeoffs between road user cost reduction and business cost reduction associated with optimal scheduling, (b) role of the project type (rehabilitation and capacity expansion) on the solution methodology, and (c) lack of solution algorithm to address the problem complexity by deriving the optimal solution. In addressing these gaps, this paper adopts a novel approach for developing an optimal project schedule for multiple road projects within a construction horizon. The goal is to minimize the overall cost of the projects to road users and adjacent businesses over the construction horizon. The project scheduling problem is formulated as a mixed-integer nonlinear program. We solve the problem using a local decomposition method. The methodology is demonstrated using the Sioux Falls city network with two project types: capacity expansion and rehabilitation. The results of the numerical experiment suggest that (i) the solution algorithm converges to optimal solution in finite iterations and (ii) a network-wide scheduling of urban road projects using explicit optimization can yield a significant reduction in business disruption costs while incurring a relatively smaller increase in system travel time, and overall, is superior to a schedule developed only considering the total system travel time.*

1. INTRODUCTION

1.1. Research Background

Scheduling of transportation infrastructure projects in metropolitan areas continues to receive significant attention in the literature (Kumar and Mishra, 2017). Although these projects are ultimately intended to enhance urban mobility and accessibility, they cannot be implemented efficiently without establishing construction work zones with full or partial closure of specified roads in the network. Work zones last for rather small durations compared to the infrastructure life; however, work zones have several negative impacts on users and communities including increased traffic delay and reduced safety during the construction period, particularly during morning and evening peak commutes. The FHWA (2016) estimates that work zones constitute about 10% of overall congestion, which in 2014 translated into an estimated annual fuel loss of over 310 million gallons. In addition, construction work zones can decrease accessibility to locations with socio-economic significance and subsequently cause reductions in business revenue (referred to as business disruption) to commercial entities located in the work zone influence area (Yavuz et al., 2017). For example, in 2016 the Indiana Department of Transportation (INDOT) implemented a \$22 million project in Lafayette, Indiana, that caused significant

reduction in revenue to businesses located near the construction work zones; the project consequently received opposition from neighborhood businesses (Ambrose, 2016). Woldemariam et al. (2019) conducted business surveys and found that during the construction season, the area businesses lose approximately 10% of their customers. To minimize the negative safety and mobility impacts associated with work zones, it is essential to develop planning tools to optimally schedule construction work zones. An example of such a tool is a framework that can help agencies schedule their projects in a manner that minimizes the adverse impacts of construction.

1.2. Literature Review

The associated literature on this topic can be classified into two groups based on project duration. The first group deals with scheduling short-term projects with the duration of few hours or a few days (typically within a week) (Chien et al., 2002; Jiang and Adeli, 2003; Chen and Schonfeld, 2004; Ma et al., 2004; Cheu et al., 2004; Cheu and Ma, 2002; Fwa et al., 1998; Adeli and Ghosh-Dastidar, 2004; Lim et al., 2014; Ponz-Tienda et al., 2015; Jong and Schonfeld, 2001). Tseng and Chen (2006) investigated the project scheduling problem under resource constraints. They proposed a hybrid metaheuristic method and show its efficiency in solving the problem. The second group deals with scheduling of long-term projects with the duration of a few months. In contrast to the first group, this group does not address work zone configuration design or timing of work zones within a day or within a week (for example, nighttime work or weekend work). The current paper falls into the second group.

This latter group can be further classified into three subgroups depending on the goals of the transportation agency decision-maker. In the first subgroup, the objective is to address the goal of system operator, i.e., minimizing the construction cost. In a seminal paper on this subject, Adeli and Karim (1997) developed a mathematical formulation to obtain the optimal scheduling of highway construction projects to minimize the construction cost. In their study, the authors factored the project cost-duration tradeoffs, a consideration that was later echoed by Lee et al. (2015). The Adeli and Karim (1997) study provided the greater flexibility for transportation agency decision-maker to determine the optimal duration of each project. Subsequently, in other pioneering studies, Senouci and Adeli (2001) extended the model proposed by Adeli and Karim (1997) to capture the resource leveling which decrease fluctuation in the resource usage. Otherwise, the construction schedule can lead in short-term hiring of less experienced workers and increasing the employment processing costs. Karim and Adeli (1999) proposed an object-oriented information model for construction scheduling using the neural network technique that was used in their previous study, and Adeli and Karim (2001) developed a neural dynamic construction scheduling and cost optimization problem framework that used both linear and nonlinear relationships between cost and project duration. These studies threw much light on the scheduling of both road rehabilitation and capacity expansion projects, and laid the groundwork for subsequent studies that made

various contributions including the consideration of post-project capacity expansion. Szeto et al. (2010) proposed a single-level single-objective optimization program for construction project scheduling to maximize the societal benefits including toll and transit revenues.

The second subgroup of studies deal with project scheduling with the goal of minimizing the impact on road users. Early studies in this field tackled the problem using either control theory or dynamic programming. On the other hand, Janson et al. (1991) formulated a mathematical program to schedule network improvements for U.S. highway networks in a way that minimizes the total user delay. They proposed a heuristic method to solve the optimization problem. Their heuristic provided a good solution for small highway networks but could not guarantee the solution's optimality. Jong and Schonfeld (2001) developed a genetic algorithm to schedule infrastructure projects in any sector including highways and waterways. They applied the model to a water distribution system with 20 nodes and estimated the corresponding service delays under different combinations of project schedules. Later, Shayanfar et al. (2016) reformulated the objective function in terms of total user delay and integrated it into the genetic algorithm proposed by Jong and Schonfeld (2001). Shayanfar et al. (2016) also investigated other metaheuristic methods, such as tabu search and simulated annealing, but concluded that the genetic algorithm was the most efficient method for converging to the optimal solution. Tao and Schonfeld (2006) proposed an island model, as a variation of genetic algorithm, to optimize the road construction selection and scheduling under resource constraints. Kim et al. (2008) developed a model to sequence and schedule new road construction projects under a year-to-year budget constraint. They showed that simulated annealing method is more efficient in solving the model compared to genetic algorithm. Lo and Szeto (2009) developed the road construction selection and scheduling model that maximizes travelers surplus where transportation agency uses the toll revenue to improve traffic network. The proposed model is solved using the generalized reduced gradient algorithm. They showed that toll revenue can address the issue of shortage of available budget to improve the transportation infrastructure.

Gong and Fan (2016) developed an optimization model to minimize user delay by deriving the optimal starting dates of projects in the network. The developed model is only applicable to road rehabilitation projects without considering the post-implementation effects of projects on road capacities. Kumar and Mishra (2017) proposed a two-step methodology to determine the optimal sequence of a given set of projects located at the links of a network. First, they determined the optimal capacity improvement for a set of links. In the second step, they determined the optimal sequence of projects that minimized travel time increases during the construction horizon due to construction zones. However, in estimating the costs and benefits of the construction work zones, they did not consider the interdependency among the different projects. Kumar and Mishra (2017) also assumed equal distribution

of construction costs of each project across the construction horizon. On the other hand, this paper considers not only interdependencies among the various projects, but also the practical realization that the construction costs of each project are not necessarily distributed equally during the construction horizon. Bagloee et al. (2018) proposed a bi-level model to select, prioritize and schedule new road construction projects that minimizes travel delays. It incorporates two main characteristics, (i) prerequisite conditions and (ii) interdependency of the benefit of projects' completion. The proposed model is solved using a hybrid heuristic method consisting of a supervised learning technique and optimization method.

In the third subgroup of studies, project schedules are developed that minimize the adverse impacts of construction work zones on the community. For example, Jiang and Szeto (2015) proposed a mathematical optimization where the objective of the transportation agency decision-maker is to maximize the travel cost reduction and minimize the health costs (traffic emissions, noise, and accidents) due to the network improvement projects. They solved their model using the artificial bee colony technique.

Table 1 summarizes the literature related to the construction scheduling problem. The goal is to identify the optimal combination of project start dates that satisfies different goals or concerns of the transport decision-maker and the road users. It can be seen that the studies did not explicitly address the impacts of construction work zones on the revenues of surrounding businesses. Further, although several studies exist that captured the interdependency between the agency's planning level decisions and the travelers' operations-level decisions in road project scheduling, they did not consider both the capacity reduction during project implementation and the capacity expansion after the project completion. Finally, the existing studies in the literature used heuristic methods, which typically face much difficulty in ensuring solution optimality.

There also exist other studies that addressed the problem of scheduling from the perspective of resource constraints (Davis and Patterson, 1975; Cheng and Gen, 1997; An et al., 2017) and cost-duration tradeoffs that account for the non-constant nature of project duration (Talbot, 1982; Zhang et al., 2015).

Table 1. Construction scheduling problem: A synthesis of selected literature

Project durations	Stakeholder	Reference	Solution algorithm	Project types	Bi-level model (Yes/No)	Peri-constr. Cap. Red. and Post-constr. Cap. Incr.**
Short-term	System users	Fwa et al (1998)	Genetic algorithm	Road rehabilitation	No	N/A*
		Cheu and Ma (2002)	Genetic algorithm	Road rehabilitation/ Capacity expansion	No	N/A
		Ma et al. (2004)	Genetic algorithm	Road rehabilitation	No	N/A
		Cheu et al. (2004)	Genetic algorithm	Road rehabilitation/ Capacity expansion	No	N/A
	System operator and users	Chien et al. (2002)	Heuristic procedure	Road rehabilitation	No	N/A
		Jiang and Adeli (2003)	Neural network	Road rehabilitation/ Capacity expansion	No	N/A
		Chen and Schonfeld (2004)	Simulated annealing	Road rehabilitation	No	N/A
Long-term	System operator	Adeli and Karim (1997)	Artificial neural network	Road rehabilitation/ Capacity expansion	No	No
		Karim and Adeli (1999)	Object-oriented information model	Road rehabilitation/ Capacity expansion	No	No
		Adeli and Karim (2001)	Neural dynamic algorithm	Road rehabilitation/ Capacity expansion	No	No
		Szeto et al. (2010)	Premium solver platform	Capacity expansion	Yes	No
	System users	Janson et al. (1991)	Rank-add-and-swap heuristic algorithm	Capacity expansion	No	No
		Shayanfar et al. (2016)	Genetic algorithm /Tabu search	Capacity expansion	Yes	No
		Gong and Fan (2016)	Genetic algorithm	Road rehabilitation	Yes	No
		Kumar and Mishra (2017)	Gradient algorithm	Capacity expansion	Yes	No
	Community	Jiang and Szeto (2015)	Artificial bee colony	Capacity expansion	Yes	No
	System users and community	Our paper	Local decomposition method	Road rehabilitation/ Capacity expansion	Yes	Yes

*N/A: Not applicable

** Peri-construction capacity reduction and Post-construction cap increase

1.3. Research Approach and Contributions

The present paper develops a bi-level formulation to solve the project scheduling problem. The bi-level structure has a vast application in various areas in transportation planning such as locating hydrogen refueling stations (Miralinaghi et al., 2017). At the upper level, the transportation agency decision-maker's goal is to schedule construction projects to minimize the project impacts on road users and the community. These impacts can manifest in two ways. First, construction work zones generally lead to higher travel times because work zones cause travelers to slow down on the regular route or to detour. Further, construction work zones impact the community by reducing accessibility to the surrounding businesses, which leads to reduced revenue for these business entities (Woldemariam et al., 2019). At the lower level, travelers seek to minimize their travel time by making travel decisions, e.g., route choice, based on the project schedule derived at the upper level. A detailed review on the lower level model is given by Sheffi (1985), Miralinaghi (2016) and Amirgholy and Gonzales (2017). Therefore, this paper develops a bi-criteria optimization program for scheduling construction projects to minimize total system travel time and business disruption costs. The framework of this paper is applicable to at least two classes of construction projects at existing highways; and is demonstrated using two classes: road rehabilitation and capacity expansion (lane-addition).

In a typical construction scheduling problem setting, the transportation agency decision-maker divides the construction horizon into multiple construction periods, where each period duration is typically a few months. The projects then are scheduled during construction horizon over a few years. This may be subject to budget constraints. It is assumed that any excess construction funds (the part of the budget left unused) in each period can be carried over to future periods. The projects include road capacity expansion and rehabilitation projects that typically last a few months. All projects must be completed before the end of the entire construction horizon. For capacity expansion projects, the road capacity decreases during the implementation period and increases after these projects are completed. For road rehabilitation projects, the road capacity decreases during the project implementation and returns to the initial capacity after the project implementation. The average travel demand and road capacity are leveraged as benchmarks for the travel demand and road capacity, respectively, within each period. Therefore, they are constant within each period of the construction horizon but can vary across periods.

The project scheduling problem is a mixed-integer nonlinear program with complementarity constraints. For a given set of projects to implement in a construction season, there are two extreme possibilities for scheduling them, (a) implement all the projects within the same period (leading to total gridlock during that period but freeing up the entire network thereafter), and (b) spread out the projects uniformly or even randomly in various construction periods across the construction horizon. In between these two extremes, there is a multitude of possible construction schedules. For a typical network with n projects and τ time

periods, there exist τ^n combinations by which the projects can be scheduled. For example, for 18 projects to be scheduled within 6 construction periods, then there are 6^{18} possible construction schedules (i.e., 1.016E14). Although mixed-integer linear problems (MILP) have been extensively studied in literature (Hsu et al., 2018, 2019; Bogenberger et al., 2015; Hammad et al., 2017; García-Nieves et al., 2019), we formulate this problem as mixed-integer nonlinear model. It is classified as an NP-hard problem and very difficult to solve (Bazaraa et al., 2013). Hence, to solve the problem in a finite number of iterations, we adopt the local decomposition method (Zhang et al., 2009).

The contributions of this paper are fourfold. First, the paper develops a multi-period, bi-criteria mathematical program that minimizes the effect of construction work zones on total system travel time and business revenue in the surrounding communities. Second, for capacity expansion projects, past studies have developed project scheduling methodologies that consider the effect of capacity expansion completion of such projects. There is no evidence in the literature that any past study on this topic considered both the capacity reduction during project implementation and the capacity expansion after the project completion. In this paper, the latter consideration is captured by accounting for the inter-project interdependencies. Third, in contrast to previous studies, the present paper assumes that the durations of capacity expansion projects can exceed one period, which is considered more representative of current contract conditions in the practice. Fourth, in contrast to existing studies on this topic, this paper does not use heuristic methods but instead adopts a local decomposition method that can provide the optimal solution in a finite number of iterations.

The remainder of this paper is organized as follows. First, the bi-level model for obtaining the optimal project schedule is formulated. Then, the solution algorithm is developed to solve the bi-level model. Next, a case study is presented and the results of numerical experiments are used to demonstrate the efficacy of the proposed approach. Finally, some concluding comments are provided to guide implementation of this study and to offer directions for possible future research.

2. METHODOLOGY

In this section, the project scheduling problem is formulated as a bi-level problem. At the upper level, the transportation agency decision-maker decides the optimal sequence of construction projects to minimize the weighted sum of the travel system travel time and business disruption costs due to construction work zones during the construction horizon. At the lower level, travelers make their travel decisions based on the effect of the sequence of projects scheduled at the upper level. Travelers choose routes with the minimum travel time between each origin-destination (O-D) pair.

In the next section, we first present some preliminaries and assumptions of this paper. Then, we present the upper-level model for determining the optimal schedule of

construction projects. Next, we formulate the lower-level model as a nonlinear program with complementarity constraints. Finally, we present the integration of the upper- and lower-level models.

2.1 Preliminaries and Assumptions

This section introduces some preliminaries and states assumptions of this paper. The construction horizon is divided into τ periods each of a few months' duration. There are two sets of project types: (i) road capacity expansion and (ii) road rehabilitation. During the implementation of these projects, there can be full closure or partial closure with reduced capacity. The project duration is expressed in terms of the number of periods. For example, if the period duration is one month and the project duration is four months, the project duration is equal to four periods. The construction budget B^t in each period is known *a priori* and can vary across periods. The notations used in the paper are shown below.

In this paper, the link travel time σ_{ij}^t is assumed to follow the Bureau of Public Roads (BPR) function, as follows:

$$\sigma_{ij}^t = f_{ij}^t + b_{ij}^t \cdot (v_{ij}^t)^4 \quad \forall (i, j) \in A \quad (1)$$

where f_{ij}^t is the free-flow travel time on link (i, j) in period t . The travel time function parameter b_{ij}^t can be calculated as follows:

$$b_{ij}^t = \frac{0.15f_{ij}^t}{(y_{ij}^t)^4} \quad \forall (i, j) \in A \quad (2)$$

where y_{ij}^t denotes the capacity of link (i, j) in period t . If the construction project on link (i, j) starts in period t , i.e., $e_{ij}^t = 1$ or $\gamma_{ij}^t = 1$, its capacity in period $t' \geq t$ is equal to $c_{ij}^{t'-t+1}y_{ij}^t$, where $c_{ij}^{t'-t+1}$ is referred to as the modification factor for the capacity of link (i, j) at $t' - t + 1$ periods after the initiation of the construction project. For example, if $c_{ij}^{t'-t+1} = 0$, then link (i, j) is fully closed at $t' - t + 1$ periods after the start of the construction project. To derive the capacity of links during the project construction, the neural network proposed by Jiang and Adeli (2003) can be used; this leverages several interacting variables such as the project type and weather condition. In a subsequent research, Jiang and Adeli (2004a) developed an object-oriented model to derive the capacity of links during the construction project implementation. In another seminal study, Jiang and Adeli (2004b) estimated the capacity using the clustering-neural network with the capability to forecast reliably using limited data. The construction cost of each project can be also estimated using the neural network concept proposed by Adeli and Wu (1998).

In this paper, the construction scheduling problem entails the following assumptions. First, it is assumed that construction projects impact only the link capacities and do not impact the free-flow speed. Further, although the road rehabilitation projects can improve the pavement surface quality, such increase in quality is assumed to have no effect on the road capacity and free-flow speed. In addition, it is

assumed that both capacity expansion and road rehabilitation projects are completed before the end of the construction horizon. Furthermore, the leftover budget funds in each period can be carried over into future periods. Also, it is assumed that the set of projects can be scheduled during the planning horizon such that travelers are always able to fulfill their travel needs. In other words, construction projects can be scheduled without isolating any node in the traffic network due to the closure of all its connecting links. Next, the travel demand is assumed to be an elastic and decreasing function of only travel time. Further, this paper assumes that travel demand is deterministic throughout the construction horizon. In addition, in our paper, we assume that travelers have full information on road traffic conditions before departing from the trip origins. This information is typically obtained from traveler information systems, advanced navigation technologies such as smartphones, or experience/familiarity gained over multiple days of the road network use. Therefore, the model ignores the enroute changes in the traveler's route decisions. Further, it is assumed that businesses are located at nodes and transportation agency is able to forecast the average number of customers of each business and their expenditure. Finally, the interest rate is not accounted for in the planning problem of this paper, for at least two reasons. First, the duration of construction horizon is only a few months. Second, this assumption can be considered reasonable for countries with relatively stable economies such as developed countries.

2.2 Upper-Level Model

At the upper level, the transportation agency decision-maker seeks to minimize the weighted sum of the total system travel time and business disruption costs. The weights of total system travel time and business disruption costs are denoted by W_1 and W_2 , respectively (that is $W_1 + W_2 = 1$). The upper-level model is subject to a period-specific construction budget B^t in each period t . After each period t , any leftover construction budget ξ^t is carried over to the next period $t + 1$.

To measure the impacts of construction on surrounding businesses, let $q_i^{r,t}$ denote the travel demand between origin r and destination i in period t . This travel demand is assumed to be an elastic, decreasing, and convex function $D_{r,i}$ of minimum travel time between each O-D pair. Further, let $\beta_{i,m}^{r,t}$ denote the percentage of demand of O-D pair (r, i) that represents the customers of business m at node i in period t . It is assumed that each customer spends $q_{i,m}^t$ dollars in business m of node i in period t . Then, the revenue of business m located in node i in period t , $\zeta_{i,m}^t$, can be calculated as follows:

$$\zeta_{i,m}^t = q_{i,m}^t \sum_r \beta_{i,m}^{r,t} q_i^{r,t} \quad \forall t \quad (3)$$

Let $\zeta_{i,m}^{0,t}$ be the revenue of business m in period t in the no-construction scenario. Then, the business disruption cost of business m located at node i in period t can be expressed as follows:

$$\varpi_{i,m}^t = \zeta_{i,m}^t - \zeta_{i,m}^{0,t} \quad \forall t \quad (4)$$

The upper-level model, with objective Z^U , can be formulated as a mixed-integer nonlinear model as follows:

$$\min_{e,\gamma} Z^U = W_1 \sum_{t=1}^T \sum_{(i,j) \in A} \alpha \sigma_{ij}^t (v_{ij}^t) v_{ij}^t - W_2 \sum_{t=1}^T \sum_{(i,m)} \zeta_{i,m}^t \quad (5)$$

$$\sum_{(i,j) \in \bar{A}} \kappa_{ij}^1 \gamma_{ij}^1 + \sum_{(i,j) \in \bar{A}} \kappa_{ij}^1 e_{ij}^1 + \xi^1 = B^1 \quad (6)$$

$$\sum_{t=1}^l \left(\sum_{(i,j) \in \bar{A}} \kappa_{ij}^{l+1-t} \gamma_{ij}^t + \sum_{(i,j) \in \bar{A}} \kappa_{ij}^{l+1-t} e_{ij}^t \right) + \xi^l = B^l + \xi^{l-1} \quad l = 2, \dots, \tau \quad (7)$$

$$\sum_{t=1}^{\tau} t e_{ij}^t + d_{ij} \leq \tau + 1 \quad \forall (i,j) \in \bar{A} \quad (8)$$

$$\sum_{t=1}^{\tau} t \gamma_{ij}^t + d_{ij} \leq \tau + 1 \quad \forall (i,j) \in \bar{A} \quad (9)$$

$$\sum_{t=1}^{\tau-d_{ij}+1} e_{ij}^t = 1 \quad \forall (i,j) \in \bar{A} \quad (10)$$

$$\sum_{t=1}^{\tau-d_{ij}+1} \gamma_{ij}^t = 1 \quad \forall (i,j) \in \bar{A} \quad (11)$$

$$b_{ij}^{t'} - 0.15 \frac{f_{ij}^{t'}}{(c_{ij}^{t'-t+1} y_{ij}^{t'})^4} \leq M(1 - e_{ij}^t) \quad \begin{matrix} \forall (i,j) \in \bar{A}, \\ t' = 1, \dots, \tau, \\ t' \geq t, c_{ij}^{t'-t+1} > 0 \end{matrix} \quad (12)$$

$$b_{ij}^{t'} - 0.15 \frac{f_{ij}^{t'}}{(c_{ij}^{t'-t+1} y_{ij}^{t'})^4} \geq -M(1 - e_{ij}^t) \quad \begin{matrix} \forall (i,j) \in \bar{A}, \\ t' = 1, \dots, \tau, \\ t' \geq t, c_{ij}^{t'-t+1} > 0 \end{matrix} \quad (13)$$

$$b_{ij}^{t'} - 0.15 \frac{f_{ij}^{t'}}{(y_{ij}^{t'})^4} \leq M \left(\sum_{l=t'-d_{ij}+1}^{t'} e_{ij}^l \right) \quad \forall (i,j) \in \bar{A}, \quad t' = 1, \dots, \tau \quad (14)$$

$$b_{ij}^{t'} - 0.15 \frac{f_{ij}^{t'}}{(y_{ij}^{t'})^4} \geq -M \left(\sum_{l=t'-d_{ij}+1}^{t'} e_{ij}^l \right) \quad \forall (i,j) \in \bar{A}, \quad t' = 1, \dots, \tau \quad (15)$$

$$b_{ij}^{t'} - 0.15 \frac{f_{ij}^{t'}}{(c_{ij}^{t'-t+1} y_{ij}^{t'})^4} \leq M(1 - \gamma_{ij}^t) \quad \begin{matrix} \forall (i,j) \in \bar{A}, \\ t' = 1, \dots, \tau, \\ t' \geq t, c_{ij}^{t'-t+1} > 0 \end{matrix} \quad (16)$$

$$b_{ij}^{t'} - 0.15 \frac{f_{ij}^{t'}}{(c_{ij}^{t'-t+1} y_{ij}^{t'})^4} \geq -M(1 - \gamma_{ij}^t) \quad \begin{matrix} \forall (i,j) \in \bar{A}, \\ t' = 1, \dots, \tau, \\ t' \geq t, c_{ij}^{t'-t+1} > 0 \end{matrix} \quad (17)$$

$$b_{ij}^{t'} - 0.15 \frac{f_{ij}^{t'}}{(y_{ij}^{t'})^4} \leq M \left(\sum_{l=t'-d_{ij}+1}^{t'} \gamma_{ij}^l \right) \quad \forall (i,j) \in \bar{A}, \quad t' = 1, \dots, \tau \quad (18)$$

$$b_{ij}^{t'} - 0.15 \frac{f_{ij}^{t'}}{(y_{ij}^{t'})^4} \geq -M \left(\sum_{l=t'-d_{ij}+1}^{t'} \gamma_{ij}^l \right) \quad \begin{matrix} \forall (i,j) \in \bar{A}, \\ t' = 1, \dots, \tau \end{matrix} \quad (19)$$

$$\xi^t \geq 0 \quad t = 1, \dots, \tau \quad (20)$$

$$e_{ij}^t \in \{0,1\} \quad \forall t, \forall (i,j) \in \bar{A} \quad (21)$$

$$\gamma_{ij}^t \in \{0,1\} \quad \forall t, \forall (i,j) \in \bar{A} \quad (22)$$

where α denotes the value of travel time. The objective function (5) seeks to minimize the difference between the total system travel time cost and weighted business revenue. Constraints (6) and (7) are the budget conservation constraints. Constraint (6) stipulates that in the first period, the budget is equal to the construction costs of all implemented projects and any leftover funds that carry over into the second period. If the construction or rehabilitation project on link (i, j) starts in period t , i.e., $e_{ij}^t = 1$ or $\gamma_{ij}^t = 1$, its construction cost is equal to $\kappa_{ij}^{t'-t+1}$ in period t' . Constraint (7) states that the sum of the construction budget for period t and the leftover funds from period $t - 1$ is equal to the sum of the construction and rehabilitation costs and the leftover budget in period t . Constraints (8) and (9) ensure that road capacity expansion and rehabilitation projects should be completed within the construction horizon. Constraints (10) and (11) state that once each road capacity expansion and rehabilitation project starts, it should be completed without disruption. Constraints (12) and (13) update the travel time function parameter in period t' , $b_{ij}^{t'}$, if the capacity expansion project on link (i, j) starts in period t using modification factor $c_{ij}^{t'-t+1} > 0$. Constraints (14) and (15) prevent updating the travel time function parameter in period t' , $b_{ij}^{t'}$, if the capacity expansion project on link (i, j) is not implemented in that period. The modification factor $c_{ij}^{t'-t+1}$ is greater than one after the capacity expansion project is completed. Constraints (16) and (17) state that if the road rehabilitation project on link (i, j) starts in period t , then the travel time function parameter in period t' , $b_{ij}^{t'}$, should be updated using modification factor $c_{ij}^{t'-t+1} > 0$. The modification factor $c_{ij}^{t'-t+1}$ is equal to 1 after the road rehabilitation project is completed. Constraints (16) and (17) prevent updating the travel time function parameter in period t' , $b_{ij}^{t'}$, if the road rehabilitation project on link (i, j) is not implemented in that period. Constraint (20) indicates the non-negativity of the leftover construction budget. Constraints (21) and (22) denote the binary nature of e_{ij}^t and γ_{ij}^t .

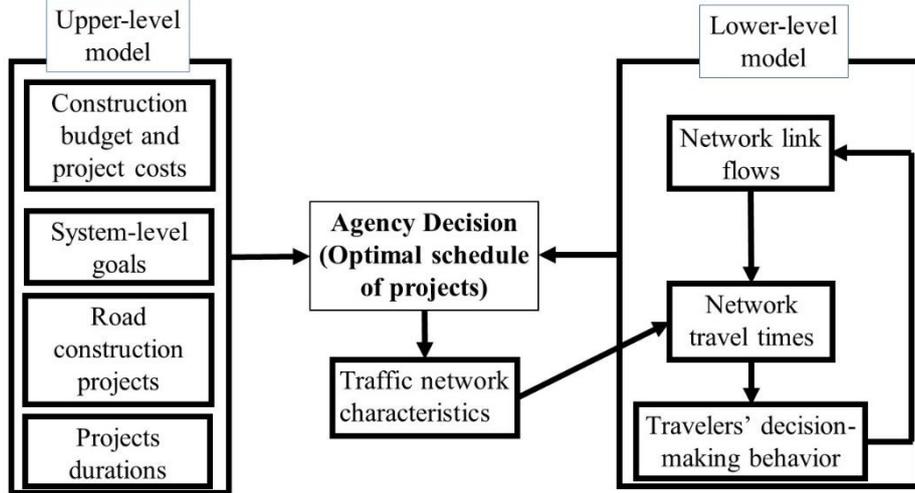


Figure 1 Structure of bi-level model.

2.3 Lower-Level model

The lower-level model seeks to capture the decision-making process of travelers under the sequence of project start dates decided by the transportation agency decision-maker at the upper level. The travelers aim to minimize their travel time under the optimal sequence by selecting the routes with the minimum travel time. Under the equilibrium condition, travelers cannot further reduce their travel times by unilaterally changing their route. Let $\pi_i^{r,t}$ denote the travel time from node r to node i in period t . Given the project schedule parameters (e and γ) determined in the upper level, the lower-level model can be formulated as the following mathematical program with equilibrium constraints (MPEC):

$$0 \leq v_{ij}^{r,t} \perp (\sigma_{ij}^t(v_{ij}^t) + \rho_{ij}^t + \pi_i^{r,t} - \pi_j^{r,t}) \geq 0 \quad \forall (i,j) \in A, \forall r \in N, t = 1, \dots, \tau \quad (23)$$

$$q_i^{r,t} = \begin{cases} \sum_i D_{r,i}(\pi_i^{r,t}) & r = i \\ 0 & r \neq i \text{ and } (r,i) \notin Q \\ -D_{r,i}(\pi_i^{r,t}) & (r,i) \in Q \end{cases} \quad t = 1, \dots, \tau \quad (24)$$

$$\pi_r^{r,t} = 0 \quad \forall r \in N, t = 1, \dots, \tau \quad (25)$$

$$v_{ij}^{t'} \leq M \cdot (1 - e_{ij}^{t'}) \quad \forall (i,j) \in \bar{A}, t' = 1, \dots, \tau, t' \geq t, c_{ij}^{t'-t+1} = 0 \quad (26)$$

$$\rho_{ij}^{t'} \leq M \cdot e_{ij}^{t'} \quad \forall (i,j) \in \bar{A}, t' = 1, \dots, \tau, t' \geq t, c_{ij}^{t'-t+1} = 0 \quad (27)$$

$$v_{ij}^{t'} \leq M \cdot (1 - \gamma_{ij}^{t'}) \quad \forall (i,j) \in \bar{A}, t' = 1, \dots, \tau, t' \geq t, c_{ij}^{t'-t+1} = 0 \quad (28)$$

$$\rho_{ij}^{t'} \leq M \cdot \gamma_{ij}^{t'} \quad \forall (i,j) \in \bar{A}, t' = 1, \dots, \tau, t' \geq t, c_{ij}^{t'-t+1} = 0 \quad (29)$$

$$\sum_{j:(i,j) \in A} v_{ij}^{r,t} - \sum_{j:(j,i) \in A} v_{ji}^{r,t} = q_i^{r,t} \quad \forall i, \forall r \in N, t = 1, \dots, \tau \quad (30)$$

$$\sum_{r \in N} v_{ij}^{r,t} = v_{ij}^t \quad \forall r, \forall (i,j) \in A, t = 1, \dots, \tau \quad (31)$$

$$\rho_{ij}^{t'} \geq 0 \quad \forall (i,j) \in \bar{A}, t' = 1, \dots, \tau \quad (32)$$

$$v_{ij}^{r,t} \geq 0 \quad \forall r \in N, \forall (i,j) \in A, t = 1, \dots, \tau \quad (33)$$

where $\rho_{ij}^{t'}$ is the full closure cost of link (i,j) in period t' . When the transportation agency closes a road due to construction project, travelers on the affected route may change their original route to the least-cost route of the available alternative routes. The travel time on the selected route is exceeds that of the original route (that is, before the road closure); the additional time is referred to as *full closure cost*. It is equal to zero on roads where there are no construction projects. The complementarity constraint (23) denotes the link-based user equilibrium (UE) condition. It states that link (i,j) is utilized in period t by travelers originating from node r , i.e., $v_{ij}^{r,t}$, if the link is a part of the shortest path tree with origin r to other nodes in the traffic network. Constraints (24) state that travel demand is a function of travel time from node r to node i in period t . Constraints (25) state that travel time from node r to node r is equal to zero. Constraints (26)-(29) ensure that if the road capacity expansion or rehabilitation project on link (i,j) is initiated in period t and the road is closed in period t' (i.e., $c_{ij}^{t'-t+1}$ is equal to zero in period t'), then its flow is equal to zero in period t' . Further, the constraints state that $\rho_{ij}^{t'}$ can be positive if link (i,j) is closed in period t' . This parameter ensures that although link (i,j) has a minimum travel time due to zero traffic flow, it is not a constituent link of the shortest route of any O-D pair in period t' due to

its full closure. Constraints (30), which represent the flow conservation constraints, state that for any node i , the inflow to node i is equal to the sum of the outflow and the demand originating from node r . Constraint (31) calculates the aggregate link flow. Constraint (32) ensures that the full closure cost of link (i, j) in period t is greater than or equal to zero. Constraint (33) represents the non-negative decision variables in the lower-level model. MPEC (23)-(33) can be formulated as the following minimization program with linear constraints (MPLC):

$$\min_v Z^L = \sum_t \sum_{(i,j) \in A} \int_0^{v_{ij}^t} \sigma_{ij}^t(w) dw - \sum_t \sum_i \sum_r \int_0^{q_i^{r,t}} D_{r,i}^{-1}(w) dw \quad (34)$$

$$\sum_{j:(i,j) \in A} v_{ij}^{r,t} - \sum_{j:(j,i) \in A} v_{ji}^{r,t} = q_i^{r,t} \quad \forall r \in N, t = 1, \dots, T \quad (35)$$

$$\sum_{r \in N} v_{ij}^{r,t} = v_{ij}^t \quad \forall (i, j) \in A, t = 1, \dots, T \quad (36)$$

$$v_{ij}^{t'} \leq M \cdot (1 - e_{ij}^t) \quad \forall (i, j) \in \bar{A}, t' = 1, \dots, \tau, t' \geq t, c_{ij}^{t'-t+1} = 0 \quad (37)$$

$$v_{ij}^{t'} \leq M \cdot (1 - \gamma_{ij}^t) \quad \forall (i, j) \in \bar{A}, t' = 1, \dots, \tau, t' \geq t, c_{ij}^{t'-t+1} = 0 \quad (38)$$

$$v_{ij}^{r,t}, v_{ij}^t \geq 0 \quad \forall r \in N, \forall (i, j) \in A, t = 1, \dots, T \quad (39)$$

where Z^L denotes the objective function in the lower-level model. It can be easily shown that the first-order condition, i.e., the Karush-Kuhn-Tucker (KKT) condition, of the MPLC is equivalent to MPEC (23)-(33). Given e and γ determined by the upper-level model, the MPLC is a convex problem and is easier to solve compared to MPEC (23)-(33).

2.4 Bi-Level Model

This section presents the integration of the upper- and lower-level models into an integrated bi-level model (Figure 1). In the upper level, the transportation agency decision-maker determines the optimal schedule of the construction projects based on traffic network characteristics (e.g., free flow travel time and capacity), construction budget, project durations, and travelers' decision-making behavior. Given the optimal project schedules, travelers make their travel decisions in the lower-level model, i.e., whether or not to travel and, if affirmative, the route choice based on the network travel times and the given schedule of construction projects developed in the upper level. The bi-level model can be formulated as the following mathematical program with complementarity constraints (MPCC):

$$\min_{e, \gamma, v} Z^U = W_1 \sum_{t=1}^T \sum_{(i,j) \in A} \alpha \sigma_{ij}^t(v_{ij}^t) v_{ij}^t - W_2 \sum_{t=1}^T \sum_{(i,m)} \zeta_{i,m}^t \quad (40)$$

(6)-(33)

MPCC ((6)-(33),(40)) consists of integer variables and complementarity constraints, which make the problem NP-hard and difficult to solve. In departure from existing studies in the literature that used heuristic solution methods, this paper used a local decomposition method.

3. SOLUTION ALGORITHM

This section develops a solution algorithm to solve the construction project scheduling problem. As discussed in the previous section, the proposed bi-level MPCC model contains integer variables and complementarity constraints. Hence, it is difficult to solve due to its nonconvex nature and its violation of the Mangasarian-Fromovitz constraint qualification (MFCQ) at every feasible point (Scholtes and Stöhr, 1999). To solve an MPCC, various techniques have been proposed in the literature, such as non-smooth penalization (Scholtes and Stöhr, 1999), smooth regularization (Bayındır et al., 2007), direct relaxation of the complementarity constraints, and solving the MPCC as a nonlinear program (Yin and Lawphongpanich, 2007). These techniques require approximation or relaxation of complementarity constraints. However, the proposed MPCC ((6)-(33),(40)) consists of integer variables. Even using relaxation methods, it still contains mixed-integer nonlinear variables. As we noted in a previous section of this paper, this makes the problem rather difficult to solve.

In this paper, we adopt a local decomposition method known as an active set algorithm (Zhang et al., 2009; Scheel and Scholtes, 2000; Luo et al., 1996). Zhang et al. (2009) demonstrated that this algorithm converges to the optimal solution in finite iterations. The main idea of the algorithm is first to solve a restriction of MPCC upon the active sets corresponding to a particular construction plan. By solving the restricted MPCC, we can obtain the multipliers corresponding to the active sets. Specifically, the values of the multipliers can measure the impacts of changing the current active sets or construction plan on the objective value. Based on those multipliers, a binary knapsack problem is then constructed and solved to update the active sets, i.e., the construction plan. A new construction plan is thus obtained, which may improve the value of the objective function. The construction plan is updated iteratively until there is no better plan. The efficiency of such an algorithm has been emphasized by Zhang et al. (2009) and has been applied to solve various deployment or construction problems, such as deployment of electric charging infrastructure (He et al., 2013; Chen et al., 2016a), promotion of electric vehicles (Miralinaghi and Peeta, 2019), and deployment of autonomous vehicle lanes (Chen et al., 2016b). To apply this algorithm in this study, the optimal project schedule is determined by using dual variables associated with an index-set-based restriction of

the MPCC ((6)-(33), (40)). To do so, the algorithm is initialized with a feasible project schedule. Let \bar{e} and $\bar{\gamma}$ denote the feasible project schedules for the capacity expansion and road rehabilitation projects, respectively. Based on the feasible schedule for the capacity expansion projects, let $I(\bar{e}) = \{(i, j, t) | \bar{e}_{ij}^t = 0\}$ and $I^c(\bar{e}) = \{(i, j, t) | \bar{e}_{ij}^t = 1\}$. Similarly, let $I(\bar{\gamma}) = \{(i, j, t) | \bar{\gamma}_{ij}^t = 0\}$ and $I^c(\bar{\gamma}) = \{(i, j, t) | \bar{\gamma}_{ij}^t = 1\}$ for the road rehabilitation projects. Then, the index-set-based restriction of MPCC ((6)-(33),(40)) (IMPCC) can be formulated as follows:

$$\min_{e, \gamma, v} Z^U = W_1 \sum_{t=1}^T \sum_{(i,j) \in A} \alpha \sigma_{ij}^t (v_{ij}^t) v_{ij}^t - W_2 \sum_{t=1}^T \sum_{(i,m)} \zeta_{i,m}^t \quad (41)$$

$$e_{ij}^t = 0 \quad (i, j, t) \in I(\bar{e}) \quad (42)$$

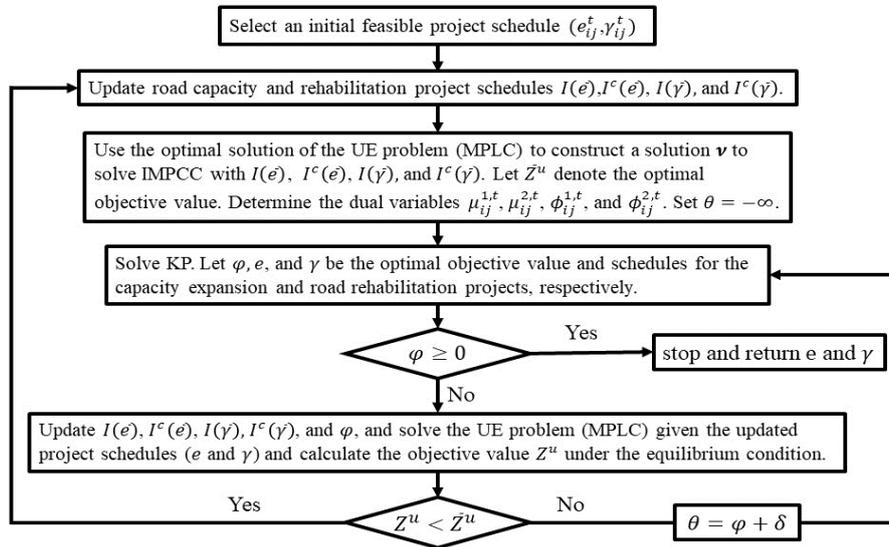
$$e_{ij}^t = 1 \quad (i, j, t) \in I^c(\bar{e}) \quad (43)$$

$$\gamma_{ij}^t = 0 \quad (i, j, t) \in I(\bar{\gamma}) \quad (44)$$

$$\gamma_{ij}^t = 1 \quad (i, j, t) \in I^c(\bar{\gamma}) \quad (45)$$

(6)-(33)

Although the IMPCC is also an MPCC, it is less computationally expensive compared to MPCC ((6)-(33), (40)) because its solution can be directly obtained by solving the associated UE problem. Let $\mu_{ij}^{1,t}$, $\mu_{ij}^{2,t}$, $\phi_{ij}^{1,t}$, and $\phi_{ij}^{2,t}$ denote the dual variables associated with constraints (42), (43), (44), and (45), respectively. They represent the potential for reducing the objective function (41) by updating the right-hand sides. Therefore, they can be used as references to update the project schedule by considering the following knapsack problem (KP):



(a) Solution algorithm

```

Model
* Defining model IMPCC
* Defining model KP
Step 0: Select an initial feasible project schedule.
Step 1: Update road capacity and rehabilitation project schedules
Step 2: Use the optimal solution of the UE problem (MPLC) to construct a solution to solve IMPCC .
Step 3: Solve KP and obtain the associated Lagrangian multipliers
Step 4: If phi=0, update I and solve the UE problem (MPLC) given the updated project schedules and calculate the objective value under the
equilibrium condition. Go to Step 5 and continue.
If Z^u < Z^u_bar, go to Step 1 and continue.
Step 5: If Z^u > Z^u_bar, set theta=phi+delta, then go to Step 3 and continue.

```

(b) Pseudo Code

Figure 2 Local decomposition algorithm

$$\min_{p, x, e, \gamma} \varphi = \sum_t (\sum_{(i,j,t) \in I(\bar{e})} p_{ij}^t \mu_{ij}^{1,t} - \sum_{(i,j,t) \in I^c(\bar{e})} p_{ij}^t \mu_{ij}^{2,t} + \sum_{(i,j,t) \in I(\bar{\gamma})} x_{ij}^t \phi_{ij}^{1,t} - \sum_{(i,j,t) \in I^c(\bar{\gamma})} x_{ij}^t \phi_{ij}^{2,t}) \quad (46)$$

$$e_{ij}^t = 1 - p_{ij}^t \quad (i, j, t) \in I^c(\bar{e}) \quad (47)$$

$$e_{ij}^t = p_{ij}^t \quad (i, j, t) \in I(\bar{e}) \quad (48)$$

$$\gamma_{ij}^t = 1 - x_{ij}^t \quad (i, j, t) \in I^c(\bar{\gamma}) \quad (49)$$

$$\gamma_{ij}^t = x_{ij}^t \quad (i, j, t) \in I(\bar{\gamma}) \quad (50)$$

$$\sum_t (\sum_{(i,j) \in I(\bar{e})} p_{ij}^t \mu_{ij}^{1,t} - \sum_{(i,j) \in I^c(\bar{e})} p_{ij}^t \mu_{ij}^{2,t} + \sum_{(i,j) \in I(\bar{\gamma})} x_{ij}^t \phi_{ij}^{1,t} - \sum_{(i,j) \in I^c(\bar{\gamma})} x_{ij}^t \phi_{ij}^{2,t}) \geq \theta \quad (51)$$

$$p_{ij}^t, x_{ij}^t, e_{ij}^t, \gamma_{ij}^t \in \{0,1\} \quad (52)$$

(6)-(11)

where p_{ij}^t and x_{ij}^t indicate whether the project schedules for the capacity expansion and road rehabilitation projects need to be updated. In other words, p_{ij}^t and x_{ij}^t indicate whether to flip the values of \bar{e}_{ij}^t and $\bar{\gamma}_{ij}^t$, respectively. Constraints (47) update the values of e_{ij}^t for $(i, j, t) \in I^c(\bar{e})$ and state that $e_{ij}^t = 0$ if one decides to flip its value ($p_{ij}^t = 1$); otherwise, e_{ij}^t is equal to one. Similarly, constraints (48) also update the values of e_{ij}^t . Constraints (49) and (50) are similar to constraints (39) and (48), except that they apply to road rehabilitation schedules $I(\bar{\gamma})$ and $I^c(\bar{\gamma})$. The dual variables of constraints (42)-(45) calculate the change of the objective value by making marginal changes to e_{ij}^t and γ_{ij}^t . However, as the actual change of e_{ij}^t and γ_{ij}^t can be only zero or one, the new updated project schedule may not necessarily lead to a reduction of the objective value. Constraint (51) ensures that if the generated optimal project schedule does not lead to reduction of the value of the objective function, we can generate another suboptimal project schedule by setting $\theta = \varphi + \delta$, where φ and δ denote the optimal objective value and small non-negative value, respectively, and the initial value of θ is $-\infty$. Constraints (6)-(11) are budget constraints, ensuring the feasibility of the new project schedule obtained by KP ((6)-(11), (46)-(52)). The solution algorithm is depicted in Figure 2(a).

4. COMPUTATIONAL EXPERIMENTS

The efficacy of the proposed approach is demonstrated on the Sioux Falls, South Dakota, network. The proposed solution algorithm is coded in the General Algebraic Modeling System (GAMS) shown in Figure 2(b) using the CONOPT and CPLEX solvers (Rosenthal, 2015). The

results are obtained using a PC computer with 8 gigabytes of RAM and a 2.6 gigahertz Core i7 CPU.

The Sioux Falls network (Figure 3) consists of 24 nodes and 76 links. The characteristics of the Sioux Falls network are presented in Leblanc et al. (1975). Travel demand levels are obtained as follows:

$$q_i^{r,t} = \bar{q}_i^{r,t} \exp(-3\pi_i^{r,t}) \quad \forall (i, r, t) \quad (53)$$

where $\bar{q}_i^{r,t}$ denotes the potential travel demand for O-D pair (i, r) in period t . In the first period, it is assumed that travel demands are equal to those suggested by Leblanc et al. (1975). Travel demand is assumed to follow a step function and grows at a rate of 25% over the construction horizon as follows:

$$q_i^{r,t} = (1.25)^{t-1} q_i^{r,1} \quad (54)$$

It is assumed that 50% of travel demand for each O-D pair consists of shoppers who spend an average of \$100 in the businesses located at the destinations (Woldemariam et al, 2019). If construction projects are not implemented during the construction horizon (referred to as a “No-Construction” condition), the total business revenue is equal to \$165,251 per hour. The value of time is assumed to be equal to \$15/hr. It should be noted that these values are used for illustrative purposes only, to demonstrated the developed model.

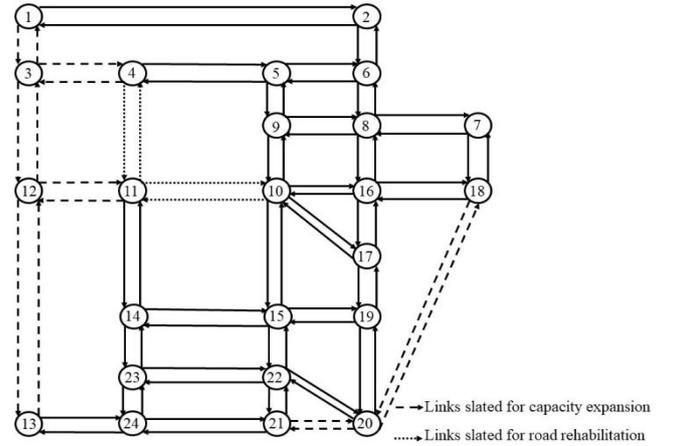


Figure 3. Sioux Falls road network

It is sought to schedule 18 construction projects on selected links of the Sioux Falls network over 6 time periods. Table 2 presents the costs of each project after initiation. The construction budgets for periods 1 through 6 are 175, 80, 80, 160, 160, and 160 in thousands of dollars, respectively. The link construction cost is greater than zero during construction implementation and is equal to zero afterward. Table 3 illustrates the modification factor for the capacity of each link after its project is initiated. A modification factor equal to zero implies that the link is fully closed during the project implementation in that period. For road rehabilitation projects (e.g., links 4 through 11), the modification factor is equal to 1.0 after the project is completed. For capacity expansion projects (e.g., links 3 through 12), the modification factor is greater than 1.0 after

project completion. The business revenue under No-Construction plan is \$165,251.

Table 2. Link Construction Costs (In \$1,000)

Links	Periods					
	1	2	3	4	5	6
1-3	20	10	15	0	0	0
3-1	10	20	10	0	0	0
3-4	15	15	0	0	0	0
3-12	30	20	20	10	0	0
4-3	15	15	0	0	0	0
4-11	10	0	0	0	0	0
10-11	45	0	0	0	0	0
11-4	10	0	0	0	0	0
11-10	45	0	0	0	0	0
11-12	15	15	15	0	0	0
12-3	30	20	20	10	0	0
12-11	15	15	15	0	0	0
12-13	20	10	10	10	0	0
13-12	20	10	10	10	0	0
18-20	30	30	10	0	0	0
20-18	30	30	10	0	0	0
20-21	45	0	0	0	0	0
21-20	45	0	0	0	0	0

Table 3. Link Modification Factors

Links	Periods					
	1	2	3	4	5	6
1-3	0	0	0	1.5	1.5	1.5
3-1	0.5	0.5	1.5	1.5	1.5	1.5
3-4	0	0	1.5	1.5	1.5	1.5
3-12	0	0	0	0.5	1.5	1.5
4-3	0	0	1.5	1.5	1.5	1.5
4-11	0	1	1	1	1	1
10-11	0	1	1	1	1	1
11-4	0	1	1	1	1	1
11-10	0	1	1	1	1	1
11-12	0	0	0	1.5	1.5	1.5
12-3	0	0	0	0.5	1.5	1.5
12-11	0	0.5	0.5	1.5	1.5	1.5
12-13	0	0	0	0.5	1.5	1.5
13-12	0	0	0	0.5	1.5	1.5
18-20	0	0	0.5	1.5	1.5	1.5
20-18	0	0	0	1.5	1.5	1.5
20-21	0	0	1.5	1.5	1.5	1.5
21-20	0.5	0.5	1.5	1.5	1.5	1.5

First, we present the optimal project schedule when the transportation agency decision-maker assumes that \$1 of total system travel time cost is equivalent to \$1 of business revenue and therefore considers the total system travel time and business revenue with identical weights into the objective function (i.e. $W_1, W_2 = 0.5$ in objective function (5)). Figure 4, which illustrates the change in the optimal objective value vs. the CPU time, shows that the proposed algorithm solves the bi-level model within a finite number of iterations. Figure 5 illustrates the optimal schedule. It takes 2,080 seconds to obtain the optimal

construction plan. Under this plan, the business revenue is equal to \$152,429, which indicates that the disruption cost is equal to \$12,822 (i.e., an 8% revenue reduction compared to the No-Construction condition). The total system cost and travel time are equal to \$25,750 and 861.9 veh. hrs, respectively.

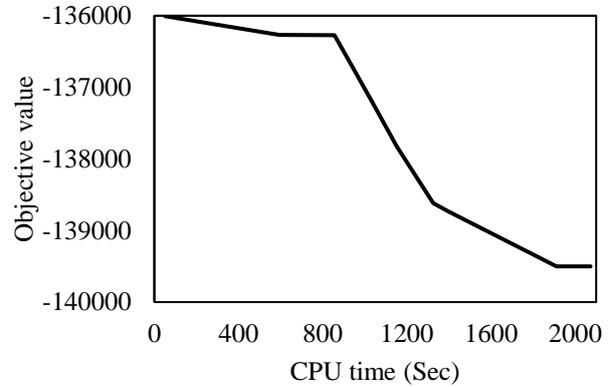


Figure 4. Change of the objective function (total system cost) vs. CPU time under proposed solution algorithm

Links	Periods					
	1	2	3	4	5	6
1-3	█	█	█	█	█	█
3-1						█
3-4		█	█	█	█	█
3-12	█	█	█	█	█	█
4-3	█	█	█	█	█	█
4-11		█	█	█	█	█
10-11						█
11-4						█
11-10						█
11-12			█	█	█	█
12-3			█	█	█	█
12-11			█	█	█	█
12-13	█	█	█	█	█	█
13-12		█	█	█	█	█
18-20				█	█	█
20-18				█	█	█
20-21					█	█
21-20		█	█	█	█	█

Figure 5. Optimal project schedule with $W_1, W_2 = 0.5$

To illustrate the importance of considering the business disruption cost, the optimal schedule that only minimizes the total system travel time during the construction horizon (i.e., $W_2 = 0$ in objective function (5)), is obtained. It takes 346 seconds to solve this scheduling problem; The minimum value of total system travel time is equal to 823.50 veh. hrs.

Figure 6 presents the optimal project schedule. For this problem setting, it shows that road rehabilitation

projects are mostly scheduled toward the end of construction horizon. This is because, unlike capacity expansion projects, road rehabilitation projects do not contribute to system travel time and business revenue by increasing road capacities in the periods following project completion. Under this plan, the total business revenue in the traffic network is equal to \$148,357 per hour, which indicates that the disruption cost is equal to \$16,894 (i.e., a 10% revenue reduction compared to the No-Construction scenario). The total system cost, including total system travel time and business disruption costs, is \$29,246. It implies that if transportation agency decision-maker factors the business disruption cost in the objective function, the optimal schedule reduces the total business disruption cost by 24% while the total travel time only increases by 4%. Further, the total system cost is reduced by 12%. It can be conjectured that this is a tradeoff that the community might be willing to make.

Links	Periods					
	1	2	3	4	5	6
1-3	█					
3-1		█				
3-4			█			
3-12				█		
4-3					█	
4-11						█
10-11						
11-4						
11-10						
11-12						
12-3						
12-11						
12-13						
13-12						
18-20						
20-18						
20-21						
21-20						

Figure 6. Optimal project schedule for minimizing the total system travel time ($W_1 = 1, W_2 = 0$)

Next, we conduct the sensitivity analysis in Figure 7 to understand the impact of different relative weights of travel time (W_1) and business revenue (W_2). As W_1 increases relative to W_2 , the optimization program aims to further minimize the total system travel time as it has a higher weight in objective function. Although it leads to lower total system travel time, it increases the business disruption cost through business revenue reduction. This illustrates the importance of relative weights in the objective

function, and how they allow the transportation agency decision-maker to achieve the target system objectives.

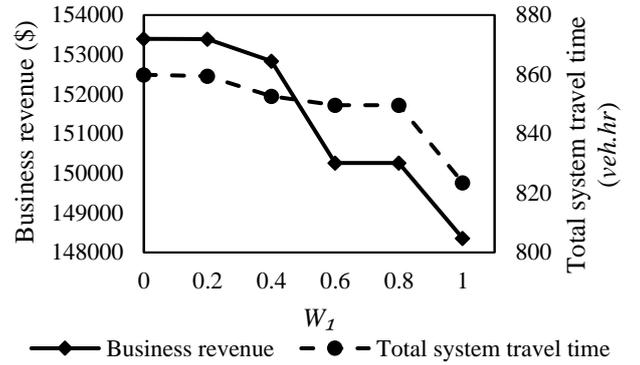


Figure 7. Impact of different weight of travel time (W_1) on the optimal total system travel time and business revenue

Figure 8 illustrates the impact of the value of time on total system travel time and business revenue, assuming a given (fixed) relative weight ($W_1 = 0.88$). It is observed as the value of time increases, the transportation agency decision-maker needs to further minimize the total system travel in order to reduce the user costs compared to business revenue. Therefore, as the value of time increases, there is a reduction of the optimal system travel time and business revenue. This implies that as the value of time increases, the total system travel time (user costs) decreases to a greater extent compared to the business disruption cost (community cost).

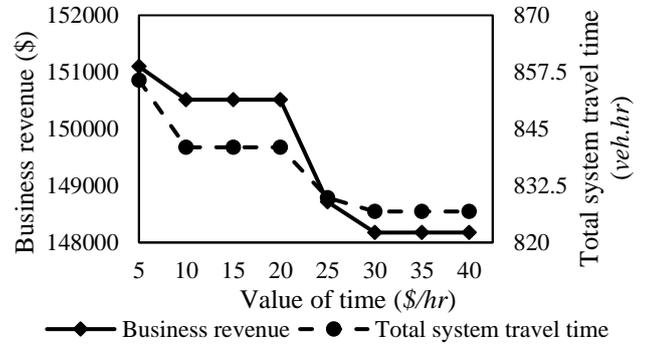


Figure 8. Impact of value of time on total system travel time and business revenue

To understand the importance of considering the business revenue in the bi-criteria optimization framework of this study, we conducted a simulation by generating 30 samples for value of time and expenditure of each customer at business. We use a continuous uniform distribution for this simulation where $\alpha \sim (0,30)$ and $q_{i,m}^t \sim (0,200)$. For each sample, we obtain the business disruption cost and total system travel time under two optimization programs with and without factoring the business revenue in objective function. Figure 9 illustrates the percentage increase in the business revenue with respect to the percentage increase in the total system travel time under each sample. This figure

is presented to show not a predictor-outcome relationship but simple one of a statistical association between the change in business revenue and total system travel time. The average percentages of increase in business revenue and total system travel time are 9.6% and 3.5% with the standard deviations of 5.9% and 1.8%, respectively. This illustrates the importance of considering the business revenue in optimization framework to prevent significant monetary loss of businesses where the impact on total system travel time is not considerable compared to its impact on business revenue loss. When the expenditure of each customer at business is much lower compared to value of time, the optimal construction schedule under two optimization frameworks are identical and consequently, the percentage increases in business revenue and total system travel time are equal to zero.

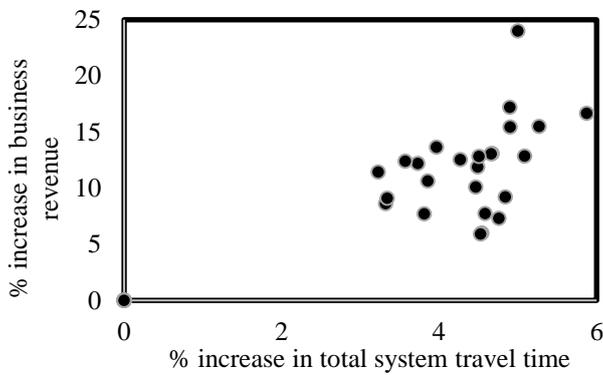


Figure 9. Percentages of increase in business revenue and total system travel under simulation

Links	Periods					
	1	2	3	4	5	6
1-3	█	█	█			
3-1				█	█	█
3-4	█	█	█			
3-12			█	█	█	
4-3	█	█	█			
4-11				█	█	█
10-11				█	█	█
11-4	█	█	█			
11-10				█	█	█
11-12				█	█	█
12-3		█	█	█		█
12-11				█	█	█
12-13	█	█	█		█	█
13-12			█	█	█	
18-20				█	█	█
20-18				█	█	█
20-21		█	█	█		
21-20					█	█

Figure 10. Optimal project schedule under uncertain road project construction durations

Road construction project duration is highly uncertain in practice because it depends on several factors such as weather condition and resource availability. Therefore, we investigated the sensitivity of the optimal solution to the road construction duration. To do this, we consider the scenario in which road rehabilitation project of links (4,11), (11,4), (10,11) and (11,10) can be completed in 3 periods instead of 1. In this scenario, the road construction costs and capacity modification factors over 3 periods are identical to those presented in Table 2 and Table 3. Under this plan, the road rehabilitation projects are pushed toward earlier periods of the construction season, which results in delays of the capacity expansion starting periods (Figure 10). For this scenario, the total business revenue in the traffic network is equal to \$147,129 per hour, which indicates that the disruption cost is equal to \$18,122 per hour. The total system cost, including total system travel time and business disruption costs, is \$30,947 per hour, compared to \$25,750 for the scenario where the project durations are 1 period each. This infers that variability or uncertainty in the project durations can be very consequential. It is seen that tripling the road project durations, for example, result in approximately 20% increase in the total system (user+business) costs. This could result in serious public relations problems for the agency.

5. DISCUSSION OF PRACTICAL ISSUES

This paper develops the optimal construction schedule considering a number of factors that were not explicitly considered in previous studies. Yet still, a few factors were considered due to data and other constraints, and therefore requisite assumptions were made. The authors believe that these assumptions were not unduly restrictive and did not jeopardize the overall integrity of the model results. Nevertheless, some results of the model could be attributed to these assumptions. For example, from the model’s computational experiments, it was determined that the optimal solution typically has the road rehabilitation projects mostly scheduled toward the end of the planning horizon and the capacity expansion projects mostly scheduled at the early stages of the planning horizon; this outcome arose from the assumption that the capacity expansion projects offer a far greater reduction in travel time which was duly recognized by the algorithm. On the other hand, the model does not incorporate the speed reduction effects of a poor road condition. Another assumption that impacted the paper’s findings is the deterministic forecasts of travel demand, and the number of business customers and the customers’ average expenditures per business. In reality, there is significant variation in the forecasts of these variables across businesses and across time not only in the pre- and post-construction periods, but also across these two periods. The model also assumed that the travel demand is a function of travel time. However, in practice, travel demand is also heavily influenced by other factors including travel distance, road class, pavement condition, and noise. Further, the model assumed that the projects are link

projects not node projects, specifically, capacity expansion and road rehabilitation projects. In reality, the road construction practice includes a gamut of project types that are of either (i) long-term nature and are carried out at nodes such as intersections, interchanges, or roundabouts, or (ii) short-term nature and are carried out at links or nodes of the network such as road sign installation. While there is much to be learned from the optimal scheduling of these project types, they were not considered in the current paper.

Related to business revenue, our results indicate that after road project completion, the customers may change their business-patronizing choices due to changes in the road network that cause changes in accessibility to rival businesses. This implies that it may be unduly restrictive to assume that the road project completion will help increase the number of business customers. It is also assumed that transportation planner only aims to minimize the construction and business disruption costs during the construction horizon. However, the road construction projects have a long-term impact that leads to increase the business revenue after construction horizon. This impact is ignored in this paper. Further, it is assumed that transportation agency is able to estimate the business revenue using some parameters such as average customer expenditure. However, these parameters are extremely difficult to obtain due to privacy issues. Finally, when road projects are of unduly lengthy duration, businesses can go bankrupt. This could be modeled by including a parameter that measures the propensity of a business to go bankrupt based on a given reduction of customer access during the project and project duration.

6. CONCLUDING REMARKS

This paper investigated the development of optimal construction schedules for road infrastructure projects. These projects include capacity expansion and road rehabilitation. The scheduling problem is formulated as a bi-level program. In the upper level, the transportation agency decision-maker seeks to obtain the best start time for each project in order to minimize the total cost of system disruption (which, the case study, consist of the business disruption and travel time costs). The objective function is subject to budgetary constraints, and all the projects must be completed within the construction horizon. The upper level is formulated as a mixed-integer program. The lower-level model captures the route choices of travelers give the network link availability and attributes associated with the optimal project schedule obtained in the upper level. It is formulated as a mathematical program with equilibrium constraints. The integrated bi-level program, classified as an NP-hard problem, is traditionally known for its difficulty of solution. Studies in the field of project scheduling typically propose heuristic methods to obtain the optimal project schedule. In contrast, we have adopted a local decomposition method to solve the problem to optimality in a finite number of iterations. This algorithm leverages the dual variables associated with an index-set-based restriction of the program.

This research contributes to the body of knowledge because it (i) develops optimal road construction project schedules that consider the impacts on revenue of the neighborhood businesses, (ii) accounts for road capacity reductions during the project implementation, (iii) considers multiple-period durations for the projects and (iv) leverages the use of a local decomposition method that can converge to the local optimal solution within finite iterations. The numerical experiments indicate that this algorithm can yield the optimal project schedule. The results also show that if the transportation agency decision-maker duly considers the business disruption costs as a decision factor, the resulting optimal project schedule significantly reduces the business monetary losses that arise from construction work zones. This research can assist practitioners in identifying optimal road construction plans that are sustainable both from user and community perspectives, and receive lower public opposition.

This research can be extended in several directions. First, this paper deals only with scheduling predetermined projects. It would be worthwhile to investigate both the selection and scheduling of projects as a unified program. Second, this paper assumes that travel demand is deterministic throughout the construction horizon. However, the forecast of travel demand is often uncertain during the construction horizon, which can span a few years. Hence, it is necessary to develop a robust project schedule that can mitigate the potential increase in system costs due to inaccurate travel demand forecasts. Third, this paper deals only with business disruption cost and total system travel time during the construction horizon. Future research could investigate the optimal construction schedule to minimize vehicular emissions, fuel consumption and noise. In addition, this paper develops the optimal construction project schedule in long-term planning context. Further research could address the operational context in order to further reduce the business disruption and total system travel time within the construction period (For example, implementation of work at night or on weekends). Further, realizing that long-duration road projects can cause businesses to go bankrupt, extended work on this topic could include a parameter that measures the propensity of a business to go bankrupt based on a given reduction of customer access during the project and project duration. Next, this paper deals with projects that are implemented on the links such as adding a lane or road resurfacing. An interesting research direction could be to investigate the optimal construction project schedule that includes projects implemented at the network nodes such as intersection work. Furthermore, the proposed planning model can be potentially combined with models aim to manage freeway work zones. For example, Karim and Adeli (2003) proposed a case-based reasoning system that allows traffic engineers to develop the traffic control plans with reducing effect on traffic congestion. Further, Hooshdar and Adeli (2004) proposed the neural network model to develop intelligent variable message signs (VMS) system to reduce congestion. The synergic effects of the aforementioned models can help transportation agency to achieve further reduction of traffic congestion. Finally, another interesting

direction of research is to conduct a sensitivity analysis on construction budget, modification factor for capacity of link and construction cost for each link.

7. Acknowledgments

This study is sponsored by the Indiana Department of Transportation and Center for Connected and Automated Transportation (CCAT) Region V University Transportation Center funded by the U.S. Department of Transportation, Award #69A3551747105. The authors are grateful to the constructive comments provided by five anonymous reviewers. Any errors are those of the authors alone.

8. APPENDIX: NOTATIONS

Set

N	Set of nodes
A	Set of links
\bar{A}	Set of capacity expansion projects on existing links
$\bar{\bar{A}}$	Set of road rehabilitation projects on existing links
Γ	Set of time periods
Q	Set of O-D pairs

Parameters

T	Number of periods in a construction horizon
B^t	Construction budget in period t
κ_{ij}^l	Construction cost on link (i, j) after l periods from the initiation of the project
d_{ij}	Duration of a project on link (i, j)
c_{ij}^l	Modification factor for capacity of link (i, j) after l periods of initiating the project
f_{ij}^t	Free-flow travel time on link (i, j) in period t
y_{ij}^t	Capacity of link (i, j) in period t
b_{ij}^t	Travel time function parameter
$\beta_{i,m}^{r,t}$	Percentage of demand of O-D pair (r, i) that includes customers of individual business m at node i in period t
$q_{i,m}^t$	Expenditure of each customer at business m of node i in period t
$\zeta_{i,m}^{0,t}$	Revenue of business m at node i in period t in the pre-construction period
α	Value of time
M	Constant with a large value

Variables

Z^U	Objective function in the upper-level model
Z^L	Objective function in the lower-level model
ξ^t	Leftover construction budget after period t
$q_i^{r,t}$	Travel demand between O-D pair (r, i) in period t
$\omega_{i,m}^t$	Business disruption cost at business m of node i in period t
v_{ij}^t	Flow of link (i, j) in period t
$v_{ij}^{r,t}$	Flow of link (i, j) with origin r in period t
σ_{ij}^t	Travel time on link (i, j) in period t
$\pi_i^{r,t}$	Travel time on O-D pair (r, i) in period t
e_{ij}^t	=1 if new road construction project on link (i, j) in period t is implemented; 0 otherwise
γ_{ij}^t	=1 if road rehabilitation project on link (i, j) in period t is implemented; 0 otherwise

9. REFERENCES