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A Decision Support System for Optimal Maintenance Strategies in Highway Work Zones

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Abstract

This paper describes a decision support system to evaluate the trade-offs among cost, schedule, quality, safety, and motorist/public satisfaction in highway work zone projects and to assist the user in choosing the most suitable contracting strategy for a particular project under consideration. The method described in this paper is advantageous to assist the user in considering, at a macro level, the interrelationships between the critical factors impacting the project. The proposed methodology is applicable to work zone projects on four-lane interstate highways or urban freeways.

Key words

Highway construction, decision making, work zone, rehabilitation, simulation

1. Introduction

Highway projects are challenging for state Departments of Transportation and highway contractors due to their unique nature. Such projects are often located in urban areas and impact local traffic, community, environment, and businesses. The major need faced today in highway work zone projects is to optimize the dynamic relationship and competing interests of the state highway agency, contractor, and road users with respect to the main project performance indicators, i.e., cost, schedule, quality, public satisfaction, and safety while taking the factors that can potentially impact the project under consideration into account. The development of a decision support system that can give the planners the flexibility to evaluate a number of competing contracting alternatives before making a final decision is essential.

The dynamic relationship between the three parties to a highway work zone project, i.e., state highway agency, contractor, and road user, is facilitated through certain interrelated tangible and intangible factors such as project location, work zone length, work window, difficulty of work, site constraints, traffic volume, planned detour, lane closure strategy, inconvenience to users, disturbance to nearby community, business disruption, public perception, political considerations, fuel cost, delay cost, accident cost, and contractor incentives. Therefore, for achieving optimal trade-offs under different options and constraints, it is important to identify the factors that are relevant to highway work zone projects as well as study their cumulative impact on the project performance indicators that establish the relevant trade-offs in project planning, i.e., cost, schedule, safety, and quality.

The purpose of this paper is to investigate the major performance trade-offs in highway work zone projects and to introduce a prototype decision support system to assist the user in developing a suitable contracting strategy to achieve the optimal satisfaction with respect to the performance variables in any given highway work zone project by considering the potential impact and the interrelationships between the factors specific to the project options and constraints.

2. Performance Trade-Offs in Construction Research

Existing techniques for trade-off problems in construction research can be categorized into four areas: heuristics, mathematical programming, simulation, and genetic algorithms. Heuristic methods utilize rules of thumb that generally do not have a mathematical background. Such methods do not ensure guarantee optimal solutions (Feng et al. 2000). Some examples for heuristic methods in construction research include Fondahl's method (1961), Prager's structural model (1963), Siemens's effective cost slope model (1971), and Moselhi's structural stiffness method (1993) (Feng et al. 2000; Zheng et al. 2004).

Mathematical programming methods use linear programming, integer programming, or dynamic programming to find optimal solutions (Feng et al. 2000). Meyer and Shaffer (1963) and Patterson and Huber (1974) solved time-cost problems by using mixed integer programming. Kelly (1961), Hendrickson and Au (1989), and Pagnoni (1990) used linear programming to solve the time-cost trade-off problem. Robinson (1975), Elmagraby (1993), and De et al. (1995) utilized dynamic programming to solve time-cost trade-off problems. Liu et al. (1995), Burns et al. (1996), and Mattila and Abraham (1998) introduced the use of linear and integer programming together to find the solution to the time-cost trade-off problems. Gomar et al. (2002) illustrated that includes optimization of the allocation of multi-skilled work crews by the use of integer linear programming. Moussourakis and Haksever (2004) developed an integer programming tool for use in optimization of linear or discrete cost functions.

Simulation techniques have been utilized to improve the study of stochastic project networks (Feng et al. 2000). Examples include Wan (1994) and Kidd (1987). Isidore and Back (2002) combined the techniques of range estimating and probabilistic scheduling using multiple simulation analysis to help mitigate the risks in construction projects. Genetic algorithms involve a set of tools that use natural selection and the mechanisms of population genetics (Holland 1975; Goldberg 1989). They utilize a random yet directed search for finding the globally optimal solution (Li and Love 1997). Osyczka (2002) indicated that genetic algorithms perform better than the conventional optimization methods if applied to difficult real world construction optimization problems. Feng et al. (1997) introduced a genetic algorithm model for optimizing time and cost simultaneously. Li et al. (1999) proposed an improved genetic algorithm model for representing linear continuous time–cost relationship. Leu and Yang (1999) developed a genetic algorithm based multi-criteria optimal model for construction scheduling that included a combination of time/cost trade-off and resource allocation as well as the second resource leveling. Hegazy (1999) proposed a genetic algorithm model by implementing genetic algorithm protocols within commercially available scheduling software. Feng and Burns (2000) used genetic algorithms together with simulation for stochastic construction time-cost trade off analysis with a focus on accounting. Hegazy and Wassef (2001) developed a tool for cost optimization in projects that include repetitive non-serial activities. Que (2002) integrated a project management system with the genetic algorithm system for more practicability in finding solutions to the time-cost optimization problem. Hegazy and Kassab (2003) used genetic algorithms together with simulation in order to solve resource optimization problems. Zheng et al. (2004) used genetic algorithms in a multi-objective approach for time-cost optimization. Hegazy et al. (2004) proposed the use of genetic algorithms to select the optimal construction methods, work order, and project costs for large infrastructure projects. Finally, El-Rayes and Kandil (2005) developed a multi-objective genetic algorithm to provide the capability of quantifying and considering quality in construction optimization.

In regard to the abundant research on the subject matter, the point important to make is that existing methods search for an optimal resource utilization plan at the activity level and do not consider, at a macro level, the influence of many important factors on the performance trade-offs in construction projects commencing from the dynamic relationship between the stakeholders such as the owner, contractor, and road users.

3. Modeling Using Bayesian Belief Networks

To facilitate the evaluation of the trade-offs in highway work zone projects, a detailed list of the factors that have a potential impact on those project variables were identified through a comprehensive literature review and a series of interviews with personnel from the Indiana Department of Transportation that are involved in various aspects of highway work zone projects. Based on the interrelationships between the factors, a generic influence pattern illustrating the influence of the factors on each other and also on the project variables under consideration was established. In establishing the influence pattern of factors for the purposes of this research, a probabilistic Bayesian belief network model was developed to identify the relationships between the different factors under consideration.

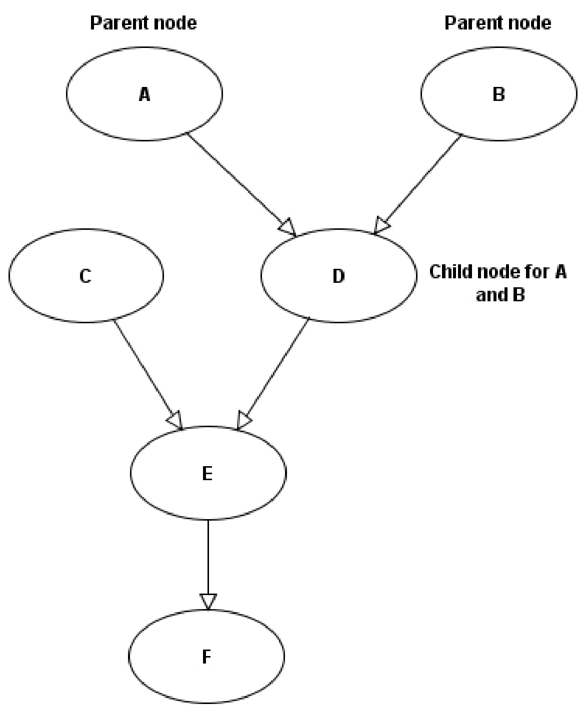

Figure 1: A simple Bayesian Belief Network with six Nodes

A Bayesian belief network represents the conditional dependences among a group of variables. As shown in Figure 1, the network consists of nodes that represent variables that are connected with directional arrows that represent conditional dependence relationships between those nodes. The node at the tail of the arrow (the parent node, Node A) has an influence on the node to which the arrow points (the child node, Node D) (Jensen 1996; McCabe et al. 1998). A conditional probability indicates the likelihood of a state of a variable that is dependent on the state of another variable. Bayes' theorem is used to recalculate the belief about the state of a node depending on the evidence introduced for another node (Jensen 1996; McCabe et al. 1998). The application of Bayesian belief networks to construction research is limited. McCabe et al. (1998) developed an automated approach using belief networks to provide diagnostic functionality to the performance analysis of construction operations. McCabe (2001) introduced Bayesian belief networks for engineering applications. Attoh-Okine (2002) presented the application of belief networks to make inferences in highway construction costs. Nasir et al. (2003) developed a construction schedule risk model using a Bayesian belief network as the modeling environment.

A complete discussion and justification of the factors that were taken into consideration for the purposes of this study as well as the approach undertaken in developing the generic influence pattern representing the dependence relations among the factors are provided in detail in Bayraktar 2006. The following section briefly discusses the three main steps of the proposed decision support system.

3.1 Model Customization

The decision support system introduced in this paper has three main steps. For a particular project under consideration, the objectives of these steps are (i) to customize the generic influence pattern according to the features of the project and to identify possible contracting alternatives to be evaluated, (ii) to quantify the relationships in the belief network, and (iv) to establish the trade-offs among the performance variables for each contracting alternative to support the user in decision making.

The first part of model customization includes calibration of the model variables with respect to the features and constraints of the specific project under consideration. Every highway work zone project is unique and may involve different factors that influence and impact the cost, schedule, quality, and safety components of the project considerably. The fact that the factors and the availability of data regarding these factors may not be the same for all projects requires a subjective assessment of the generic belief network by the user of the model to make sure that nothing is left out for the specific project under consideration. This step also involves identification of the feasible contracting alternatives to be evaluated. The user can evaluate feasible combinations of the states of the relevant nodes in the belief network to assist in selecting the most suitable contracting alternative with respect to the project objectives and constraints.

3.2 Relationship Quantification

For the quantification of the relationships in the belief network, four types of probabilities are needed to be provided by the user: (i) decision node prior probabilities, (ii) starting node prior probabilities, (iii) intermediate node conditional probabilities, and finally (iv) target node conditional probabilities.

The decision nodes are nodes without parents where the user of the model selects a state at each decision node to define the alternatives under consideration. After a selection is made at a decision node, i.e., an absolute observation is provided for that node, the prior probability of the selected state becomes %100, while the probabilities of the other states of that particular node are forced down to %0. The starting nodes are those nodes that have no parents and that are the only exposure points of the belief network to the external factors such as the inflation rate or bidding volume index. The external factors are not shown in the influence pattern but may impact the project indicators through the starting nodes. Such impacts are integrated in the prior probabilities of the starting nodes as appropriate and are further reflected in the children nodes of the starting nodes through conditional probabilities.

Intermediate nodes are the nodes which have both parents and children in the belief network. Associated with each intermediate node is a node probability table which expresses the conditional probabilities of the states of that particular node given all possible combinations of states for the node parents. In this step of the model, the values required for the node probability tables of the intermediate nodes are provided by the user of the model taking into consideration the perceived probabilistic node outcomes associated with the expected project conditions. For the purposes of this research, target nodes were defined as the nodes which only have parent nodes in the belief network. There are seven target nodes in the belief network proposed for highway work zone projects including: (i) Public satisfaction, (ii) Motorist satisfaction, (iii) Safety, (iv) Quality, (v) Labor productivity, (vi) Equipment productivity, and (vii) Material management. Each of these target nodes have five states including: (i) very low, (ii) low, (iii) medium, (iv) high, and (v) very high. The relationship quantification step of the model provides the user with the target node state probabilities of the seven performance indicators for the contracting alternatives under consideration.

3.3 Quantification of the Trade-Offs among Performance Indicators using Monte Carlo Simulation

The last step of the model attempts to quantify the value of the evaluated contracting alternatives with respect to the seven performance indicators based on the user's preferences for the particular project under consideration. In order to facilitate the evaluation of the trade-offs, the performance indicators are first categorized into two different groups: (i) scaled indicators and (ii) measured indicators. The scaled indicators include public satisfaction, motorist satisfaction, quality, and safety, whereas the measured indicators include labor productivity, equipment productivity, and material management.

The states of the scaled indicators are assessed on a common scale from 0 (zero) to 10 (ten), i.e. very low (0-2), low (2-4), medium (4-6), high (6-8), very high (8-10). For the purposes of simulation, these ranges are treated as uniform distributions, while the probability values for each range are assumed to represent a normal distribution with a mean and standard deviation received from the evaluation of the belief network in Step-2. The indicator score (IS) for a scaled node is defined as the sum of the scores from each of the five states, whereas the score for each state is calculated by multiplying the probability value of the state by a number picked from the appropriate range discussed above. This process is repeated many times through the use of Monte Carlo simulation and an average indicator score for each of the four scaled indicator is received. After this step, a weighted average of these indicator scores is calculated to get a performance score (PS) for the contracting alternative under consideration. The relative weights assigned to each performance indicator represent the relative importance of the performance indicators for the particular project under consideration and are determined by the model user through the Analytic Hierarchy Process (AHP). Finally, the performance scores calculated for each contracting alternative can be summarized as shown in Table 1.

Table 1: Performance and Indicator Scores for a Hypothetical Project with three Alternatives

Contracting Strategies	Performance Score	Indicator Score		
		Labor Productivity	Equipment Productivity	Material Management
Alternative-1	4.18	4.01%	2.07%	-3.04%
Alternative-2	5.78	6.34%	6.62%	-2.46%
Alternative-3	6.12	-5.75%	-10.25%	6.92%

The measured indicators include labor productivity, equipment productivity, and material management. These indicators are assessed with respect to their impact on the project duration and project cost. To facilitate such an assessment, the states of the measured indicators are first evaluated with respect to the severity of their impact on their own performance indicator. At this point of the proposed model, user input is sought to establish the severity of impact of each node state. The user is required to provide an assumption for each state of the measured indicators to represent a percent increase or decrease from the average node values, i.e., labor productivity, equipment productivity, and material management, which are used to develop the engineer's estimate by the state highway agency or to develop the bid by the contractor. Table-2 illustrates as an example the assumptions required for the "Labor Productivity" node.

Table 2: Example Assumptions for the Labor Productivity Node

Percentage Change in Labor Productivity			
State	**Minimum**	**Most Likely**	**Maximum**
Very Low	-%20	-%30	-%50
Low	-%15	-%25	-%35
Medium	-%10	0	%10
High	%10	%15	%20
Very High	%20	%25	%30

Once the assumptions are made by the user, the approach outlined in the previous paragraphs to calculate the performance scores for the scaled indicators can also be applied to the measured indicators for the same purpose. The only difference in the calculation is that, instead of a scale with uniform distribution and equal range widths, the user input (Table 2) is used to establish the severity of impact of each node state through a triangular distribution, while the state probabilities are again assessed using a normal distribution. After calculating the indicator scores (IS) for the measured nodes by Monte Carlo simulation (Table 1), the cost and duration of the project under consideration can be estimated for the alternatives analyzed in based on the procedure developed by Carr 2000.

Table 3: Effectiveness Ratios for a Hypothetical Project with three Alternatives

	Alternative-1	**Alternative-2**	**Alternative-3**
Performance Score	4.180	5.780	6.120
Total Cost (M$)	6.010	5.640	7.100
Duration (days)	304	288	392
Effectiveness Ratio (ER)	***0.696***	***1.025***	***0.862***
Effectiveness Rank	3	1	2

The final step in the proposed model includes calculation of the effectiveness ratio (ER) for the contracting alternatives under consideration. The effectiveness ratio (ER) for a contracting alternative is defined as the ratio of the alternative's performance score (PS) to the alternative's estimated total cost (TC). The effectiveness ratios calculated for different alternatives can be summarized as shown in Table 3. The alternative with the highest effectiveness ratio (ER) is the most effective and hence top ranking alternative.

4. Conclusions

This paper introduced a decision support system to evaluate the trade-offs among important project variables in highway work zone projects and to assist the user in choosing the most suitable contracting strategy for a particular project under consideration. Moreover, an overview of the state-of-art of project performance trade-offs in construction research was presented and the limitations of the existing methods were discussed. The method described in this paper is advantageous to assist the user in considering, at a macro level, the interrelationships between the critical factors impacting the project. The proposed methodology is applicable to work zone projects on four-lane interstate highways or urban freeways.

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