AN INTELLIGENT DECISION SUPPORT SYSTEM FOR WORK ZONE TRAFFIC MANAGEMENT AND PLANNING

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Summary and Organization of the Report

Periodic resurfacing, rehabilitation, restoration, and reconstruction work is needed on the aging highway system in the state of Ohio to maintain a desired level of service for the traveling public. However, temporary work zones on highways disrupt the normal flow of traffic and reduce the level of service. The increasing demand in maintaining an efficient highway system provides the impetus to develop rational and rigorous computer models to help work zone engineers create effective work zone traffic plans.

The objectives of the proposed research are to develop new computational models for estimating the work zone capacity and queue length as a function of a large number of factors impacting the work zone and queue length estimation and implement them into a user-friendly interactive object-oriented software system for effective management of traffic in work zones. This research will explore the use of several recent computing and information technologies: a) case-based reasoning (CBR), b) neural networks, c) fuzzy logic, and d) object-orient programming.

This report consists of six parts or manuscripts as follows:

Part I. CBR Model for Freeway Work Zone Traffic Management

Part II Freeway Work Zone Traffic Delay and Cost Optimization Model

Part III Radial Basis Function Neural Network for Work Zone Capacity and Queue Estimation

Part IV Neuro-Fuzzy Logic Model for Freeway Work Zone Capacity Estimation

Part V IntelliZone: Object-Oriented Model for Freeway Work Zone Capacity and Queue Delay Estimation

Part VI Clustering-Neural Network Models and Parametric Study of Work Zone Capacity

In Part I, a CBR model is presented for freeway work zone traffic management. The model considers work zone layout, traffic demand, work characteristics, traffic control measures, and mobility impacts. A four-set case base schema or domain theory is developed to represent the cases based on the above characteristics of the problem. It includes a general information set, a problem description set, a solution (or control) description set, and an effects set. To improve the interactivity of the CBR system and its user-friendliness, a hierarchical object-oriented case model is developed for work zone traffic management. Three examples are presented to show the practical utility of the CBR system for work zone traffic management.

In Part II, a new freeway work zone traffic delay and cost optimization model is presented in terms of two variables: the length of the work zone segment and the starting time of the work zone using *average hourly traffic* data. The total work zone cost defined as the sum of user delay, accident, and maintenance costs is minimized. Number of lane closures, darkness factor, and seasonal variation travel demand normally ignored in prior research are included. In order to find the global optimum solution, a Boltzmann-simulated annealing neural network is developed to solve the resulting mixed real variable-integer cost optimization problem for short-term work zones. The new model can be used as an intelligent decision support system a) to find the optimum work zone segment length and the optimum starting time, b) to study the impact of various factors such as number of lane closures and darkness, and c) to observe the relation between the total work zone cost versus the work zone segment length and starting time in a quantitative and rational way quickly.

The work zone capacity cannot be described by any mathematical function because it is a complicated function of a large number of interacting variables. In Part III, an adaptive computational model is presented for estimating the work zone capacity and queue length and delay taking into account the following factors: number of lanes, number of open lanes, work zone layout, length, lane width, percentage trucks, grade, speed, work intensity, darkness factor, and proximity of ramps. The model integrates judiciously the mathematical rigor of traffic flow theory with the adaptability of neural network analysis. A radial-basis function neural network model is developed to learn the mapping from quantifiable and non-quantifiable factors describing the work zone traffic control problem to the associated work zone capacity. This model exhibits good generalization properties from a small set of training data, a specially attractive feature for estimating the work zone capacity where only limited data is available. Queue delays and lengths are computed using a deterministic traffic flow model based on the estimated work zone capacity.

In Part IV, a novel adaptive neuro-fuzzy logic model is presented for estimation of the freeway work zone capacity. Seventeen different factors impacting the work zone capacity are included in the model. They are 1) percentage of truck, 2) pavement grade, 3) number of lanes, 4) number of lane closures, 5) lane width, 6) work zone layout (lane merging, lane shifting, and crossover), 7) work intensity (work zone type), 8) length of closure, 9) work zone speed, 10) interchange effects (proximity of ramps), 11) work zone location (urban or rural), 12) work zone duration (long-term or short-term), 13) work time (daytime or night), 14) work day (weekday or weekend), 15) weather condition (sunny, rainy or snowy), 16) pavement conditions (dry, wet, or icy), and 17) driver composition (commuters or non-commuters such as tourists). A neural network is employed to estimate the parameters associated with the bell-shaped Gaussian membership functions used in the fuzzy inference mechanism. An optimum generalization strategy is used in order to avoid over-generalization and achieve accurate results. Comparisons with two empirical equations demonstrate that the new model in general provides a more accurate estimate of the work zone capacity, especially when the data for factors impacting the work zone capacity are only partially available. Further, it provides two additional advantages over the existing empirical equations. First, it incorporates a large number of factors impacting the work zone capacity. Second, unlike the empirical equations, the new model does not require selection of various adjustment factors or values by the work zone engineers based on prior experience.

Existing computer models used to estimate queue delay upstream of the work zone have a number of shortcomings. They do not provide any model to estimate work zone capacity, which has a significant impact on the congestion and traffic queue delays. They cannot be used to perform scenario analysis for work zones with various characteristics such as work zone layout, number of closed lanes, work intensity and work time. In Part V, an object-oriented (OO) model is presented for freeway work zone capacity and queue delay and length estimation. The model is implemented into a interactive software system, called *IntelliZone*, using Microsoft Foundation Classes (MFC) and a hierarchy of multiple specialized *frameworks*. A three-layer application architecture is created to separate the application functions and classes from MFC classes. The high-level application domain layer is divided into *packages*. *IntelliZone*'s capacity estimation engine is based on pattern recognition and neural network models incorporating a large number of factors impacting the work zone capacity. This research provides the foundation for a new generation of advanced decision support systems for effective management of traffic at work zones. *IntelliZone* allows work zone engineers to perform scenario analysis and create traffic management plans consistently, reliably, and efficiently.

In Part VI, two neural network models, called clustering-RBFNN and clustering-BPNN models, are created for estimating the work zone capacity in a freeway work zone as a function of seventeen different factors through judicious integration of the subtractive clustering approach with the radial basis function (RBF) and the backpropagation (BP) neural network models. The clustering-RBFNN model has the attractive characteristics of training stability, accuracy, and quick convergence. The results of validation indicate that the work zone capacity can be estimated by clustering-neural network models in general with an error of less than 10%, even with limited data available to train the models. Extensive parametric studies have been performed on the influence of fifteen factors on the work zone capacity using these models. The results of the parametric studies of main factors impacting the work zone capacity can assist work zone engineers and highway agencies to create effective traffic management plans for work zones quantitatively and objectively.

It must be pointed out that the development of the computational models and their implementation into a software system is the major undertaking in this research project. The neural network models developed in this research have been trained by data obtained from several states. No data from Ohio were available to the authors and none was provided by ODOT. Neural networks are known for their high adaptability. Similar to human beings, their *intelligence* increases with additional training. As additional data become available the neural network models can be retrained to improve their accuracy with a relatively small effort.

Part I

CBR Model for Freeway Work Zone Traffic Management

CBR MODEL FOR FREEWAY WORK ZONE TRAFFIC MANAGEMENT

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ABSTRACT: A case-based reasoning (CBR) model is presented for freeway work zone traffic management. The model considers work zone layout, traffic demand, work characteristics, traffic control measures, and mobility impacts. A four-set case base schema or domain theory is developed to represent the cases based on the above characteristics of the problem. It includes a general information set, a problem description set, a solution (or control) description set, and an effects set. To improve the interactivity of the CBR system and its user-friendliness, a hierarchical object-oriented case model is developed for work zone traffic management. The model is implemented into an intelligent decision-support tool to assist traffic agencies in the development of work zone traffic control plans and to better design and manage work zones for increased mobility and safety. Three examples are presented to show the practical utility of the CBR system for work zone traffic management.

INTRODUCTION

Periodic reconstruction and maintenance of the freeway system is necessary to ensure that it fulfils its long-term purpose of serving the transportation needs of the public efficiently and economically. During the construction and maintenance operations the normal flow of traffic is disrupted by either a change in the freeway geometry or a temporary freeway closure. Closure of a freeway segment is not a feasible option on most freeways today. Therefore, reconstruction and

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maintenance operations have to be carried out without entirely closing the freeway segment and in close proximity to traffic flow. Work zones on freeways have to be designed and managed to ensure safety and mobility. The Manual on Uniform Traffic Control Device (FHWA, 2000a) provides guidelines for the use of traffic control devices that inform and guide motorists through the work zone with adequate protection for the workers. These guidelines were developed over the years from studies of traffic control devices and their effectiveness in improving work zone safety.

Recently, the Federal Highway Administration (FHWA) reviewed the state-of-practice in work zone traffic management and found that no uniform and objective procedure exists for quantifying the effects of various factors and determining the life cycle costs of work zone traffic management plans (FHWA, 2000b). They also outlined several steps that should be taken by state and local agencies to satisfy the expectations of the customer (the traveling public). Among the policy, planning, design, and management related steps outlined is the recommendation to "*develop and/or enhance user friendly software to model work zone delay, queues and crashes; calculate defendable road-user costs and proposed contract time, evaluate proposed changes to the traffic control plan as well as analyze work zone crashes. All software must be sufficiently flexible to allow for variable parameters to meet unique state/local conditions*." (FHWA, 2000b) Towards this end, a Microsoft Excel-based software, called QuickZone, is being developed for the FHWA for work zone user delay and cost quantification (Mitretek, 2000). The software allows planners to model work zones and their associated traffic control plans and provides them with basic delay and queue information that can be used for decision-making. A simple macroscopic input-output traffic analysis is adopted in the software to arrive at the estimates.

The practical usefulness of the software, however, is limited because it does not maintain a history of previous decisions nor does it learn from them in reaching a better decision. Furthermore, an input-output analysis assumes that the planner knows the effect of each work zone configuration in terms of the reduction in roadway capacity (maximum number of vehicles that can pass through a roadway segment in one hour under prevailing conditions, and expressed as vehicles per hour per lane). This information is usually not available and the planner has to make an educated guess, which may or may not be accurate thus leading to erroneous conclusions.

Case-based reasoning (CBR) is a methodology for storing and retrieving previous design decisions or cases and adapting them to the solution of new problem cases not found in the case base (Leake, 1996; Maher and Pu, 1997). The CBR approach does not require a low-level physical model of the problem. Rather, in a manner similar to human reasoning and decision-making, it uses generic and problem specific similarity metrics to induce best solutions from previously solved cases. This approach is appropriate for the work zone traffic management problem for the following reasons: (1) Accurate mathematical models of work zone traffic flow are not available, (2) there are only a finite number of cases to be considered, and (3) traffic agencies can use previously solved cases to set up the case base and then build it up gradually.

WORK ZONES AND TRAFFIC MANAGEMENT

A work zone is a region within an existing freeway's roadway where active maintenance, rehabilitation, and/or reconstruction work is carried out. The freeway is not closed and traffic and freeway work exist in close proximity to each other. A work zone thus represents a spatial and temporal restriction on a freeway's roadway that impacts the normal flow of traffic negatively. The impact appears in the form of increased congestion, travel times, accidents, and a greater level of dissatisfaction among the traveling public. Work zones are designed and managed to minimize these effects and the overall cost.

Work zone costs are often divided into three components: construction/contracting cost (CCC), road user cost (RUC), and maintenance of traffic cost (MTC) (Figure 1). Construction and contracting cost is the amount charged by the contractor for the work plus any litigation and liability cost. Road user cost is the result of the negative impact of the work zone on the normal flow of traffic. Road user cost can be quantified in several ways including delay time, queue length, lost productivity, fuel wastage, and pollution. There is also a non-quantifiable aspect to the road user cost, that of dissatisfied travelers. Non-quantifiable parameters, as the name indicate, are those that cannot be readily expressed in numbers. They are categorized under linguistic terms that are understood by traffic engineers. Maintenance of traffic cost is the cost of labor and equipment needed for maintaining traffic through and around work zones. It includes the cost of traffic control devices such as variable message signs, maintenance of alternate routes, construction and maintenance of temporary pavements, and public dissemination of information through mass media advertisements.

Ideally, management of work zone requires the minimization of the total cost. However, from the highway traffic agency's perspective the road user cost is the most important cost to consider in a work zone project. All other costs are given lesser priority. The Ohio Department of Transportation (ODOT), for example, has identified four objectives (in no particular preferential order) to rate traffic control plans. These are (1) to reduce motorist complaints, (2) to maximize corridor capacity, (3) to minimize duration of motorist inconvenience, and (4) to maximize motorist/work safety. These objectives then become the basis for determining the relative effectiveness of new traffic control plans with respect to previously implemented plans for similar work zone conditions. Currently, this procedure is done manually by traffic engineers based on their previous experiences. This research advocates case-based reasoning as an effective approach for formalizing and automating this procedure to achieve greater reliability and efficiency.

CASE-BASED REASONING

Case-based reasoning (CBR) evolved from cognitive science research into an intelligent problem solving approach that relies on previous experiences in the form of cases of previously solved similar problems. CBR is a multidisciplinary subject that is viewed with different perspectives in cognitive science, artificial intelligence, and knowledge engineering (Aha, 1998). It is loosely based on human reasoning and problem solving which is essentially experiential and episode based. For example, an experienced traffic engineer can plan a work zone by recalling the knowledge gained from similar scenarios that he or she had solved previously and avoiding starting from scratch. Thus, CBR can be thought of as a high level model of human reasoning and problem solving, which is the view adopted in cognitive science. In artificial intelligence and knowledge engineering, modeling of human reasoning is not the goal per se but the basis for the development of computational models for the solution of real world problems. Case-based reasoning systems thus mimic human reasoning by retrieving and revising cases from memory (previous experiences) to find solutions for new problems in a given domain.

CBR systems differ from rule-based and model-based systems (Adeli, 1998; Adeli and Balasubramanyam, 1988; Adeli, 1990a&b) in that they require little low-level domain knowledge and rely more on general rules for retrieving and adapting saved solutions. A major drawback of rule-based systems is the difficulty in eliciting knowledge in the form of low-level rules from experts to be used by an inference engine that chains these rules to arrive at a reliable solution. Model-based systems, on the other hand, assume that an accurate mathematical model for the problem exists. This is often not the case for complex engineering problems such as the work zone traffic control problem.

The development of a CBR system requires the specification of several procedures. A schematic description of these procedures is given in Figure 2. These procedures represent typical operations in a CBR system. As such they may also be thought of as typical CBR system components. Case-based reasoning is a methodology for solving problems and not a specific artificial intelligence technique (Watson, 1999). A typical case-based reasoning and problem solving cycle is shown in Figure 3. A new problem is first represented into a reference case. This case specifies the problem requirements, which may or may not be complete, and their relative importance. Using this reference case the CBR system ranks cases in the case base according to their degree of similarity to the reference case. If the retrieved cases do not provide a satisfactory solution, which is usually the case, then they are used as the starting solution to be revised and adapted in order to obtain an improved or satisfactory solution. The retrieval performance of a CBR system improves as the number of reliable cases in the case base increases. Initially, a functional CBR system may have only a few cases in the case base; new cases are consequently added as new problems are solved. This is how *learning* occurs in a CBR system.

CBR systems have been developed for design, planning, decision support, and diagnosis in diverse fields such as engineering, medicine, law, and business (Aha, 1998; Lenz et al., 1998; Maher and Pu, 1997; Leake, 1996). However, the development of a CBR system for work zone traffic planning and management has not been reported in the literature.

OBJECTIVES

In this research a case-based reasoning approach is used for the development of a decision support system for work zone traffic management with the following objectives:

1. To provide traffic engineers with an intelligent decision support tool for design of freeway (and divided highway) work zone traffic control plans with the goal of reducing the road user cost (reduced complaints, increased corridor capacity, reduced delays, and improved safety).
2. To develop a case base schema or domain theory to represent the cases based on factors such as work zone layout, traffic demand, work characteristics, traffic control measures, and mobility impacts,
3. To develop work zone traffic control plans that are reliable and defendable;
4. To archive previous experiences of work zone traffic control for quick reference, and;
5. To serve as learning and training tool for work zone traffic control under different work zone scenarios.

SCOPE AND CATEGORIZATION OF PARAMETERS

The scope of applicability of the CBR system for work zone traffic management is defined and parameters involved are categorized in this section.

Work Zone Type

Several types of work zones are used in practice. The scope of the CBR system is limited to temporary stationary work zones on divided highways or freeways. Short-duration or mobile work zones (with duration of less than an hour) are not considered because standard traffic control plans are often adequate for maintaining traffic flow through such work zones. For a given work zone a separate traffic control plan is developed for each direction of flow independent of flow in the other direction. This simplifies the modeling and understanding of work zone traffic flow by reducing the number of variables to consider.

Work Zone Layout

The CBR system can consider part-width construction (lane merging), lane shifting, and crossover layouts. In part-width construction one or more lanes are closed to traffic and traffic is merged into the remaining open lanes. Such a layout is usually represented by [*a, b*] ($a > b$) where *a* and *b* are the number of open lanes before and after the establishment of the work zone, respectively. In lane shifting layout the number of lanes is not reduced and traffic is shifted around the work zone on temporary pavements or shoulders. No merging operation occurs in a lane shifting work zone layout. Crossover layouts are the combination of lane shifting and lane merging layouts where traffic is merged and shifted across the median unto lane(s) for travel in the other direction. Thus, the two streams of traffic share the same roadway in close proximity to each other.

Work Characteristics

It has been found that the capacity of a work zone depends on the type and intensity of work (Krammes and Lopez, 1994; Dixon et al., 1996). This in turn affects the flow of traffic through work zones. The proximity of heavy equipment, workers, noise, and dust tends to reduce mean speeds through work zones; work of higher intensity produces a greater impact than work of lesser intensity. These factors are considered in the CBR system by qualitative grades of intensity of work specified as part of the description of the work zone scenario.

Traffic Flow Characteristics

Traffic control plans are developed to facilitate the flow of traffic through and around work zones. To develop effective plans it is necessary to have the highway segment's traffic flow characteristics such as flow rate, traffic composition, and driver behavior. The traffic demand that needs to be handled can be specified by the hourly flow rate on the highway segment prior to the establishment of the work zone. The percentage of trucks gives an indication of the traffic stream's composition, which in turn gives an indication of flow characteristics such as average speed. The familiarity of the drivers with the highway corridor also has a significant impact. This can be captured in a qualitative manner by categorizing highways as urban, suburban, or rural. The CBR system can consider all these factors for analysis of work zone traffic flow. The hourly flow rate is required while the others are optional if reliable data is available.

Phases of Work

A work zone may go through several phases over its lifetime. Work enters a new phase whenever any of the parameters defining the work zone scenario changes. Changes in work zone scenarios are analyzed by creating a new problem description and developing traffic control plans for each one separately. The CBR system considers the duration of a phase to determine the time-dependent impact of the work zone scenario.

Traffic Control Measures

It is assumed that the requirements of the Manual on Uniform Traffic Control Devices (FHWA, 2000a) are followed for all traffic control plans. To improve mobility further, the traffic agency can take further measures such as providing signed alternate routes, advanced roadside warning and informative messages, updates on traffic conditions through the mass media, and posting reduced speed limits in the work zone. These factors are considered in the CBR system in a qualitative manner. Note that the impact of these measures will depend on traffic flow characteristics in the given highway such as flow rate and driver behavior.

Road User Cost

Road user cost is the determining criterion for the selection of a traffic control plan for a work zone. Quantifying actual cost incurred by road users is difficult. Therefore, indirect measures of the negative impacts of work zones are usually used. As a measure of motorist inconvenience, the CBR system uses the quantitative measures of maximum queue length and delay time that motorists can experience as a result of a given work zone traffic control plan. Furthermore, the CBR system considers motorists' complaints, corridor capacity, and safety in a qualitative manner. These criteria correspond to the four objectives identified by ODOT for the design of work zone traffic control plans. The CBR system works even when only one of these values is given for a work zone scenario.

A FOUR-SET CASE MODEL FOR THE WORK ZONE TRAFFIC MANAGEMENT DOMAIN

A case model or domain theory is a template for collection of information that captures a problem-solution episode. In general, this information is usually partitioned into two sets: a problem set and a solution set. The problem set contains information that describes the problem whose solution is desired. This information uniquely identifies the case in the case base. The solution set contains information that describes the solution chosen for the problem.

Considering the scope of the CBR system for work zone traffic management a two-set case model is neither adequate nor appropriate. Each case must contain all the information needed for case-based reasoning plus the information required for maintaining complete records of previous experiences for administrative purposes. Furthermore, the outputs of the system must include information on the effects of the traffic control plan chosen for a given problem description. For these reasons, in this research we create a four-set case model for work zone traffic management consisting of a general information set (G), a problem description set (P), a solution (or control) description set (S), and an effects set (E). Mathematically, a case is defined as the union of the four non-overlapping or disjoint sets as follows:

$$C = G \bigcup P \bigcup S \bigcup E \qquad (1)$$

where $\bigcup$ is the set union operator (Figure 4).

The general set contains information that identifies and describes the experience episode for future reference. Any useful information beyond that needed for the operation of the CBR system is included in this set so that a complete record of the previous experience episode is maintained in the case. The problem set contains information that defines the constants of the work zone traffic control problem. This information is known to the traffic engineer from construction plans and traffic studies and represents work zone conditions. Information in this set includes number of lanes, flow rate, duration of work, and intensity of work.

The solution or control set contains information on the work zone layout and traffic control measures adopted for the mitigation of traffic congestion. This information defines the solution, or the traffic control plan, for the work zone defined in the problem set. Information in the solution set includes number of open lanes, work zone layout, and traffic control measures such as advance motorists' warning and signed alternate routes. The effects set contains information about the impacts on the traffic in the work zone. This information forms the criteria for the selection of one case over another as a solution for a given work zone traffic control problem.

In the case model for the work zone traffic management each case is uniquely identified by the union of the problem (P) and solution (S) sets. Thus, two cases in the case base can have identical problem sets; however, their solution sets must differ. This situation may represent two experience episodes where the work zone traffic control problem is identical but a different traffic control plan is adopted for each with possibly different impacts. When querying the system the traffic engineer can specify as much of the information in the problem and solution sets. The more information the traffic engineer provides, the more specific will be the cases retrieved by the CBR system. It should be pointed out that it is not necessary to specify all the information in the problem set because the CBR approach does not require exact matching for retrieval.

Equation (1) defines a case as a set of information. The case base can then be defined as the union of all the cases $C_i = G_i \cup P_i \cup S_i \cup E_i$

$$Z = \bigcup_i C_i \qquad (2)$$

such that

$$C_i \neq C_j \Leftrightarrow P_i \cup S_i \neq P_j \cup S_j; \quad \forall i, j,\ i \neq j \qquad (3)$$

Equation (3) ensures that no two cases in the case base have the same problem and solution sets and all cases are unique. The case base given by the set Z captures the domain knowledge needed for solving the problem. The effectiveness of the CBR system increases as the number and diversity of cases in the case base increases encompassing the entire knowledge domain defined by its scope of applicability. The CBR system, however, can work even with only a few cases in the case base.

HIERARCHICAL OBJECT-ORIENTED CASE MODEL

The representation of a case as a union of information sets is most appropriate for the design of a CBR system. This representation partitions the variables involved in the problem according to their use in the CBR system: input, output, indexing, retrieval, and adaptation. However, this partitioning is not appropriate for human comprehension and the user-friendliness of the CBR system. Over the years, traffic engineers have developed a body of knowledge for work zone traffic control that categorizes information in a manner similar to that presented in a previous section. This categorization is based on key elements or components of the work zone traffic control problem and is generally more specialized than the four-set categorization defined for the set representation of the case model. A case model that provides such a level of detail is useful for the design of an effective user interface for the CBR system. An object-oriented representation is used to create such a user-interface.

A hierarchical object-oriented case model is developed for the CBR system for work zone traffic management (Figure 5). A case in the system, represented by a *Case* object uses four lower level objects, *General*, *Problem*, *Solution*, and *Effects*, corresponding to the four sets defined in the set model of the case. The *General* object uses three lower level objects, *Description*, *Time*, and *Cost* that collectively encapsulate general information needed to keep a complete record of the experience episode. The *General* object can own additional objects depending on the information needs of the user.

The *Problem* object uses three lower level objects, *Layout*, *Traffic Flow Characteristics*, and *Work Characteristics*. These objects encapsulate the work zone traffic control problem or the pre-existing geometry and flow conditions for which a traffic control plan is desired. The *Solution* object encapsulates the traffic control plan. It uses two lower level objects: *Layout* and *Traffic Control Measures*. The *Layout* object encapsulates information about the geometric conditions after the establishment of the work zone while the *Traffic Control Measures* object encapsulates the steps taken to alleviate traffic congestion. Work zone traffic control measures are often divided into those taken inside the work zone and those taken outside the work zone. The lowest objects *Inside Work Zone* and *Outside Work Zone* capture this division of information. Traffic control measures taken inside a work zone include imposing speed limits, widening lanes, and erecting gawk screens, while those taken outside the work zone include warning motorists in advance and diverting traffic through alternate routes. The *Effects* object encapsulates information on the effects of the traffic control plan, which is essentially the road user cost. The *Road User Cost* object describes the impact of the traffic control plan on motorists.

The most specialized objects in the object-oriented case model for work zone traffic management (the leaf nodes in Figure 5) define the categories readily understood by traffic engineers. Information in these categories is merged to form the four-set case model used by the CBR system.

CASE REPRESENTATION

In the case models presented in the previous section a case is defined as a collection of information objects. The information in the objects is identified by linguistic terms that are generally understood by humans but are imprecise for information processing. Information or knowledge representation involves the specification of semantics to information entities that enables machines to use well-defined operations to process them.

Since cases and objects in the CBR system for work zone traffic management are a collection of facts rather than rules or functions, an attribute-value scheme is used for information representation. An attribute-value representation of information is defined by three elements:

- An attribute or field name that identifies the information entity and gives it a meaning that can be understood by humans;
- A type that specifies the type of the attribute, and;
- A value taken from the domain that specifies the current instantiation of the attribute.

Common attribute types include choice (free-form text), alphabetic, number, integer, and positive number. A range can also be specified to further constrain and elucidate the domain defined by the type. A range specification may be a list of values, a range of values, a hierarchy of values, or values of a certain unit.

The attribute-value representation A of an information entity can be written as a 3-tuple variable:

$$A = \{name, type, value\} \tag{4}$$

Given an attribute-value representation A the elements are defined by the functions Name(A) = *name*, Type(A) = *type*, and Value(A) = *value* = *v*. Therefore, a case C_i in the CBR system for work zone traffic management can be represented by a collection of attribute-value representations of all the information entities it contains. This can be written as

$$C_i = \{A_1^i, A_2^i, A_3^i, \ldots, A_N^i\} \tag{5}$$

where A_j^i is the *j*th attribute-value representation in case *i* and *N* is the total number of attributes in a case. The *name* and *type* elements of a given attribute-value representation *i* (*i* = 1, *N*) are identical in all cases in the case base; the *value* elements, however, may be different. The attribute-value representations of the information entities that constitute a case in the CBR system for work zone traffic management and corresponding to the *General*, *Problem*, *Solution*, and *Effects* sets are defined in Tables 1 to 4. Only two types of values are used for representation: choice and number.

SIMILARITY MEASURES

The degree of similarity between numeric attribute *i* of two cases *j* and *k* is defined as

$$\text{Similarity}(A_i^j, A_i^k) = \frac{\min\left(\left|v_i^j\right|, \left|v_i^k\right|\right)}{\max\left(\left|v_i^j\right|, \left|v_i^k\right|\right)} \tag{6}$$

where $v_i^j = \text{value}(A_i^j) \neq 0$ and $|\cdot|$ denotes the absolute value. In the CBR system for work zone traffic management all values of numeric attributes are non-zero and positive. Thus, Eq. (6) computes the degree of similarity as the ratio of the minimum value to the maximum value, which ranges from greater than 0 to 1.

The degree of similarity between choice (free-form text) attribute type *i* of two cases *j* and *k* is defined by the following rule:

IF (v_i^j appears in v_i^k) OR (v_i^k appears in v_i^j)

THEN $\text{Similarity}(A_i^j, A_i^k) = 1$ ELSE $\text{Similarity}(A_i^j, A_i^k) = 0$ (7)

Since the choice type represents free-form text it may consist of numbers, alphabets, and special characters (such as spaces). Note that the similarity operations are commutative, that is, $\text{Similarity}(A_i^j, A_i^k) = \text{Similarity}(A_i^k, A_i^j)$.

CASE RETRIEVAL

An interaction with a CBR system starts with the formulation of a query that describes a situation for which a solution is desired. Based on this query the system retrieves cases from the case base as potential solutions to the problem. The retrieval process is guided by the degree of similarity (or match) of the query to the cases in the case base. In the CBR system for work zone traffic management, the query consists of two components: a reference case and a weight vector. The reference case *R* is defined as

$$\mathbf{R} = \{A_1, A_2, A_3, \ldots, A_N\} \tag{8}$$

This equation is similar to Eq. (5). Thus, a reference case has the same collection of attributes-value representations as other cases in the CBR system. The traffic engineer using the CBR system inputs values for the attributes in the reference case to describe the work zone scenario.

The weight vector w_i (i = 1, N) attaches an importance to the similarity of each attribute in the retrieval process. The suitability of the cases in the case base as solutions to the query is determined by a case or global similarity measure. This is computed as the weighed sum of the similarities of the respective case and reference case values. The case similarity function for case i, as compared with a given reference case R is defined as

$$\text{Similarity}(C_i, R) = \frac{\sum_{j=1}^{N} w_j \times \text{Similarity}(A_j^i, A_j^R)}{\sum_{j=1}^{N} \left| w_j \right|} \tag{9}$$

Case similarity scores range from 0 to 1 where 0 indicates no similarity while 1 denotes full similarity. Based on the case similarity scores the cases in the case base are ranked and presented to the user. Cases with the largest score represent potential solutions for the problem at hand.

CREATION OF THE CASE BASE

The CBR system for freeway work zone management has been implemented in Induce-It, a software shell for developing case-based reasoning systems (Induce-It, 2000). Induce-It is based on the Microsoft Excel spreadsheet software system and relies on its user interface, database, and programming capabilities to provide an environment for developing and using a CBR system. Induce-It provides built-in capabilities for case representation, indexing, storage, retrieval, and adaptation allowing the developer to concentrate on domain information collection and problem formulation. Cases are represented as a sequence of attribute-value pairs. Induce-It supports several numeric and textual field types including number, choice (free form text), and user-specified. A specific region in the spreadsheet is reserved for the case based, where cases appear in rows while case field values appear in columns.

Based on the case models presented in the preceding sections a prototype CBR system for work zone traffic management is developed using Induce-It. The case base of the CBR system presently includes twenty cases representing common work zone scenarios and their corresponding traffic control plans. The cases were created from information obtained from the Ohio Department of Transportation. The information consisted primarily of qualitative data such as work zone classification, traffic control measures, planning goals, and development procedures. The quantitative data used in the cases such as the freeway traffic flow rate (in the absence of the work zone), maximum queue length, and maximum delay time are derived from human experience of work zone traffic control. The sample case base is sufficient for testing the prototype system and can be extended easily as new cases become available.

CREATION OF WORK ZONE TRAFFIC CONTROL PLANS USING THE CBR SYSTEM

The flow chart of steps involved for creation of a suitable work zone traffic control plan using the proposed CBR system is shown in Figure 6. When a traffic engineer wants to create a traffic control plan for a given work zone scenario, he starts with some basic fixed information about the work zone under consideration such as the number of lanes and flow rate. This information is fed into the CBR system by responding to queries made by the system. This is done in an iterative manner through a number of interactive sessions until a satisfactory solution case is obtained or a retrieved case is adapted to obtain a desired solution.

Initially the reference case is created with the minimum information needed to describe the work zone situation, that is, the number of lanes and the flow rate. This ensures that a wide spectrum of cases is retrieved by the system. If after evaluating the retrieved cases based on the case scores no suitable solution is found the reference case is modified in the subsequent interactive sessions by adding more information known about the work zone scenario. In general, the reference case is modified in the sequence shown in the top-left corner of Figure 6 where at each subsequent interactive session the information in the next lower box is added to the reference case. This procedure ensures that the solution is narrowed down gradually and minimizes the possibility of missing good solutions by first starting with minimum required input.

The traffic engineer using the CBR system can use his judgement to assign weights to various attributes. The value of each weight indicates the significance of the corresponding attribute. For example, if it is desired that at least two lanes be open then the number of open lanes attribute should be given a larger weight. Also, a weight can indicate the reliability of a given value. For example, if the flow rate is not known accurately then a lower weight should be assigned to it. In general, the weights need not be changed from one interactive session to the next. However, the CBR system user can modify them for the same reference case to tune the output of the system.

The retrieved cases are compared according to their case similarity scores computed by the CBR system. A higher score indicates a closer match to the reference case and the weights inputted by the user. In addition to this automatic suitability measure the CBR system user can also evaluate the retrieved cases for their impacts on motorists, the number and type of traffic control measures, and the maintenance of traffic cost. This evaluation will guide the traffic engineer to modify the reference case and the associated weights, accepting a case as the desired solution, or modifying a case to obtain an improved solution.

Case adaptation is attempted after several interactive sessions yield no desired solution from the case base. Using the retrieved cases as guide the traffic engineer can modify them to arrive at a desirable solution. This solution may then be included in the case base for future perusal.

ILLUSTRATIVE EXAMPLES

In this section the CBR system for work zone traffic management is used to solve three examples. Figures 7 to 10, considered side-by-side, show the CBR system's user interface. They display the attribute-value representation of the information, the reference case, the weights, and the case similarity scores. Figures 7-10, respectively, show the portion of the case base corresponding to the *General*, *Problem*, *Solution*, and *Effects* objects of the case model. Each case is displayed in a separate row, starting from row 11. The field names and values appear in columns, starting from column C. The reference case is defined in row 8 and the weights indicating the relative importance of the values in the reference are specified in row 7. The suitability of the cases in the case base as potential solutions to the reference case is indicated by the case score, displayed in column A (Figure 7).

Example 1

This example illustrates the use of the CBR system as a decision-support tool for creation of a work zone traffic control plan. Given the description of the work zone scenario as defined by a reference case the traffic engineer uses the CBR system in the manner shown in Figure 6 to retrieve the most relevant case(s) from the case base. The work zone scenario (reference case) is described in Table 5. The freeway has three lanes each carrying an average flow of 1400 vehicles per hour. Each phase of construction lasts for 6 hours and it is of medium intensity. These are the constants of the work zone scenario for which a traffic control plan is to be developed. In addition to these constants, it is also desired that two lanes be kept open at all times, the layout be of merging type, and a signed alternate route be provided to avoid excessive congestion. This work zone scenario is typical for lane resurfacing projects.

The CBR system is consulted in 3 interactive sessions. The reference case attribute values and weights chosen for each interactive session and their corresponding case similarity scores are summarized in Tables 5 and 6, respectively. In the first interactive session, the reference case is created with the values for the number of lanes and flow rate only, and each is given equal importance. As seen from Table 6, two cases, Case 12 and Case 17, match exactly with the reference case with a similarity score of 1. This scenario, however, is too general and many work zone scenarios have these characteristics but may require different traffic control plans because of differences in other characteristics.

In the subsequent second interactive session, the values for the work phase duration and work intensity are added to the reference case. The weights are modified to reflect the greater relative importance of flow rate and number of lanes in the choice of a traffic control plan. The phase duration is given more importance than the work intensity because the former has a more significant impact on the work zone traffic compared with the latter. In general, the longer the duration of the work zone the greater the extent of the congestion. This congestion, however, does not increase without bound as motorists tend to change their driving habits and reduce demand at the work zone site. For this second interactive session Case 17 has the highest score followed closely by Case 18. As seen from Figures 8 and 9 these two cases have similar work zone scenarios and traffic control solutions even though they are for different types of construction work (Case 17 is for culvert work and Case 18 is for pavement marking). However, the minor differences that exist in the problem and solution descriptions of these two cases result in a significant difference in the impacts on traffic. One has a queue length of 3.22 km (2 miles) and the other has a queue length of 0.81 km (0.5 miles) (column Z in Figure 10). For this reason the third interactive session is made more specific by adding the values for number of open lanes, layout, and alternate route to the reference case (Table 5). These values represent the desired characteristics of the traffic control plan that the traffic engineer feels can reduce traffic impacts. Case 1 (presented in row 11 of Figures 7 to 10) has the highest score in this interactive session (Table 6) and thus provides the best traffic control plan for the given work zone scenario.

Example 2

The CBR system for work zone traffic management can also be used for information retrieval and engineer training. For this purpose, a reference case is created that contain values desirable in the retrieved cases. The weights are normally set all equal to 1. Suppose the engineer wants to study all work zone scenarios that have a merging layout from 4 lanes to 2 lanes. To retrieve all such cases, a reference case is created with number of lanes set to 4, number of open lanes set to 2, and layout set to 'Merging.' The case similarity scores for this example are given in Table 6. Cases 5 and 6 with a case score of one match the reference case. Note that for such training information retrieval, only cases with scores of 1 are considered because exact matches are desired.

Example 3

An advantage of CBR systems for knowledge engineering is that the case base can be developed incrementally and easily by the end user. A fully functional CBR system may have only a few cases initially; the user can add more as he or she encounters new problems not found in the case base. To illustrate this, suppose the user wants to develop a traffic control plan for a 3 to 1 crossover layout in a rural location. Interacting with the system with reference case values of 3 for number of lanes, 1 for number of open lanes, 'Xover' for layout, and 'Rural' for driver behavior produces the case similarity scores shown in the last column of Table 6. No exact matches are found. Also, the case similarity scores have a narrow spread with no single case dominating the others. This indicates that a satisfactory solution case does not exist in the case base. For situations like these, the user can develop a traffic control plan from scratch (aided by the cases in the case base) and then add the new case to the case base for future perusal.

CONCLUDING REMARKS

Traffic agencies are faced with the challenge of planning, designing, and operating work zones that maximize safety and minimize motorists' inconvenience. The most pressing need is to alleviate excessive congestion by developing work zone traffic control plans that efficiently handles traffic flow through and around work zones. Presently, no rigorous procedures exist for the development of work zone traffic control plans. In this research, a case-based reasoning system is developed as an intelligent decision-support tool to assist traffic engineers in the development of work zone traffic control plans. The CBR system developed in this research is the first decision support tool to help traffic engineers create work zone traffic control plans.

The effectiveness of a work zone traffic control plan is measured by the delay experienced by motorists and/or the length of queue formed on the upstream side. To improve objectivity and reliability of traffic control plans a multi-paradigm computational model is currently being developed that maps traffic flow and work zone characteristics to delay time and queue length. The model will be integrated into the CBR system presented in this article.

ACKNOWLEDGMENT

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Table 1 Attribute-value representation of information in the *General* object

Name	Description	Type	Value representation	Example
ID	Case identification	Choice	Free-form alphanumeric	OH-5235
Description	Brief description of the work zone traffic control project	Choice	Free-form alphanumeric	Resurfacing of the southbound lane
Freeway/Direction	Freeway identification number and direction	Choice	Designation/ [NB, SB, EB, WB]	I-71/NB
Location	Geographical location of freeway	Choice	County, city	Franklin, Columbus
Start time	Start time of the project	Choice	Year, month	2000, 02
Duration	Duration of the project	Number	Days	30
CCC	Construction/contracting cost	Number	Thousand dollars	25000
MTC	Maintenance of traffic cost	Number	Thousand dollars	500
Comments	Additional comments	Choice	Free-form alphanumeric	Completed successfully

NB: northbound SB: Southbound EB: eastbound WB: westbound

Table 2 Attribute-value representation of information in the *Problem* object

Name	Description	Type	Value representation	Example
No. of lanes	Number of open lanes prior to the creation of the work zone	Number	Positive integer	3
Flow rate	Average flow at work zone site	Number	Vehicles/hour/lane	1500
Percent trucks	Percentage of heavy vehicles or trucks in traffic stream	Number	Percent	5
Driver behavior	Classification of driver behavior	Choice	[Urban, Rural]	Urban
Phase duration	Duration for the work phase	Number	Hours	4
Work Intensity	Classification of work intensity	Choice	[High, Moderate, Low]	Moderate

Table 3 Attribute-value representation of information in the *Solution* object

Name	Description	Type	Value representation	Example
No. of open lanes	Number of open lanes after the creation of the work zone	Number	Positive integer	2
Layout	Work zone layout or configuration	Choice	[Merge, Shift, Crossover]	Merge
Speed limit	Posted speed limit within work zone	Number	1.61×km/hour (niles/hour)	45
Lane width	Width of lanes within work zone	Number	0.305×m (ft)	11
Screens	Gawk/glare screens to prevent driver distractions	Choice	[Yes, No]	No
Advance warning	Advance warning of work zone before exits and alternate routes	Choice	[Yes, No]	Yes
Real-time info	Real-time info on traffic congestion ahead of work zone	Choice	[Yes, No]	No
Signed alternate route	Signed alternate routes ahead of work zone	Choice	[Yes, No]	Yes

Table 4 Attribute-value representation of information in the *Effects* object

Name	Description	Type	Value representation	Example
Queue length	Maximum queue length observed during the work phase	Number	1.61×km (miles)	2
Delay time	Maximum delay time experience during the work phase	Number	Vehicle-hours	2500
Complaints	Amount of motorists' complaints	Choice	[High, Medium, Low]	Low
Safety	Level of motorist and worker safety	Choice	[High, Medium, Low]	High
Corridor capacity	Reduction in corridor capacity	Choice	[High, Medium, Low]	Medium

Table 5 Reference case (work zone scenario) and weights for Example 1

Attribute name	Value	Weights		
		Interactive session 1	Interactive session 2	Interactive session 3
No. of lanes	3	1	2	2
Flow rate	1400 vph/lane	1	2	2
Phase duration	6	NS	1.5	1.5
Work intensity	Medium	NS	1	1
No. of open lanes	2	NS	NS	2
Layout	Merging	NS	NS	1.5
Signed alternate route	Yes	NS	NS	1

NS = no value is specified; vph = vehicle per hour

Table 6 Case scores for the illustrative examples

Case	Example 1			Example 2	Example 3
	Interactive session 1	Interactive session 2	Interactive session 3		
Case 1	0.992	0.973	0.974	0.991	0.964
Case 2	0.986	0.957	0.897	0.964	0.929
Case 3	0.986	0.957	0.897	0.964	0.929
Case 4	0.984	0.925	0.850	0.982	0.964
Case 5	0.987	0.943	0.945	1.000	0.929
Case 6	0.982	0.942	0.913	1.000	0.964
Case 7	0.992	0.936	0.877	0.973	0.929
Case 8	0.980	0.951	0.907	0.982	0.929
Case 9	0.984	0.958	0.897	0.964	0.929
Case 10	0.984	0.954	0.893	0.964	0.929
Case 11	0.988	0.970	0.862	0.964	0.964
Case 12	1.000	0.975	0.945	0.991	0.929
Case 13	0.986	0.961	0.885	0.964	0.964
Case 14	0.984	0.954	0.893	0.964	0.929
Case 15	0.986	0.957	0.881	0.982	0.929
Case 16	0.980	0.939	0.864	0.982	0.929
Case 17	1.000	0.988	0.957	0.991	0.929
Case 18	0.998	0.983	0.953	0.991	0.929
Case 19	0.985	0.972	0.921	0.988	0.929
Case 20	0.977	0.958	0.882	0.982	0.964

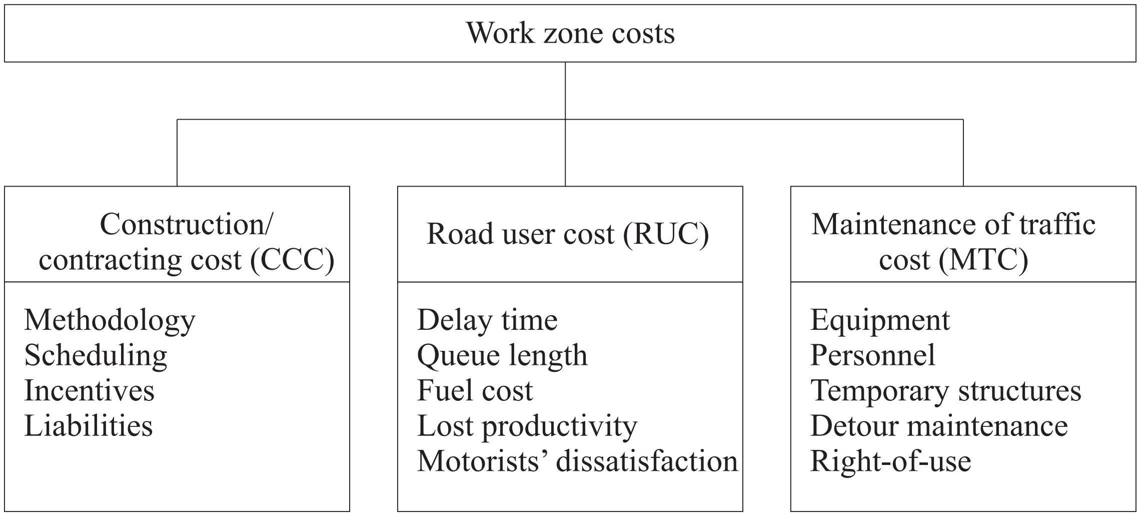


Figure 1 Freeway construction work zone costs and factors affecting them

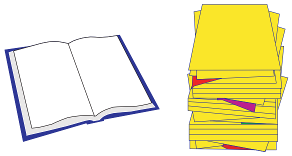
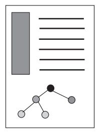
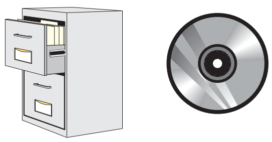
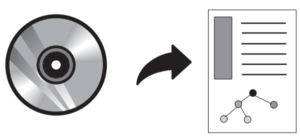
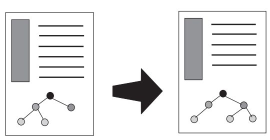
 Domain information	• Problem identification and formulation • System scope definition • Collection of experience episodes • Sources: manuals, books, drawings, engineers, etc
 Representation	• Specification of semantics and operations • Definition of a data structure • Consideration of problem and system scope • Examples: attribute-value, graph-based, object-oriented
 Indexing and storage	• Creation of an archiving system for cases • Management of storage resources • Technology: flat, relational, or object-oriented database systems
 Retrieval	• Retrieval of potential solution cases • Definition of similarity metric to determine suitability • Inexact matching • Ranking of cases using similarity metric
 Adaptation	• Modification of retrieved cases to obtain solution for specific problem • Specification of rules and/or functions for modification

Figure 2 Elements of case-based reasoning

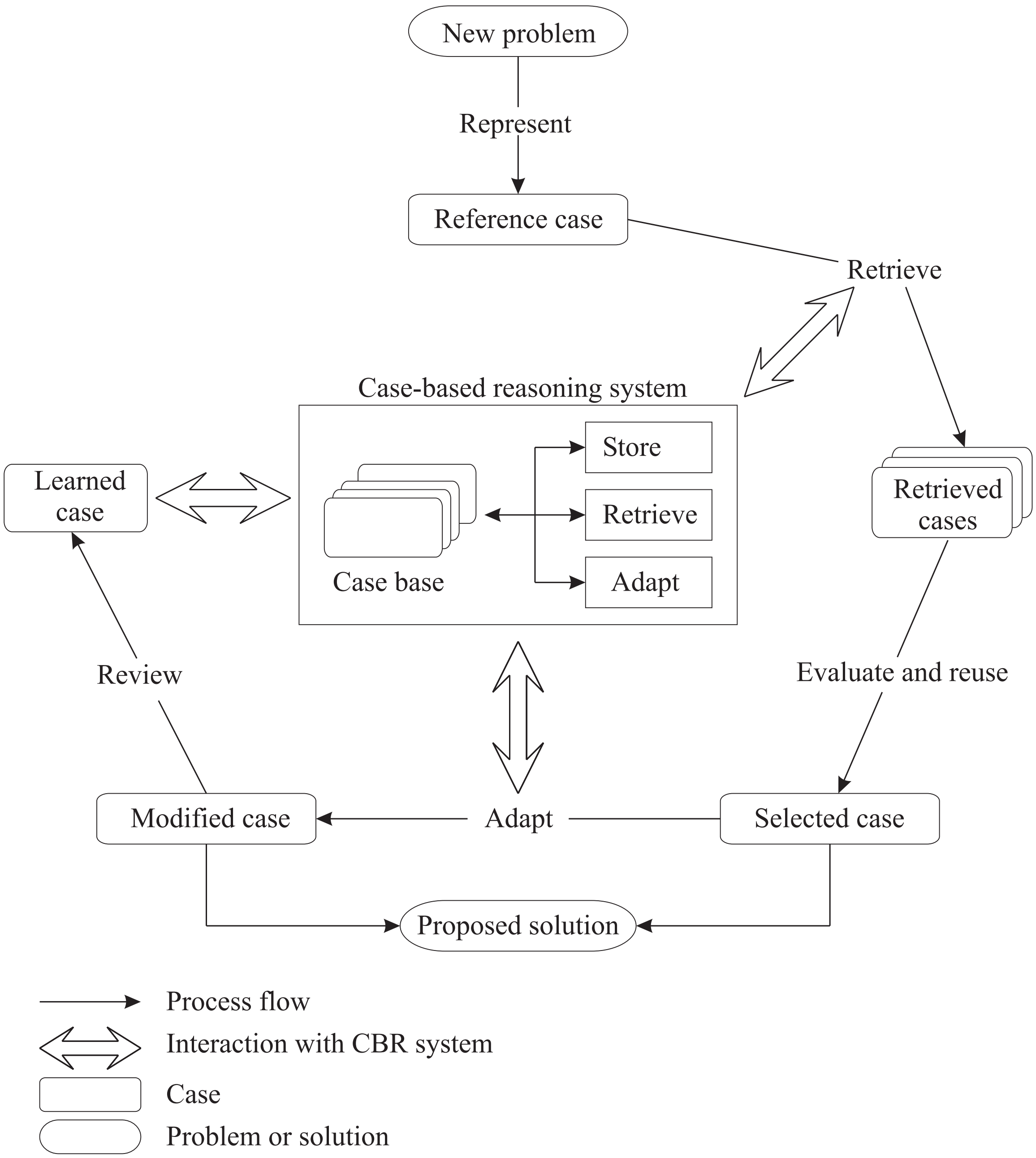
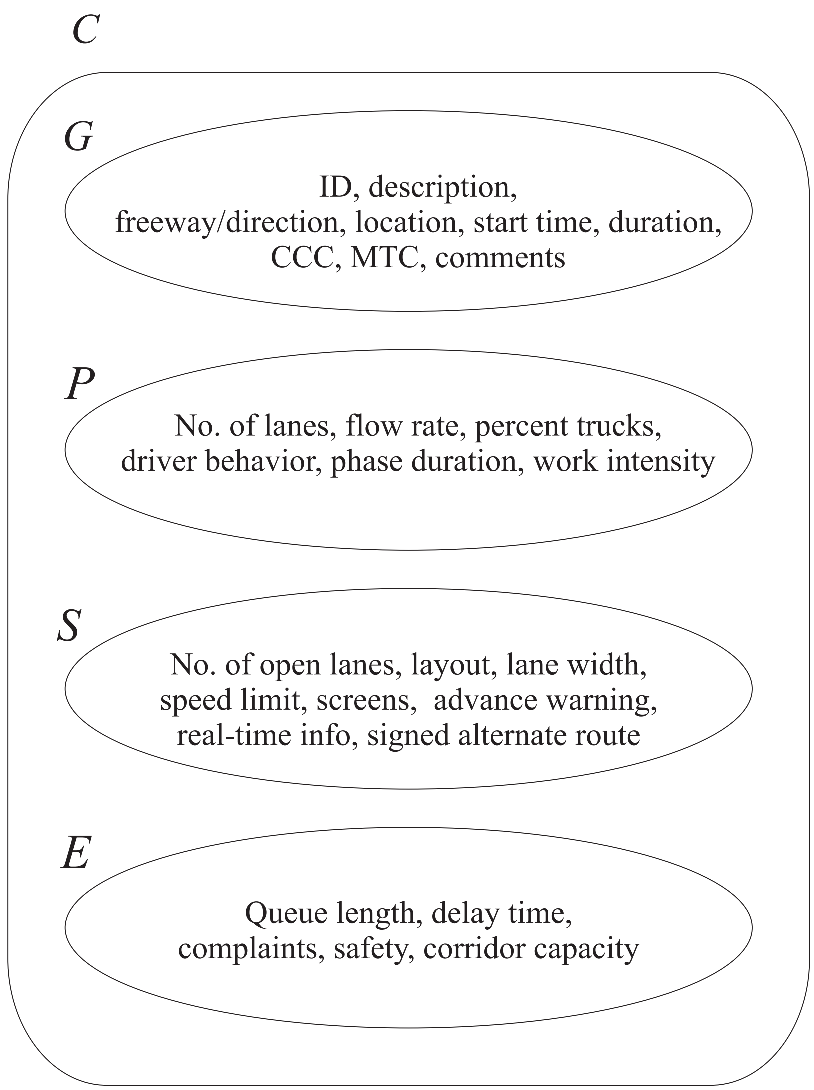


Figure 3 Typical CBR system processing cycle



$$C = G \bigcup P \bigcup S \bigcup E$$

Figure 4 Four-set case model for the CBR system for work zone traffic management

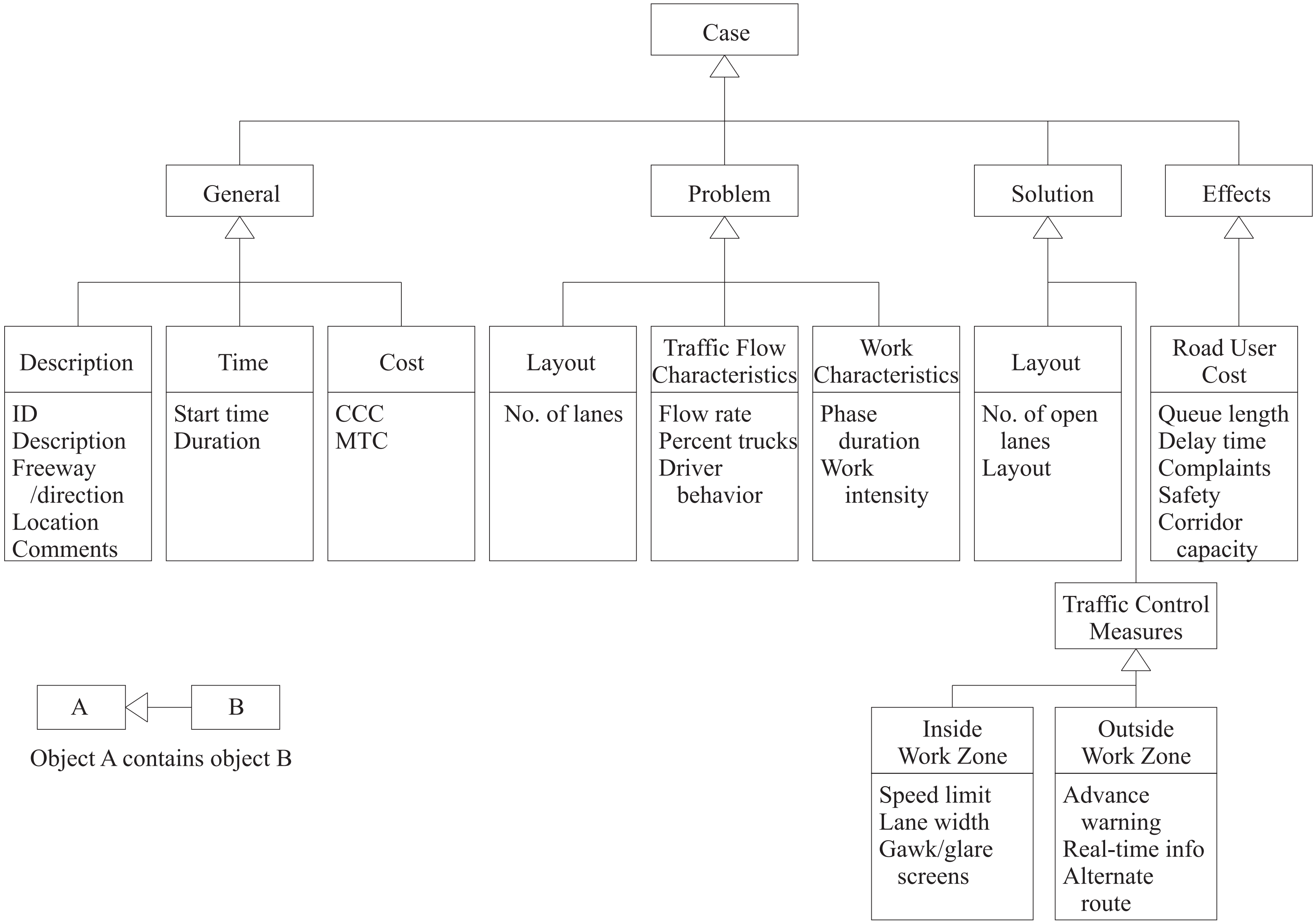


Figure 5 Object-oriented case model for the CBR system for work zone traffic management

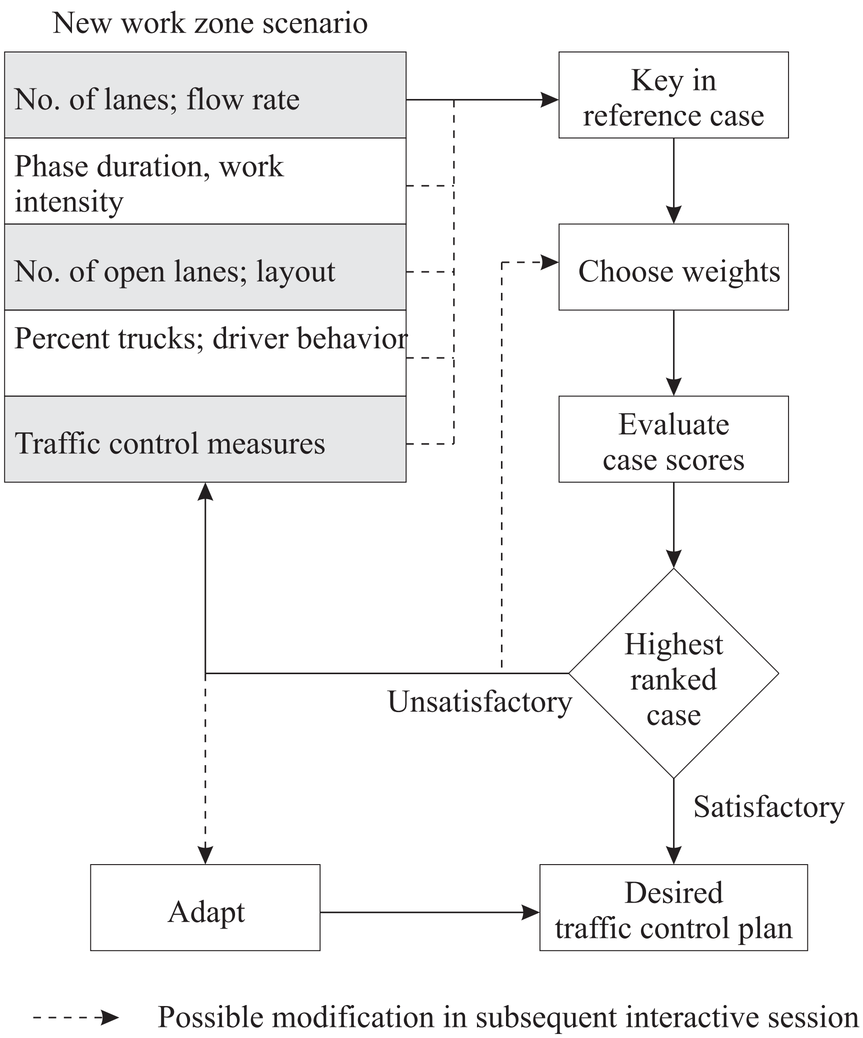
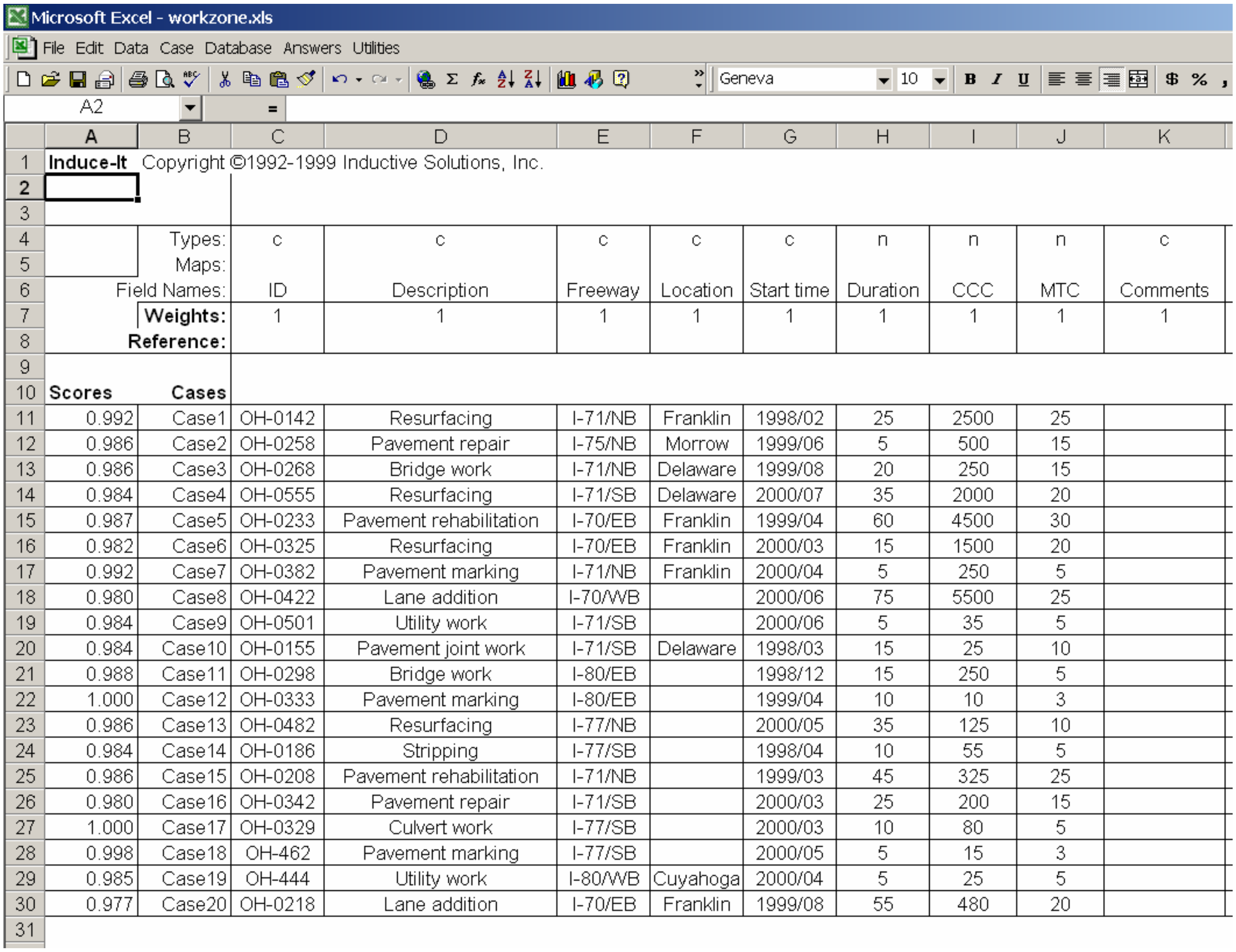


Figure 6 Procedure for creation of work zone traffic control plans using the CBR system for work zone traffic management



Microsoft Excel - workzone.xls

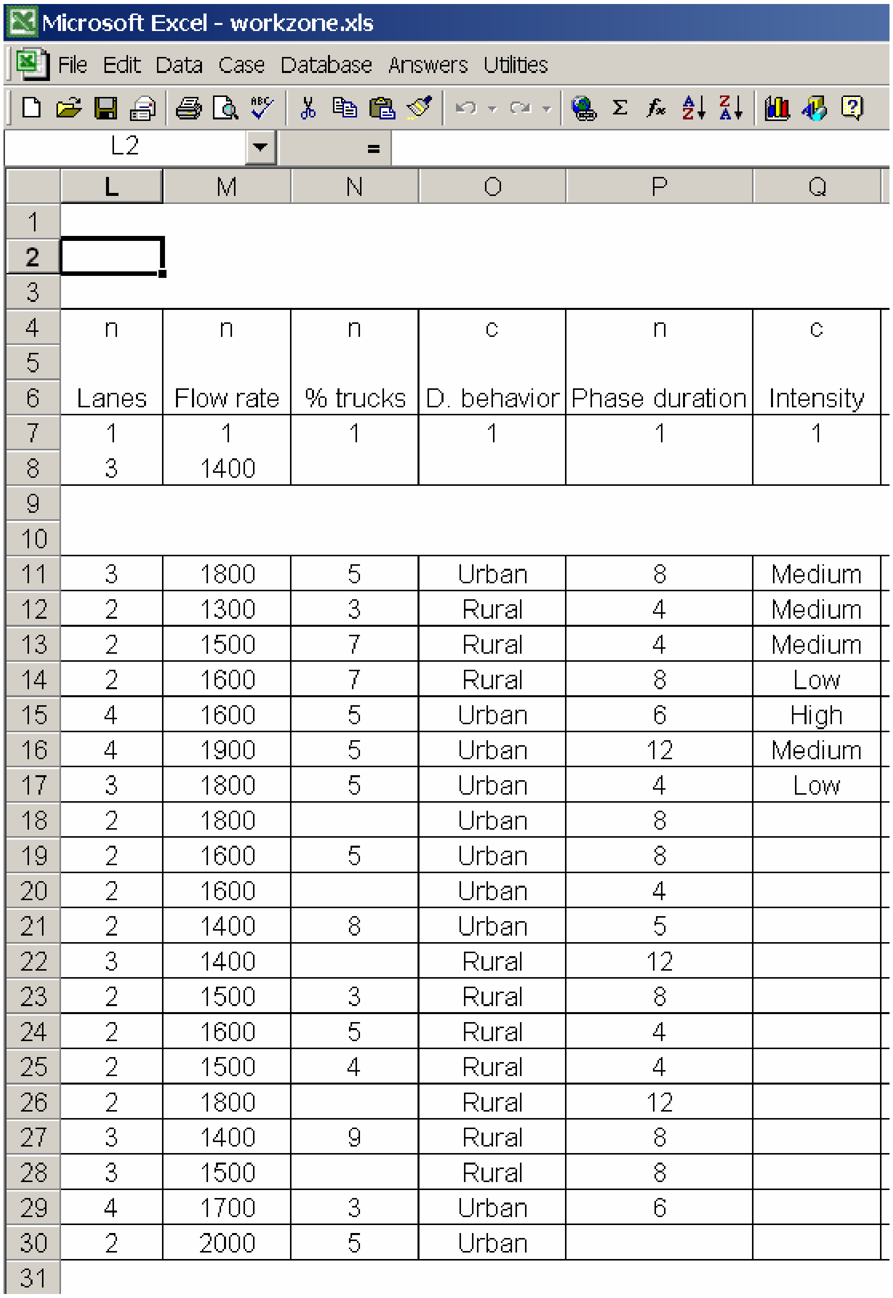
File Edit Data Case Database Answers Utilities

Geneva 10

A2 =

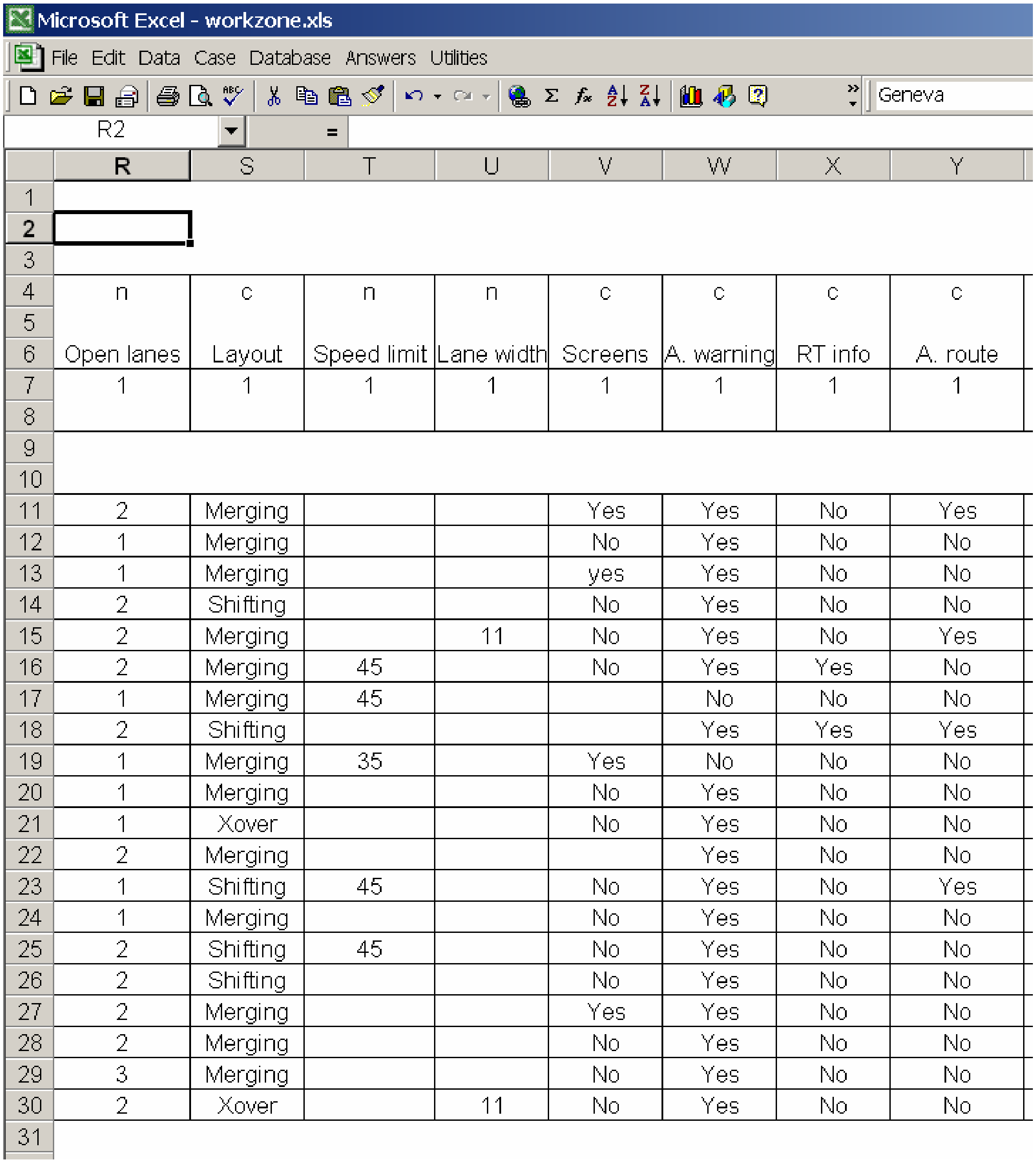
	A	B	C	D	E	F	G	H	I	J	K
1	**Induce-It**	Copyright ©1992-1999 Inductive Solutions, Inc.									
2											
3											
4		Types:	c	c	c	c	c	n	n	n	c
5		Maps:									
6		Field Names:	ID	Description	Freeway	Location	Start time	Duration	CCC	MTC	Comments
7		**Weights:**	1	1	1	1	1	1	1	1	1
8		**Reference:**									
9											
10	**Scores**	**Cases**									
11	0.992	Case1	OH-0142	Resurfacing	I-71/NB	Franklin	1998/02	25	2500	25	
12	0.986	Case2	OH-0258	Pavement repair	I-75/NB	Morrow	1999/06	5	500	15	
13	0.986	Case3	OH-0268	Bridge work	I-71/NB	Delaware	1999/08	20	250	15	
14	0.984	Case4	OH-0555	Resurfacing	I-71/SB	Delaware	2000/07	35	2000	20	
15	0.987	Case5	OH-0233	Pavement rehabilitation	I-70/EB	Franklin	1999/04	60	4500	30	
16	0.982	Case6	OH-0325	Resurfacing	I-70/EB	Franklin	2000/03	15	1500	20	
17	0.992	Case7	OH-0382	Pavement marking	I-71/NB	Franklin	2000/04	5	250	5	
18	0.980	Case8	OH-0422	Lane addition	I-70/WB		2000/06	75	5500	25	
19	0.984	Case9	OH-0501	Utility work	I-71/SB		2000/06	5	35	5	
20	0.984	Case10	OH-0155	Pavement joint work	I-71/SB	Delaware	1998/03	15	25	10	
21	0.988	Case11	OH-0298	Bridge work	I-80/EB		1998/12	15	250	5	
22	1.000	Case12	OH-0333	Pavement marking	I-80/EB		1999/04	10	10	3	
23	0.986	Case13	OH-0482	Resurfacing	I-77/NB		2000/05	35	125	10	
24	0.984	Case14	OH-0186	Stripping	I-77/SB		1998/04	10	55	5	
25	0.986	Case15	OH-0208	Pavement rehabilitation	I-71/NB		1999/03	45	325	25	
26	0.980	Case16	OH-0342	Pavement repair	I-71/SB		2000/03	25	200	15	
27	1.000	Case17	OH-0329	Culvert work	I-77/SB		2000/03	10	80	5	
28	0.998	Case18	OH-462	Pavement marking	I-77/SB		2000/05	5	15	3	
29	0.985	Case19	OH-444	Utility work	I-80/WB	Cuyahoga	2000/04	5	25	5	
30	0.977	Case20	OH-0218	Lane addition	I-70/EB	Franklin	1999/08	55	480	20	
31											

Figure 7 CBR system user interface showing reference case, weights, case scores and sample case base for work zone traffic management corresponding to the *General* object



	L	M	N	O	P	Q
1						
2						
3						
4	n	n	n	c	n	c
5						
6	Lanes	Flow rate	% trucks	D. behavior	Phase duration	Intensity
7	1	1	1	1	1	1
8	3	1400				
9						
10						
11	3	1800	5	Urban	8	Medium
12	2	1300	3	Rural	4	Medium
13	2	1500	7	Rural	4	Medium
14	2	1600	7	Rural	8	Low
15	4	1600	5	Urban	6	High
16	4	1900	5	Urban	12	Medium
17	3	1800	5	Urban	4	Low
18	2	1800		Urban	8	
19	2	1600	5	Urban	8	
20	2	1600		Urban	4	
21	2	1400	8	Urban	5	
22	3	1400		Rural	12	
23	2	1500	3	Rural	8	
24	2	1600	5	Rural	4	
25	2	1500	4	Rural	4	
26	2	1800		Rural	12	
27	3	1400	9	Rural	8	
28	3	1500		Rural	8	
29	4	1700	3	Urban	6	
30	2	2000	5	Urban		
31						

Figure 8 Sample case base for work zone traffic management corresponding to the *Problem* object



	R	S	T	U	V	W	X	Y
1								
2								
3								
4	n	c	n	n	c	c	c	c
5								
6	Open lanes	Layout	Speed limit	Lane width	Screens	A. warning	RT info	A. route
7	1	1	1	1	1	1	1	1
8								
9								
10								
11	2	Merging			Yes	Yes	No	Yes
12	1	Merging			No	Yes	No	No
13	1	Merging			yes	Yes	No	No
14	2	Shifting			No	Yes	No	No
15	2	Merging		11	No	Yes	No	Yes
16	2	Merging	45		No	Yes	Yes	No
17	1	Merging	45			No	No	No
18	2	Shifting				Yes	Yes	Yes
19	1	Merging	35		Yes	No	No	No
20	1	Merging			No	Yes	No	No
21	1	Xover			No	Yes	No	No
22	2	Merging				Yes	No	No
23	1	Shifting	45		No	Yes	No	Yes
24	1	Merging			No	Yes	No	No
25	2	Shifting	45		No	Yes	No	No
26	2	Shifting			No	Yes	No	No
27	2	Merging			Yes	Yes	No	No
28	2	Merging			No	Yes	No	No
29	3	Merging			No	Yes	No	No
30	2	Xover		11	No	Yes	No	No
31								

Figure 9 Sample case base for work zone traffic management corresponding to the *Solution* object

Microsoft Excel - workzone.xls

File Edit Data Case Database Answers Utilities

Z2 =

	Z	AA	AB	AC	AD
1					
2					
3					
4	n	n	c	c	c
5					
6	Queue length	Delay time	Complaints	Safety	C. capacity
7	1	1	1	1	1
8					
9					
10					
11	1	750	Low	High	High
12	2	1000		High	
13	0.5				
14	0.5	500			
15	0.5	300	High		
16	2	400			
17	1		Medium	High	High
18	0.5				
19	1		Low	High	
20	1.5	700			
21	3				
22	0.5	200		Medium	
23	4		High		
24	1			High	
25	2	500	Medium		
26	1		Medium		
27	2			High	Medium
28	0.5				
29	1			High	High
30	1		Low	High	
31					

Figure 10 Sample case base for work zone traffic management corresponding to the *Effects* object

Part II

Freeway Work Zone Traffic Delay and Cost Optimization Model

FREEWAY WORK ZONE TRAFFIC DELAY AND COST OPTIMIZATION MODEL

Xiaomo Jiang[3] and Hojjat Adeli, Fellow, ASCE[4]

ABSTRACT: A new freeway work zone traffic delay and cost optimization model is presented in terms of two variables: the length of the work zone segment and the starting time of the work zone using *average hourly traffic* data. The total work zone cost defined as the sum of user delay, accident, and maintenance costs is minimized. Number of lane closures, darkness factor, and seasonal variation travel demand normally ignored in prior research are included. In order to find the global optimum solution, a Boltzmann-simulated annealing neural network is developed to solve the resulting mixed real variable-integer cost optimization problem for short-term work zones. The new model can be used as an intelligent decision support system a) to find the optimum work zone segment length and the optimum starting time, b) to study the impact of various factors such as number of lane closures and darkness, and c) to observe the relation between the total work zone cost versus the work zone segment length and starting time in a quantitative and rational way quickly.

INTRODUCTION

Freeway work zones result in congestion and traffic delays leading to increased driver frustration, increased traffic accident, and increased road user delay cost. The traffic delay costs to users have been mathematically modeled and evaluated based on simplifying assumptions. Since the freeway work zone segment length has a significant impact on both the agency and

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user costs, efforts have been made to find the optimum freeway work zone segment length so as to minimize the costs to users and freeway agencies.

McCoy and Mennenga (1998) developed a simple model to find the optimum work zone segment length for minimum work zone costs in a rural four-lane freeway with one lane closure. Based on the average daily traffic (ADT), it takes into account the construction cost, user delay cost, vehicle operating cost, and accident cost. A Microsoft Excel-based model has recently been developed for predicting the work zone delay, named QuickZone Delay Estimation Program (MITRETEK, 2000) based on the deterministic queuing model for each network link in the work zone. The hourly estimation in QuickZone takes into account expected time-of-day utilization and seasonal variation in travel demand. QuickZone, however, does not have any optimization capability for finding the optimum work zone segment length or starting time of the project.

Recently, Chien and Schonfeld (2001) presented a simplified and useful model for estimating the delay cost using the average daily traffic (ADT) and finding the optimum work zone segment length in a four-lane freeway with one lane closure. They assume that if the work zone capacity is more than the ADT, no queue is formed. However, since the traffic flow varies within a day, this assumption does not hold at least during part of the day. Furthermore, the starting time of the work zone in a day (work during the day versus evening) and seasonal demand have significant effects on user delays and work zone costs. Chien and Schonfeld (2001), however, have tackled a problem of great practical significance in managing freeway work zones, which is to find the optimum work zone segment length.

A NEW TRAFFIC DELAY AND COST OPTIMIZATION MODEL FOR FREEWAY WORK ZONES

Assumptions

In this article, a new macroscopic computational model is presented for estimating traffic delays in freeway work zones based on the flow theory using neural network and optimization techniques. The model uses hourly traffic flow and takes into account the following factors: 1) number of lane closures (N_l), 2) length of the work zone segment (l), 3) anticipated hourly traffic flow of the freeway approaching the work zone, 4) starting time of the work zone (time of the day in hour), 5) darkness, 6) seasonal variation in travel demand, and 7) the duration of the work zone in hours (D).

The following assumptions are made to formulate the problem:

1) All the vehicles travel at the same speed of V_w through the work zone, and at the same speed of V_a approaching and leaving the work zone.
2) The road user delay cost is represented by an average cost per vehicle hour c_{vh} expressed in dollars per vehicle hour.
3) The anticipated hourly traffic flow approaching the work zone in vehicle per hour (vph) at time t of day (measured in hours), f_t, is known. An intersection close to work zone or a residential street in an urban area creates traffic diversion and affects the anticipated hourly traffic flow approaching the work zone. The model includes the effect of an intersection indirectly as long as the anticipated hourly traffic flow includes this effect as a percentage of diverted traffic.
4) The freeway work zone capacity, c_w, is assumed to be constant for any given number of lane closures. Also, the freeway capacity outside the work zone, c_0, is assumed to be constant.
5) The agency or maintenance cost (C_M) for maintaining a work zone segment is a linear function of the work zone segment length (l) and is expressed in the following form:

$$C_M = c_1 + (N_l c_2)l \quad (1)$$

where c_1 represents the fixed cost independent of work zone segment length and c_2 represents the average additional maintenance cost per work zone kilometer per lane.

6) The time period required to complete the maintenance for the work zone is a linear function of the work zone segment length and is expressed in the following form:

$$D = d_1 + (N_l d_2)l \quad (2)$$

where d_1 represents the setup time independent of work zone segment length and d_2 represents the additional maintenance time per work zone kilometer per lane.

The cost and time linearity assumptions 5 and 6 are also made by Chien and Schonfeld (2001). However, in this work we have included an additional parameter, that is, the number of lane closures in the formulations.

Freeway Work Zone Traffic Delay Model

The deterministic delay method is used to estimate the number of vehicles per hour in a queue. The user delay time consists of the queue delay time upstream of the work zone (t_q) and the moving delay time through the work zone (t_m). The total user delay time, t_d, during the duration, D, of the construction at the work zone is

$$t_d = t_q + t_m \quad (3)$$

It should be pointed out that these quantities are computed for all the road users and therefore expressed in terms of vehicle hours.

Within a specific time period Δt (in hours), if the anticipated hourly traffic flow approaching the work zone ($\alpha_s f_{\Delta t}$) exceeds the work zone capacity (c_w), a queue forms.

That is, a queue forms when $\alpha_s f_{\Delta t} > c_w$, where α_s is the seasonal demand factor used to adjust the short-term traffic flow for seasonal variations. For example, ODOT specifies a value for each day of the week and for every month of the year depending on a classification of highways. For annual average daily traffic (AADT) used for the whole year, the seasonal demand factor is equal to one. For various days of different months, ODOT specifies a value in the range of 0.76 and 1.72 (http://www.dot.state.oh.us/techservsite). When the real-time traffic flow measurement is used, $\alpha_s = 1.0$. The number of vehicles in a queue within the specific period Δt, $Q_{\Delta t}$, is equal to

$$Q_{\Delta t} = \alpha_s f_{\Delta t} - c_w \tag{4}$$

and the cumulative number of vehicles $T_{t+\Delta t}$ in a queue at time $t + \Delta t$ is

$$T_{t+\Delta t} = \sum_{t=t_i}^{t+\Delta t} Q_{\Delta t} \tag{5}$$

where t_i represents the starting time at the work zone in hours ranging from 1 to 24.

When $\alpha_s f_{\Delta t} < c_w$, the queue delay time is zero and the existing queue starts to disappear. In that case

$$Q_{\Delta t} = 0 \tag{6}$$

and

$$T_{t+\Delta t} = \max\{T_t - s, 0\} \tag{7}$$

where s represents the queue reduction. This parameter is formulated differently depending on whether the work zone has a long duration (more than one day) or a short duration (less than one day).

When the work zone duration is long term (defined as work zones with duration of more than one day), the queue reduction factor is (Figure 1a)

$$s = c_w - \alpha_s f_{\Delta t} \tag{8}$$

When the work zone duration is short-term (Figure 1b), the queue reduction factor is

$$s = c_0 - \alpha_s f_{\Delta t} \tag{9}$$

where c_0 represents the freeway capacity in the absence of any work zone.

The queue delay time, t_q, over the work zone duration, D, is obtained as

$$t_q = \sum_{t=t_i}^{t_i+D-1} \left(\frac{T_t + T_{t+\Delta t}}{2} \Delta t \right) \tag{10}$$

The shaded area in Figures 1(a) and (b) represents the value of the function inside the parentheses in Eq. (10). The total area under all *queue waves* during the work zone duration represents the work zone queue delay, t_q. A queue wave is the hill-shape curve representing the variation of the cumulative number of queuing vehicles over time from the start of the formation of one queue to the total dissipation of that queue. For example, there are two queue waves in Figure 1(a) and only one in Figure 1(b). The queue reduction factor over the time period Δt, s, is also shown in Figures 1(a) and 1(b).

The moving delay time, t_m, is expressed as a function of the difference between the travel times on a freeway with and without a work zone. Within a given period Δt, if the anticipated hourly traffic flow approaching the work zone exceeds the work zone capacity ($\alpha_s f_{\Delta t} > c_w$), the maximum traffic flow through the work zone is c_w. Then, the moving delay time, Δt_m, over the given period, Δt, is expressed as

$$\Delta t_m = \left(\frac{l}{V_w} - \frac{l}{V_a} \right) c_w \Delta t \tag{11}$$

When the anticipated hourly traffic flow approaching the work zone is less than the work zone capacity ($\alpha_s f_{\Delta t} < c_w$), the moving delay time Δt_m, over the given period Δt, becomes

$$\Delta t_m = \left(\frac{l}{V_w} - \frac{l}{V_a} \right) (\alpha_s f_{\Delta t}) \Delta t \tag{12}$$

Thus, the total moving delay time during the work zone duration is

$$t_m = \sum_{t=t_i}^{t_i+D-1} \Delta t_m \tag{13}$$

where Δt_m is substituted from Eq. (11) or (12) depending on whether within any given time period, the anticipated hourly traffic flow approaching the work zone exceeds the work zone capacity or not.

Freeway Work Zone Cost Optimization Model

The freeway work zone cost is defined as the sum of three components: the user delay cost (C_d), the accident cost (C_a), and the work zone maintenance cost including the setup and removal cost (C_m).

$$C_w = C_d + C_a + C_m \tag{14}$$

All these three components are defined in dollars per length (kilometer) of the work zone.

The user delay cost per work zone kilometer per lane is the total user delay time, t_d, multiplied by the average cost per vehicle hour c_{vh} divided by the work zone segment length l and the number of lane closures in the work zone, N_l:

$$C_d = \frac{c_{vh} t_d}{l N_l} \tag{15}$$

The traffic accidents considered in this study are those occurring in the work zone and queue areas. The accident cost C_a per work zone kilometer per lane incurred by the traffic flow passing through the work zone is determined from the number of accidents, n_a, per 100 million vehicle hour, multiplied by the product of the increased delay, t_d, and the average cost per accident, c_a, divided by the work zone segment length and the number of lane closures:

$$C_a = \frac{\alpha_n n_a c_a t_d}{10^8 l N_l} \tag{16}$$

In this equation, α_n, is a factor to take into account the effect of darkness and working at night. Increasingly more work zones are performed at night to ameliorate the impact of construction on road users and reduce the traffic disruptions. On the other hand, the evening construction results in reduced worker productivity at work zone, increased construction costs for utilities and labor fee, and increased risk of traffic accidents. A darkness factor of greater than one ($\alpha_n > 1.0$) is used for construction work at night. Its value is determined based on the previous experience as well as the management plan in the practical application. The accident cost used in our formulation and represented by Eq. (16) includes two new factors not considered in previous research (McCoy and Mennega, 1998; Chien and Schonfeld, 2001): number of lane closures and the darkness factor.

The maintenance cost in the work zone includes the setup and removal cost for the work zone and the average construction cost per work zone kilometer per lane, as noted in Eq. (1). The average maintenance cost C_m per work zone kilometer per lane is the total maintenance cost, C_M (defined by Eq. 1), divided by the work zone segment length and the number of lane closures modified by the darkness factor α_n:

$$C_m = \frac{\alpha_n c_1}{l N_l} + \alpha_n c_2 \tag{17}$$

Substituting Eqs. (15) to (17) into Eq. (14) yields the work zone cost function C_w per work zone kilometer per lane.

Thus, the freeway work zone cost optimization model is expressed as follows:

Minimize

$$C_w = C_d + C_a + C_m = \frac{1}{l N_l}\left(\alpha_n c_1 + \frac{\alpha_n n_a c_a + 10^8 c_{vh}}{10^8} t_d\right) + \alpha_n c_2 \tag{18}$$

Subject to the following constraints:

$$t_d \geq 0 \tag{19}$$

$$l \geq l_{\min} \tag{20}$$

where t_d is the total user delay time as expressed by

$$\begin{aligned} t_d &= t_q + t_m \\ &= \sum_{t=t_i}^{t_i+D-1}\left(\frac{T_t + T_{t+\Delta t}}{2}\Delta t\right) + \sum_{t=t_i}^{t_i+D-1}\Delta t_m = \sum_{t=t_i}^{t_i+D-1}\left(\frac{T_t + T_{t+\Delta t}}{2}\Delta t + \Delta t_m\right) \end{aligned} \tag{21}$$

and $l_{\min}$ is the minimum work zone segment length based on practical considerations. For example, a minimum work zone segment length of 0.1 km is chosen in the examples presented in this article.

There are two variables in the optimization formulation presented in this section: the work zone segment length (l), a real variable, and the starting time of the work zone in hours (t_i), an integer variable. The computational model presented in this section is general and can be used for both short-term work zone (with duration of less than one day) and long-term work zone (with duration of more than one day). In the following sections, we present an approach for solving this mixed real variable-integer nonlinear programming problem for short-term work zones.

WORK ZONE COST FUNCTION FOR SHOT-TERM WORK ZONES

For practical reasons, the work zone segment length is chosen in pre-selected increment of β kilometers (or miles), for example, β = 0.05 km or 0.1 km. The starting time of a short-term work zone can take an integer value between 1 and 24 for the twenty-four hours of a day. The maximum work zone segment length for short-term work zones is obtained from Eq. (2) by using the maximum work zone duration of 24 hours for the work duration, D:

$$l_{\max} = \frac{1}{d_2 N_l}(24 - d_1) \tag{26}$$

If the work zone segment length increment of β = 0.05 km is chosen, the number of possible work zone segment lengths becomes

$$n = \frac{l_{\max} - l_{\min}}{\beta} = \frac{l_{\max} - l_{\min}}{0.05} \tag{27}$$

In the freeway work zone cost formulation presented in this article, the starting time of work zone, t_i, affects the total work zone cost. The user delays in the work zone vary depending on the starting time of the work zone. For short term work zones, for any given work zone segment length l_i, there are 24 possible starting times for the construction work, corresponding to the 24 hours in a day, and the total work zone cost is obtained by substituting Eq. (21) into Eq. (18):

$$C_w = \frac{1}{l_i N_l}\left[\alpha_n c_1 + \frac{\alpha_n n_a c_a + 10^8 c_{vh}}{10^8} \sum_{t=t_i}^{t_i+D-1}\left(\frac{T_t + T_{t+\Delta t}}{2}\Delta t + \Delta t_m\right)\right] + \alpha_n c_2$$

$$= \frac{\alpha_n n_a c_a + 10^8 c_{vh}}{10^8 l_i N_l} \sum_{t=t_i}^{t_i+D-1}\left(\frac{T_t + T_{t+\Delta t}}{2}\Delta t + \Delta t_m\right) + \left(\alpha_n c_2 + \frac{\alpha_n c_1}{l_i N_l}\right) \qquad (28)$$

BOLTZMANN NEURAL NETWORK WITH SIMULATED ANNEALING FOR WORK ZONE COST OPTIMIZATION

A combined Boltzmann neural network-simulated annealing algorithm is developed to solve the mixed real variable-integer cost optimization problem for short-term work zones. The goal is to find the global optimum solution for the work zone segment length and starting time.

Simulated Annealing

Most optimization algorithms for solution of nonlinear programming problems with many hills and valleys encounter the so-called hill-climbing problem where the solution can get stuck in a local optimum, say one of the valleys in the minimization problem. A number of approaches have been proposed in the recent literature to overcome this problem and find the true global optimum solution such as genetic algorithms (Adeli and Cheng, 1993; Adeli and Hung, 1995) and simulated annealing (Kirkpatrick et al. 1983). Simulated annealing is inspired by the metallurgical process of annealing where a metal is heated to near melting point and then cooled slowly and intermittently until an *equilibrium* is achieved for an *optimum* material microstructure with desirable structural properties such as ductility. The material microstructure may be changed easily and rapidly at high temperatures with high kinetic energy. But, sudden cooling of the material can result in undesirable brittleness. In contrast, a gradual and carefully controlled cooling operation can result in a material with optimum microstructure. This process may be explained as removing *local pockets of stress energy* to allow the metal to escape from local *elevated energy minima* and reach a global energy minimum (Aleksander and Morton, 1991).

Metaphorically, simulated annealing for solution of nonlinear programming problems with multiple local optima can be considered as maximizing *strength* and minimizing *brittleness* by minimizing an *energy* functional (Mehrotra et al., 1997). As such, this approach requires the definition of an energy function and a temperature parameter to be lowered gradually during the optimization iterations. The selection of a candidate solution in successive iterations and the corresponding modification of the temperature parameter is guided by a probabilistic distribution. This process helps the solution to jump from one *valley* to the next *valley* in search of the true global optimum. Thus, a typical simulated annealing algorithm is implemented in two nested loops, an outer loop where the temperature parameter is reduced and an inner loop where direction of iterations is determined. In every iteration, solutions in the vicinity of the current solution are explored. Solutions that decrease the energy functional are maintained for additional moves. Further, solutions that increase the energy function with an acceptable selection probability, expressed as a function of the temperature parameter and the change in the energy from the previous iteration, are also maintained for additional move in search of the global optimum. The probability of acceptance is chosen to be larger with a larger value of the temperature parameter, similar to the metallurgical annealing process where the material microstructure is modified more easily at higher temperatures.

Boltzmann Neural Network

Artificial neural network algorithms are known to be effective for solution of complicated pattern recognition problems (Adeli and Hung, 1995; Adeli, 2001). They have also been used for solution of optimization problems. Examples include the Hopfield neural network (Hagan, et al., 1996; Mehrotra, et al., 1997; and Pham and Karaboga, 2000) and the neural dynamics model of Adeli and Park (Adeli and Park, 1998; Adeli and Karim, 2001)

A Hopfield neural network is known to converge to a local optimum. Thus suffering from the same hill-climbing problem stated earlier. To overcome this shortcoming, Ackley et al. (1985) introduced the so-called Boltzmann machine by introducing *noise* in the network trajectory to avoid the problem of entrapment in a local optimum. The concept of noise in the Boltzmann machine is analogous to the concept of temperature in the simulated annealing algorithm. The magnitude of the noise is reduced steadily based on a probability distribution till the network converges to the global optimum. A second distinction between the Hopfield network and the Boltzmann machine is that the former has no hidden layer but the latter does.

Architecture of Boltzmann Neural Network with Simulated Annealing for Work Zone Cost Optimization

The architecture of the Boltzmann-simulated annealing neural network for solving the short-term freeway work zone cost optimization problem is presented in Figure 2. The network consists of three layers: input layer, hidden layer, and output layer. Unlike the conventional Botlzmann machine, the neural network created in this research has a set of *storage* nodes in additional to the standard Boltzmann network nodes. The inputs to the neural network are the hourly traffic flows approaching the work zone (f_i, i =1,24). These values are used to calculate the 24 vectors of work zone information $\mathbf{C}_I(i,n)$ (i=1,24) assigned to the storage nodes. Each vector contains the values for nine quantities: the work zone segment length (l), starting time (t_i), queue delay time (t_q), moving delay time (t_m), user delay time (t_d), user delay cost (C_d), accident cost (C_a), maintenance cost (C_m), and the total work zone cost (C_w). The Boltzmann network nodes in the input layer are all assigned a value of one (x_i =1, i=1,24).

The number of nodes in the hidden layer is equal to the number of possible work zone segment lengths, n, as determined by Eq. (27). Similar to the input layer, the local minimum work zone information for any given work zone segment length is stored in the vector $\mathbf{C}_H(j)$ (j= 1, n), which contains the values for the same nine quantities mentioned in the previous paragraph. The Boltzmann network nodes in the hidden layer are randomly assigned values of x_j= -1 or +1 (j= 1, n).

For training the Boltzmann network, we define an energy function in the following form:

$$E = \sum_{j=1}^{n} w_{i,j} x_i x_j \tag{29}$$

where w_{ij} represents the weight of the link connecting the Boltzmann input node i to node j in the hidden layer. It is defined as

$$w_{ij} = \frac{(C_w)_{ij}}{\sqrt{\sum_{i=1}^{24} (C_w)_{ij}^2}} \qquad i=1,\ 24;\ j=1,\ n \tag{30}$$

in which $(C_w)_{ij}$ represents the total work zone cost at the input node i corresponding to the j^{th} work zone segment length.

To find the global optimal solution for the work zone cost optimization problem we need to find the global minimum solution for the energy function defined by Eq. (29). This is achieved by using the simulated annealing in two phases (Figure 2). In the first phase, simulated annealing is applied between the input layer and the hidden layer yielding the local minimum total work zone cost solutions corresponding to various work zone segment lengths. In the second phase, simulated annealing is used between the hidden layer and the output layer to obtain the global optimum solution for the work zone cost optimization problem.

The flow diagram for the Boltzmann-simulated annealing algorithm for the work zone cost optimization problem is shown in Figure 3. In phase one of the simulated annealing, the energy function (Eq. 29) is initially evaluated by summing over all hidden nodes but using the values of the weights associated with only one randomly selected input, i, for any hidden node, j. One input node x_i and one hidden node x_j are selected randomly and the value of the selected hidden node x_k is changed from –1 to 1 or from 1 to -1. Because other hidden nodes j ($j \neq k$) are not selected for updating the energy function at this step, the resulting change of energy becomes

$$\Delta E = w_{l,k} x_l x_k (t+1) - w_{i,k} x_i x_k (t)$$

$$= w_{l,k} x_k (t+1) - w_{i,k} x_k (t) \qquad (31)$$

where $x_k (t+1)$ and $x_k (t)$ represent the values of the selected k^{th} hidden node in the new and last steps, respectively, and x_l is the selected l^{th} input node. If the energy change, ΔE, is negative the change is accepted and the weight of the link connecting the selected k^{th} Boltzmann hidden node to the node in the output layer, w_k^*, is set to the weight of the link connecting the selected input node i to the selected hidden node k, w_{ik}:

$$w_k^* = w_{ik} \tag{32}$$

If the energy change, ΔE , is positive the change is accepted with a probability of

$$p = \frac{1}{1 + e^{-\Delta E / \tau}} \tag{33}$$

where parameter, τ, is the so-called temperature parameter in the simulated annealing algorithm. The initial temperature is set to some high value (e.g, 100 in this research) and is reduced in subsequent iterations by certain percentage (e.g., 1% in this research). A local optimum work zone cost solution is found when the system reaches an equilibrium point at a temperature τ when the probability p approaches one. This solution is represented as the weights between of the links connecting the nodes in hidden layer and the output node.

In phase two of the simulated annealing, a similar process is performed between the hidden layer and the output layer yielding the global minimum work zone cost solution with the corresponding global optimum work zone segment length and starting time.

APPLICATION AND EXAMPLES

Example One: Four-lane Freeway with One Lane Closure

The data for this example, summarized in Table 1, are chosen to be the same as those of Chien and Schonfeld (2001) for the sake of comparison, with the addition of values for darkness and seasonal demand factors. This example is a four-lane freeway with one-lane closure. Chien and Schonfeld (2001) use the average daily traffic only. In this work, the anticipated hourly traffic flow approaching the work zone is used.

Example 1A (ADT=1000 vph)

The anticipated hourly traffic flows approaching the work zone for this example for the duration of one day are given in Table 2, with an average daily traffic (ADT) of 1000 vph, the same value used in Chien and Schnofeld (2001). The hourly and cumulative numbers of vehicles in a queue calculated by the new computational model are presented in Table 2. The cumulative number of queuing vehicles as a function of the time of the day is also displayed graphically in Figure 4. Two queue waves are observed in this figure.

Chien and Schnofeld (2001) report an optimum work zone segment length of *l*=1.4 km (corresponding to minimum work zone cost) and duration of *D*=10.4 hours for the example data presented in Table 1 with the ADT of 1000 vph. Using the same workzone length of 1.4 km and duration of 10.4 hours, the traffic delay estimation model presented in this article yields a maximum queue delay time (t_q) of 18,624 vehicle-hours and maximum moving delay time (t_m) of 149 vehicle-hours when the maintenance work is started at 8 A.M. In contrast, when the maintenance work is started at hour 19 (7 P.M.) in the evening, the queue delay is zero and the moving delay time is reduced to 56 vehicle-hours. Chien and Schonfeld (2001) report a queue delay time of 0 and moving delay time of 141.5 vehicle-hours (Table 3). The current investigation indicates that the starting time of the work zone affects the user delay time significantly. This factor is absent in the recently published work zone delay estimate models but is taken into account in the new model.

Assuming that the work zone duration is less than one day (short-term work zone), a maximum work zone segment length of $L_{\max} = 3.65$ km is obtained from Eq. (26). The maximum number of possible work zone segment lengths from Eq. (27) is then $n = 72$. A darkness factor of $\alpha_n = 2.0$ is assumed for all the examples in this article. Figure 5 shows the variation of the work zone costs versus the work zone segment length. It should be pointed out that the data for each given work zone segment length corresponds to a local minimum solution for that particular work zone segment length for various starting times. The optimum work zone segment length corresponding to the minimum total work zone cost is the global optimum solution. In this example, it is found that the maintenance cost is a significant factor in the total work zone cost. The global optimum starting time is found to be 8 A.M. and the global optimum work zone segment length is 0.35 km resulting in the global minimum total work zone cost of 83147.55 $/km. Figure 6 shows the variation of work zone costs versus the starting time of the day for the global optimum solution. This figure demonstrates that selection of the starting time using the same work zone segment length of 0.35 km has a significant impact on the total work zone cost.

The work zone traffic delay estimate model presented in this article also allows you to choose the starting time of the work zone. This is a desirable feature as the optimum starting time provided by the model may not be acceptable for non-economical reasons. For instance, assume a starting time of 9 A.M. is selected for this example. Figure 7 shows the variation of work zone costs versus the work zone segment length. The model yields an optimum work zone segment length of 0.20 km resulting in minimum total construction cost of 84941.92 $/km. This cost is about 2% higher than the global optimum solution presented in Figure 5. The new model can be used as an intelligent decision support system to study the relation between the total work zone cost versus the work zone segment length and starting time quickly.

Example 1B (ADT=2000 vph)

This example uses the same data as example 1A with the exception of ADT= 2000 vph. The anticipated hourly traffic flows approaching the work zone in a day with ADT of 2000 vph as well as the queue delay results obtained from the new computational model are presented in Table 2.

Initially, for the sake of comparison, we use the same work zone segment length of 0.34 km and duration of 4 hours given in Chien and Schnofeld (2001). The new work zone traffic delay estimation model yields a maximum queue delay time t_q of 38,579 vehicle-hours and maximum moving delay time t_m of 35 vehicle-hours with a staring time of 3 A.M. However, if the maintenance work is performed at midnight the model yields the minimum queue delay of zero and the minimum moving delay time t_m of 4 vehicle-hours. Chien and Schnofeld (2001) report queue delay of 44804 vehicle-hours and moving delay of 66.1 vehicle hours (Table 3) without considering the effects of the starting time of the work zone.

The new model yields a global optimum value of 1.05 km for the work zone segment length and a global optimum starting time of 21 o'clock (9 P.M.) resulting in a global minimum work zone cost of 162310.22 $/km for a work duration of 8 hours.

Example Two: Six-lane Freeway

This example is created in this research to demonstrate the capability of the new work zone traffic delay estimate model to account for the number of lane closures. A six-lane freeway with three lanes in every direction is considered. Data in Table 1 are used in this example with the exception of values for freeway capacity in the absence of work zone (a value of 5400 vph is used in this example), work zone capacity, number of open lanes, and number of lane closures. The anticipated hourly traffic flows approaching the work zone in a day are presented in Table 4.

Example 2A - One-lane Closure

This example has only one lane closure. The work zone capacity is assumed to be 2980 vph per *Highway Capacity Manual* (HCM, 1985). The hourly and cumulative numbers of vehicles in a queue calculated by the new computational model are presented in Table 4. Similar to example 1, in this example, the maintenance cost is a significant factor in the total work zone cost. The global optimum work zone segment length is 1.05 km and the global optimum starting time is 7 A.M. resulting in the global minimum total work zone cost of 85107.26 \$/km and duration of 8 hours. For one-lane closure, having the work done during the day is more economical than having it done during the night.

Example 2B - Two-lane Closures

This example has two lane closures. The work zone capacity is assumed to be 1170 vph per *Highway Capacity Manual* (HCM, 1985). The hourly and cumulative numbers of vehicles in a queue calculated by the new computational model are presented in Table 4. Figure 8 shows the variation of the work zone costs versus the work zone segment length. The global optimum work zone segment length is 0.55 km and the global optimum starting time is 3 A.M. resulting in a global minimum total work zone cost of 15900.70 \$/km and duration of 5 hours. In this example, the user delay cost becomes the dominant work zone cost for work zone segment lengths of greater than about 2.7 km. For two-lane closure, having the work done during the night is more economical than having it done during the day. But, compared with example 2A the cost is increased substantially because the darkness increases the maintenance cost resulting in a considerable increase in the total work zone cost.

By comparing the results obtained for examples 2A and 2B, it is concluded that having the work done during the day with starting time of 7 A.M. with one lane closure is the most economical solution for the work zone project at hand.

Example Three: Four-Lane Highway with One-lane Closure in North Carolina

In this example, actual traffic data measured in a work zone in a four-lane highway in the state of North Carolina with one lane closure are used. The hourly traffic flows approaching a work zone on route NC 147, 0.1 miles south of SR 1171, measured by North Carolina

Department of Transportation in a day (August 28, 2000) are presented in Table 5. Data in Table 1 are also used in this example except for values of freeway capacity in the absence of work zone (a value of 2400 vph is used) and work zone capacity (a value of 1000 vph is used). The hourly and cumulative numbers of vehicles in a queue calculated by the new computational model are also presented in Table 5. The new model yields a global optimum value of 0.20 km for the work zone segment length and a global optimum starting time of 7 resulting in a global minimum work zone cost of 87954.99 $/km for a work duration of 3 hours. Figure 9 shows the variation of work zone costs versus the starting time of the day.

CONCLUSION AND FINAL COMMENTS

A new freeway work zone traffic delay estimate and total work zone cost optimization model is presented in this article. In contrast to the previous published works that are based on the average daily traffic flow the new model is based on average hourly traffic flow. A total work zone cost function is defined as the sum of the user delay, accident, and maintenance costs. It takes into account the number of lane closures, the darkness factor, and the seasonal demand factor. The work zone traffic delay and cost optimization model is applicable for both short-term (less than one day) and long-term (more than day) work zones. The model yields the global optimum values for the work zone segment length and the starting time of the work zone. A Boltzmann-simulated annealing neural network model is developed to solve the resulting mixed real variable-integer short-term work zone cost optimization problem.

Numerical examples presented demonstrate that the starting time of the work zone has a significant impact on queue formation and total work zone cost. Thus, the proposed model based on the average hourly traffic flow allows the work zone traffic engineer to prepare a more effective traffic control plan for a given work zone based on detailed and accurate quantitative information in a systematic manner resulting in substantial cost savings and minimum disruption of traffic for the travelling public. Using the proposed model, the work zone traffic engineer will be able to find the answer to important what-if questions, such as one-lane closure versus two-lane closure or selection of the starting time of the day systematically and quickly. The examples presented show how the transportation work zone engineer can observe the impact of the number of lane closures and the darkness. The model also incorporates a seasonal demand factor. That means the work zone engineer can use the model to find out the impact of seasonal demand on the user delay and total work zone costs. The model is currently being extended to find the optimum work zone segment length and starting time for long-term work zones. Further extension would be to include the impact of detours in the model.

ACKNOWLEDGMENT

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Appendix I. References

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Table 1 Input data for example 1 (chosen to be the same as those of Chien and Schnofeld, 2001, for the sake of comparison with the addition of values for darkness and seasonal demand factors)

Variable	Description	Values
c_0	Freeway capacity in the absence of the work zone	2,600 vph
c_w	Work zone capacity	1,200 vph
V_a	Average approaching speed	88.00 km/h
V_w	Average work zone speed	48.00 km/h
n_a	Number of accidents per 100 million vehicle hour	40 acc/100mvh
c_a	Average accident cost	142,000 $/acc
c_{vh}	Average vehicle delay cost per hour	12.00 $/vph
c_1	Fixed set up cost	1,000 $/zone
c_2	Average maintenance cost per work zone kilometer per lane	80,000 $/km
d_1	Fixed setup time	2 h/zone
d_2	Average maintenance time per kilometer	6 h/km
N_L	Number of lane closures in the work zone	1
N_o	Number of open lanes in the work zone	1
α_n	Darkness factor (Cost increase ratio for work at night)	2.0
α_s	Seasonal demand factor	1.0

Table 2 Queue delay results obtained from the new computational model for example 1 (Four-lane freeway with one lane closure)

Time (Hour of day)	Anticipated traffic flow approaching the work zone, f_t (vph)		Number of vehicles in the queue per hour, Q (vph)		Cumulative number of vehicles in the queue per hour, T (vph)	
	Example 1A	Example 1B	Example 1A	Example 1B	Example 1A	Example 1B
1	180	360	0	0	0	0
2	50	100	0	0	0	0
3	117	234	0	0	0	0
4	420	840	0	0	0	0
5	833	1681	0	481	0	481
6	1145	2290	0	1090	0	1571
7	2161	4322	961	3122	961	4693
8	821	1642	0	442	582	5135
9	1020	2075	0	875	402	6010
10	930	1660	0	460	132	6470
11	910	1831	0	631	0	7101
12	1320	2651	120	1451	120	8552
13	1620	3242	420	2042	540	10594
14	1728	3456	528	2256	1068	12850
15	2154	4325	954	3125	2022	15975
16	2420	4840	1220	3640	3242	19615
17	2021	4142	821	2942	4063	22557
18	1460	2920	260	1720	4323	24277
19	850	1700	0	500	3973	24777
20	700	1425	0	225	3473	25002
21	400	800	0	0	2673	24602
22	280	560	0	0	1753	23962
23	240	480	0	0	793	23242
24	210	420	0	0	0	22462

Table 3 Traffic delay estimate results (unit: vehicle-hours)

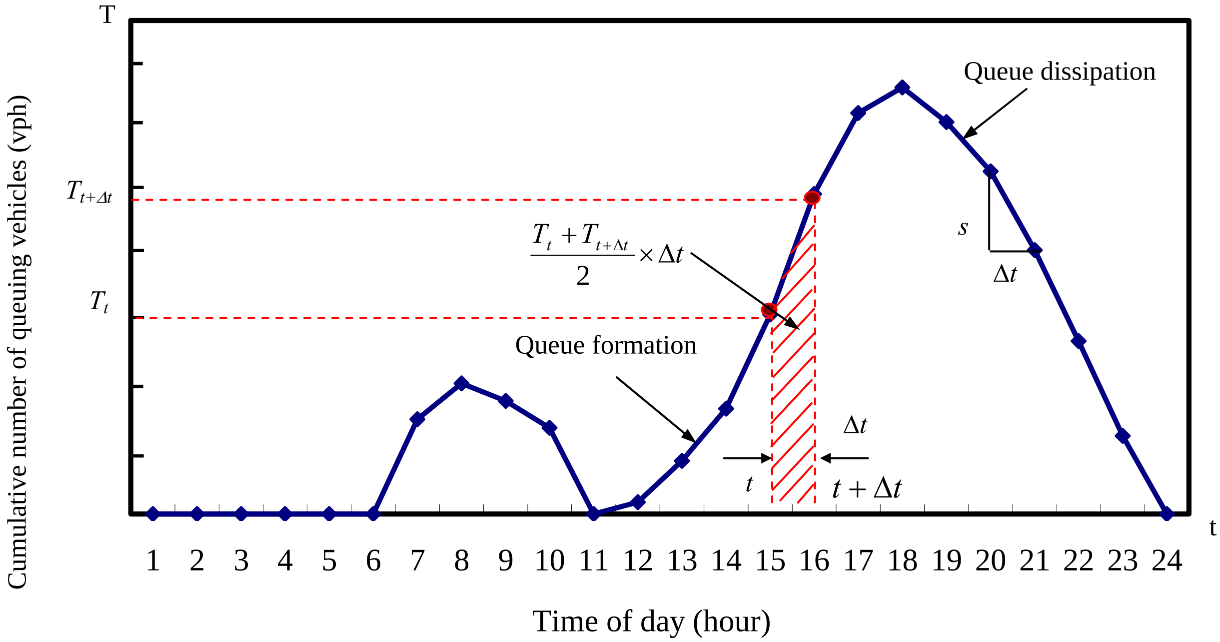
	Example 1A			Example 1B		
	ADT=1000 vph, *l*=1.4 km			ADT=2000 vph, *l*=0.34 km		
Work zone traffic delay model	Chien & Schonfeld (2001)	New model		Chien & Schonfeld (2001)	New model	
		Max	Min		Max	Min
Queue delay	0	18624	0	44804	38579	0
Moving delay	141.5	149	56	66.1	35	4

Table 4 Queue delay results obtained from the new computational model for Example 2 (Six-lane freeway with one-lane closure or two-lane closures)

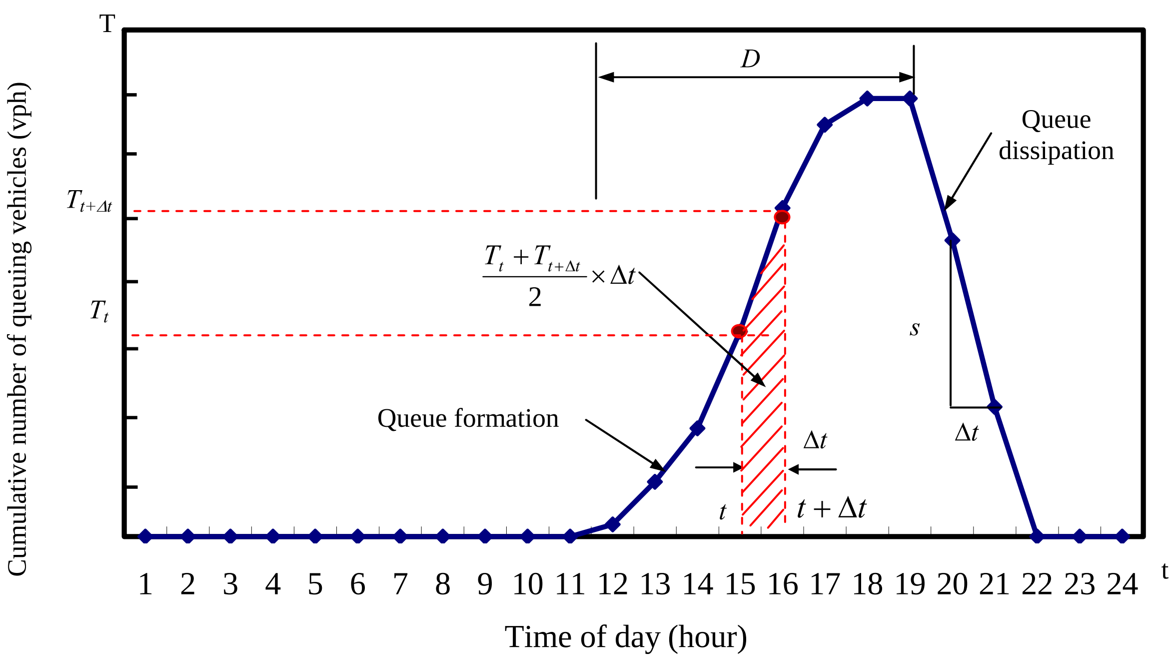
Time (Hour of day)	Anticipated traffic flow approaching the work zone, f_t (vph)	Number of vehicles in the queue per hour, Q (vph)		Cumulative number of vehicles in the queue per hour, T (vph)	
		Example 2A (one-lane closure)	Example 2B (two-lane closures)	Example 2A (one-lane closure)	Example 2B (two-lane closures)
1	682	0	0	0	0
2	431	0	0	0	0
3	304	0	0	0	0
4	323	0	0	0	0
5	312	0	0	0	0
6	580	0	0	0	0
7	1934	0	764	0	764
8	2986	6	1816	6	2580
9	2666	0	1496	0	4076
10	3067	87	1897	87	5973
11	2681	0	1511	0	7484
12	3035	55	1865	55	9349
13	2887	0	1717	0	11066
14	2761	0	1591	0	12657
15	3133	153	1963	153	14620
16	3503	523	2333	676	16953
17	3586	606	2416	1282	19369
18	4027	1047	2857	2329	22226
19	2609	0	1439	1958	23665
20	1895	0	725	873	24390
21	1591	0	421	0	24811
22	1492	0	322	0	25133
23	1423	0	253	0	25386
24	833	0	0	0	25049

Table 5 Queue delay results obtained from the new computational model for Example 3

Time (Hour of day)	Anticipated traffic flow approaching the work zone, f_t (vph)	Number of vehicles in the queue per hour, Q (vph)	Cumulative number of vehicles in the queue per hour, T (vph)
1	137	0	0
2	76	0	0
3	29	0	0
4	42	0	0
5	45	0	0
6	198	0	0
7	660	0	0
8	1055	55	55
9	784	0	55
10	1335	335	390
11	1144	144	534
12	1366	366	900
13	1326	326	1226
14	1238	238	1464
15	1109	109	1573
16	1167	167	1740
17	1321	321	2061
18	1535	535	2596
19	975	0	2571
20	639	0	2210
21	420	0	1630
22	389	0	1019
23	280	0	299
24	320	0	0

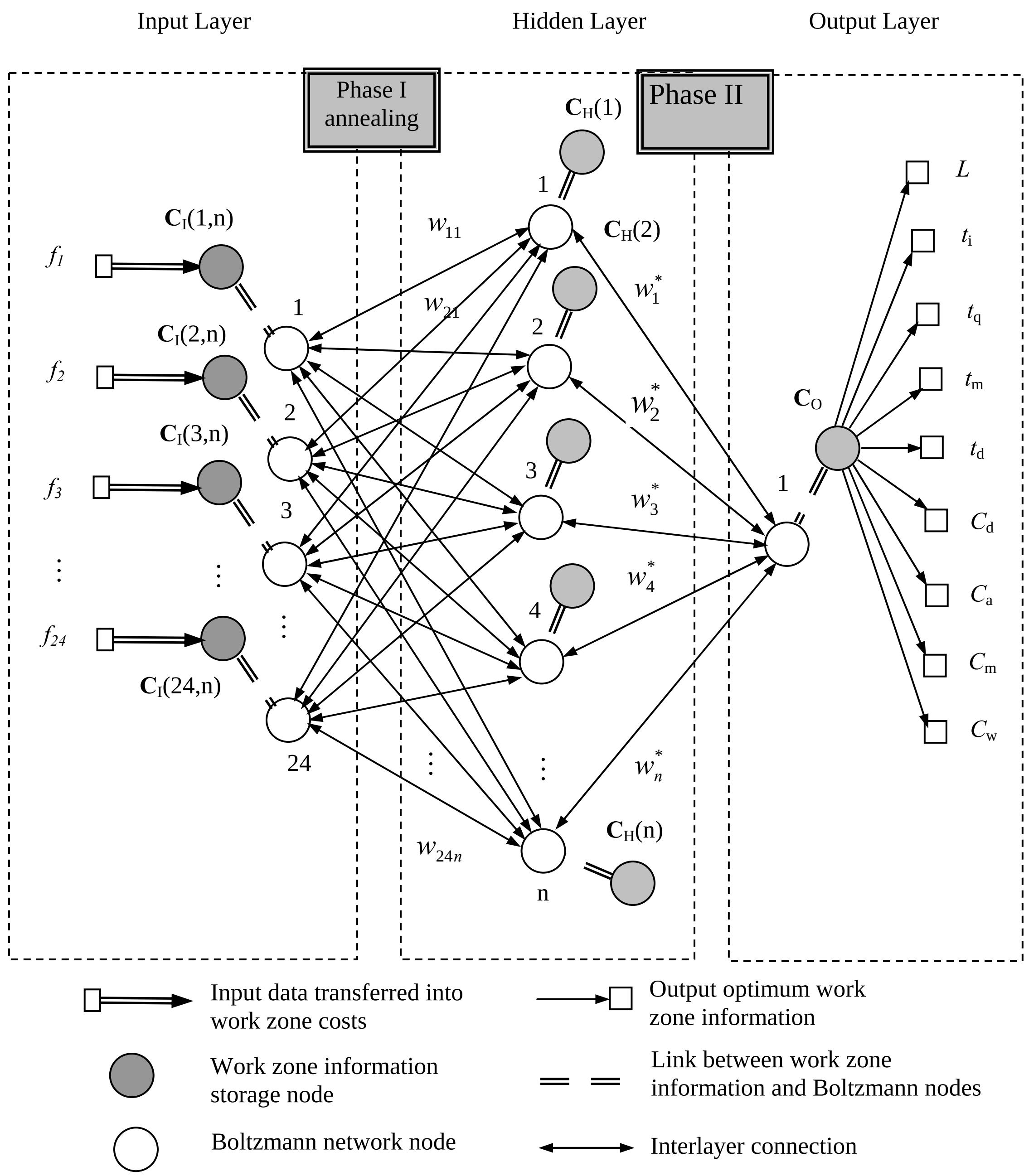


(a) Long-term work zone delay



(b) Short-term work zone delay

Figure 1 Mathematical model for work zone delay



f_i: Hourly traffic flow approaching work zone at time i (i= 1,24)

$\mathbf{C}_I$(i,n): Vector to store the work zone information in the input layer (i= 1,24)

$\mathbf{C}_H$(j): Vector to store the local minimum work zone information in the hidden layer (j= 1, n)

Co: Vector to store the optimum work zone information in the output layer

Figure 2 Architecture of the Boltzmann-simulated annealing neural network for short-term freeway work zone cost optimization problem

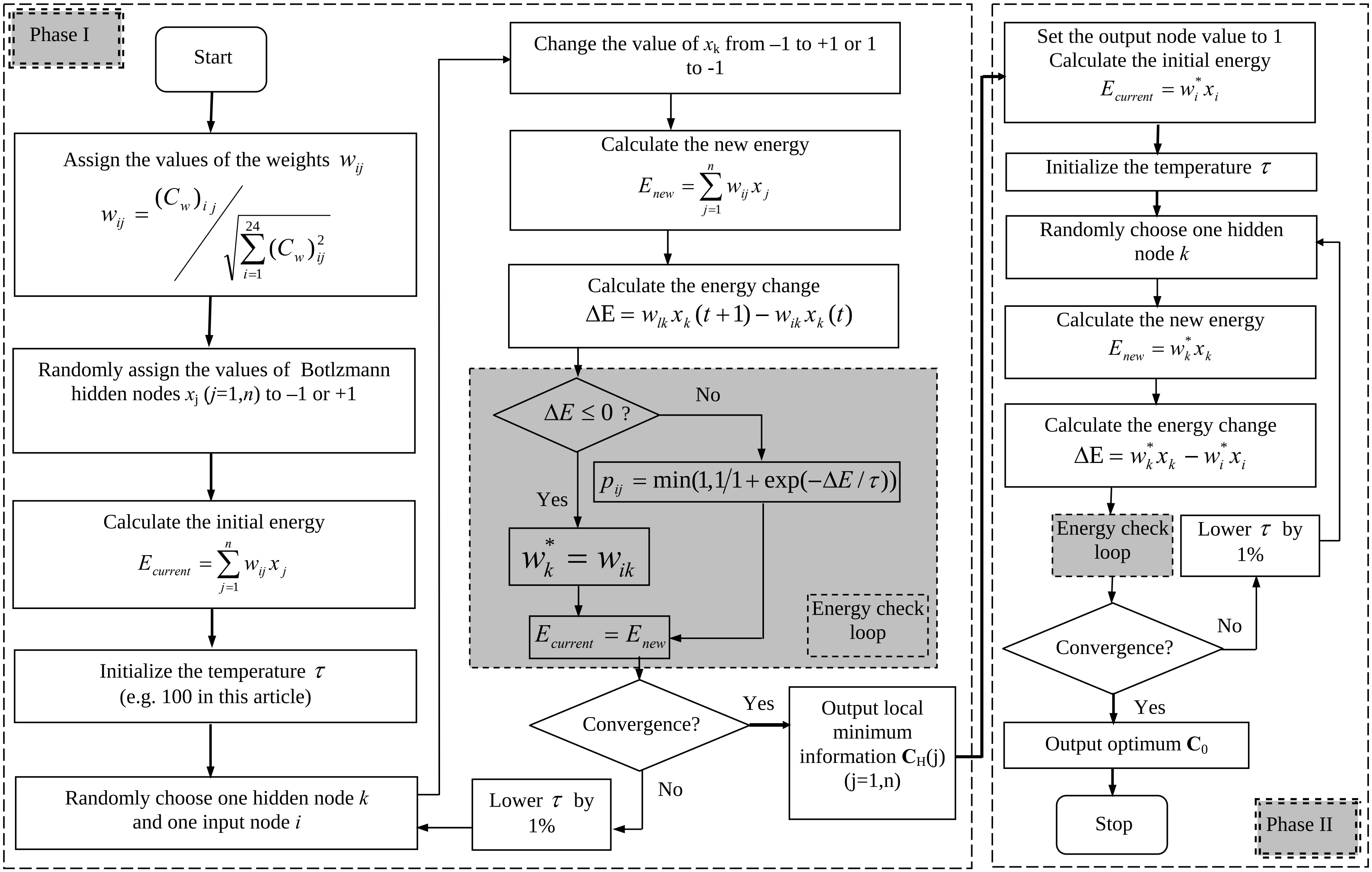


Figure 3 Flow chart of the hybrid Boltzmann neural network-simulated annealing model used to solve the mixed real-integer nonlinear programming problem

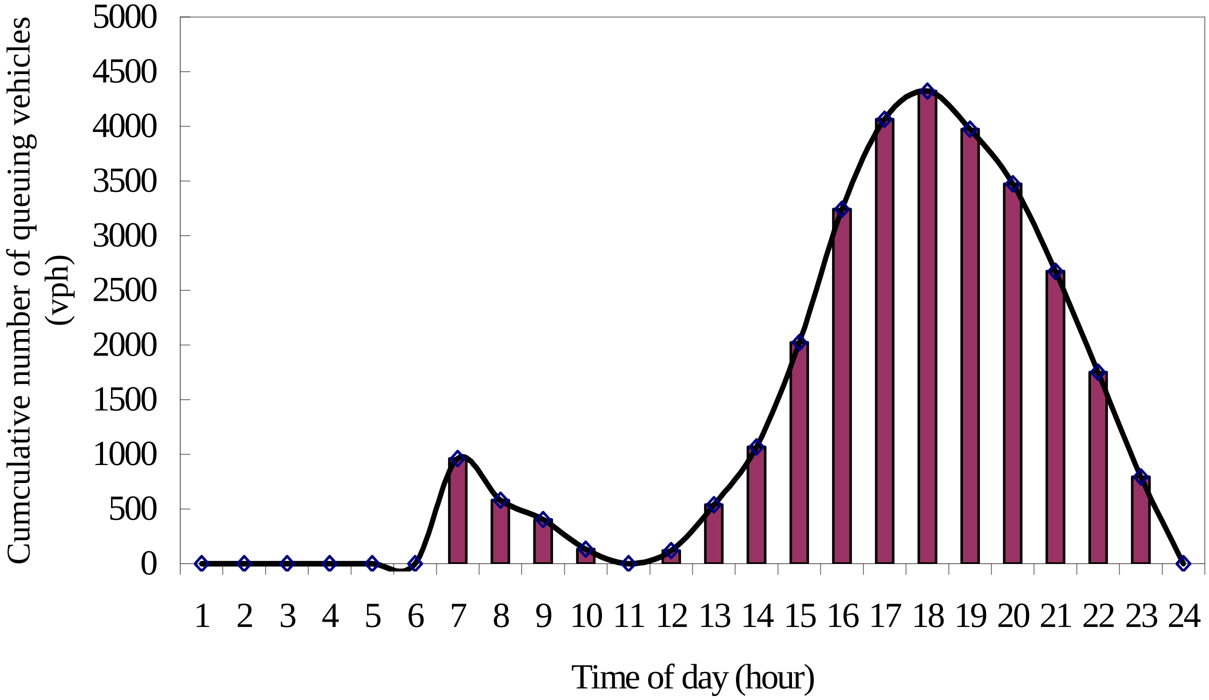


Figure 4 Cumulative numbers of queuing vehicles for Example 1A
(Four-lane freeway with one lane closure, ADT=1000 vph)

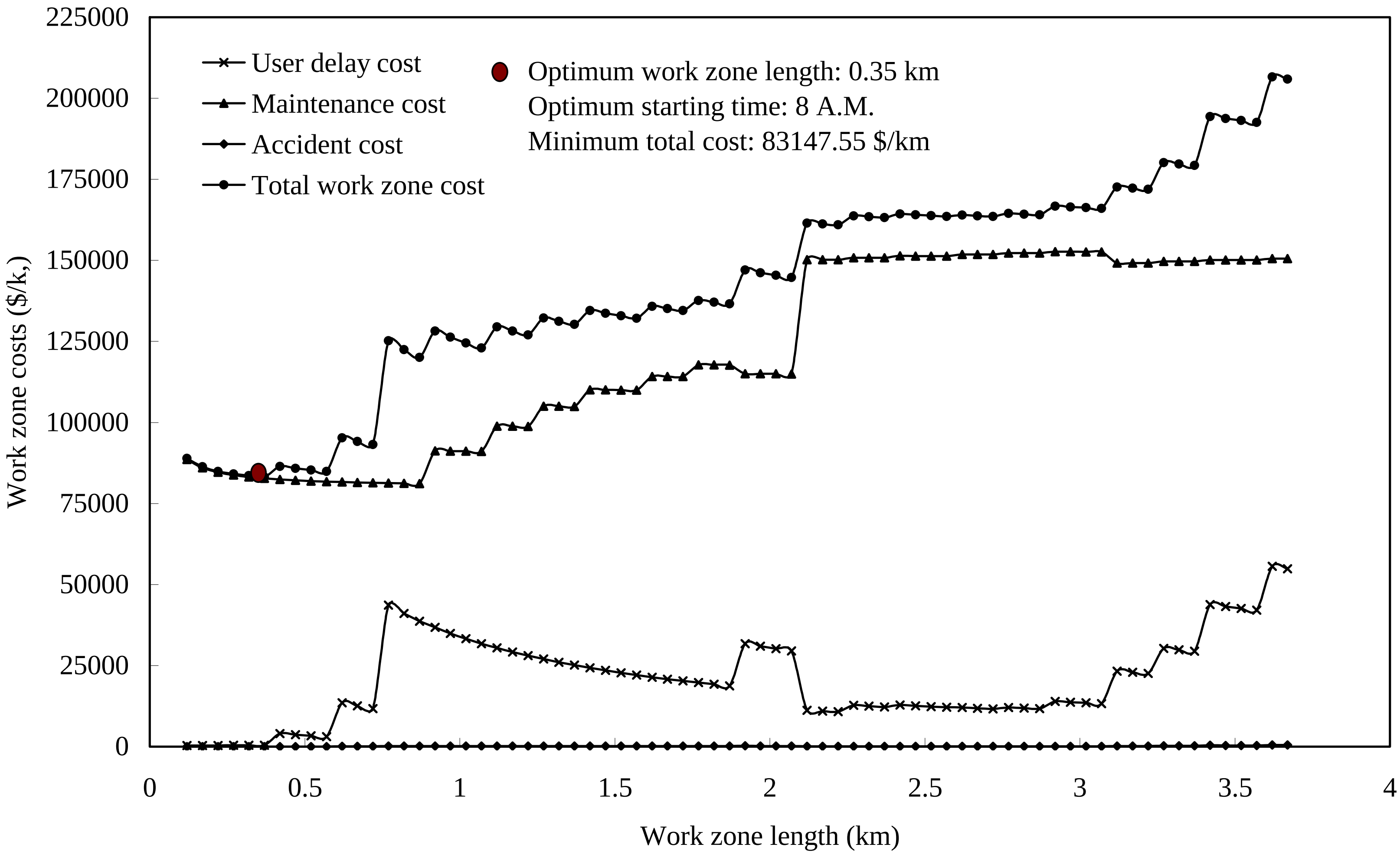


Figure 5 Variation of the work zone costs versus the work zone segment length for example 1A
(Four-lane freeway with one lane closure, ADT = 1000 vph)

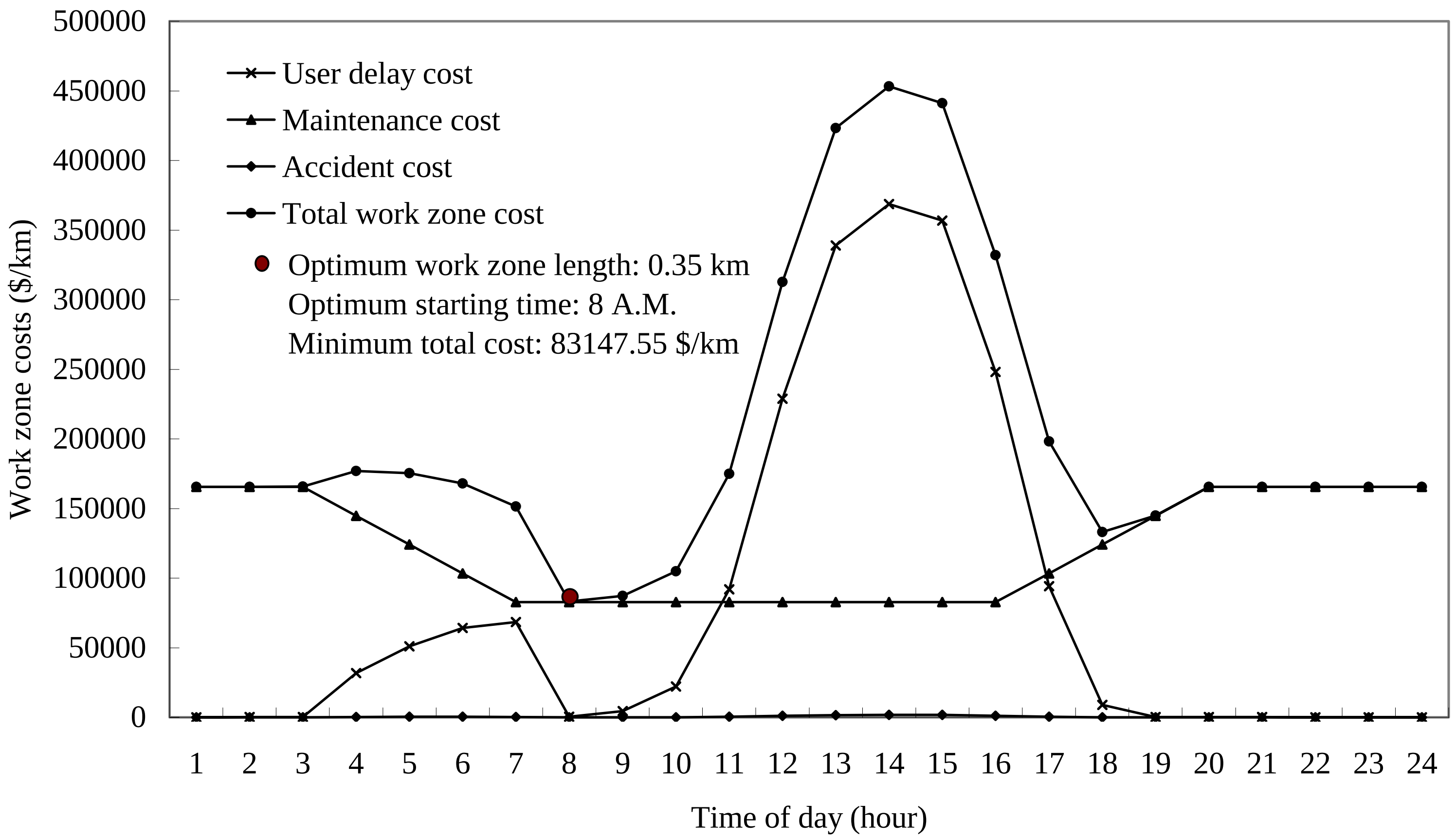


Figure 6 Variation of work zone costs versus the starting time of the day for
the global optimum solution of 0.35 km for the work zone segment length and 8 A.M. for the starting time for example 1A
(Four-lane freeway with one lane closure, ADT = 1000 vph)

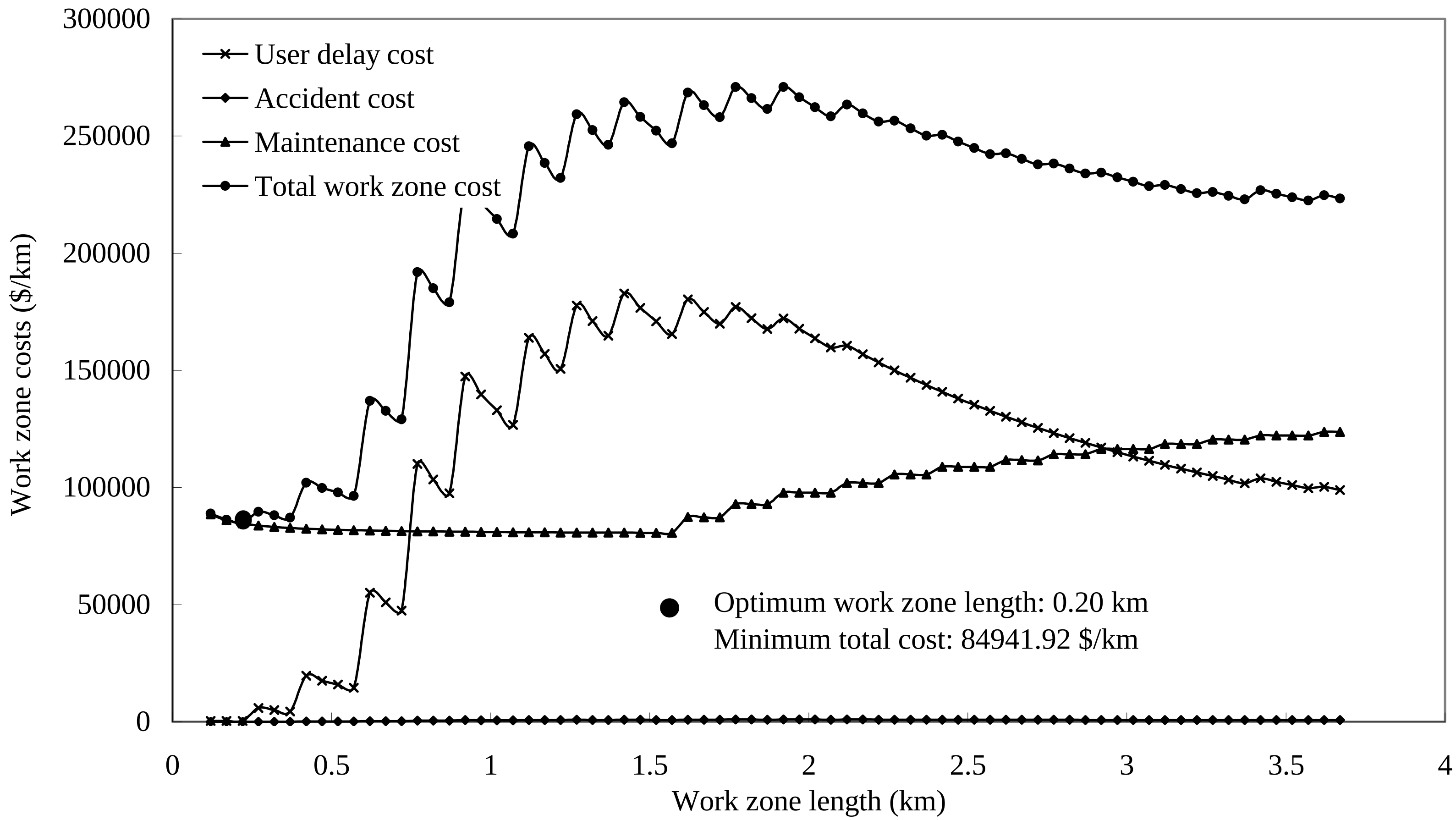


Figure 7 Variation of the work zone costs versus the work zone segment length at the starting time 9 A.M. for example 1A (Four-lane freeway with one lane closure, ADT = 1000 vph)

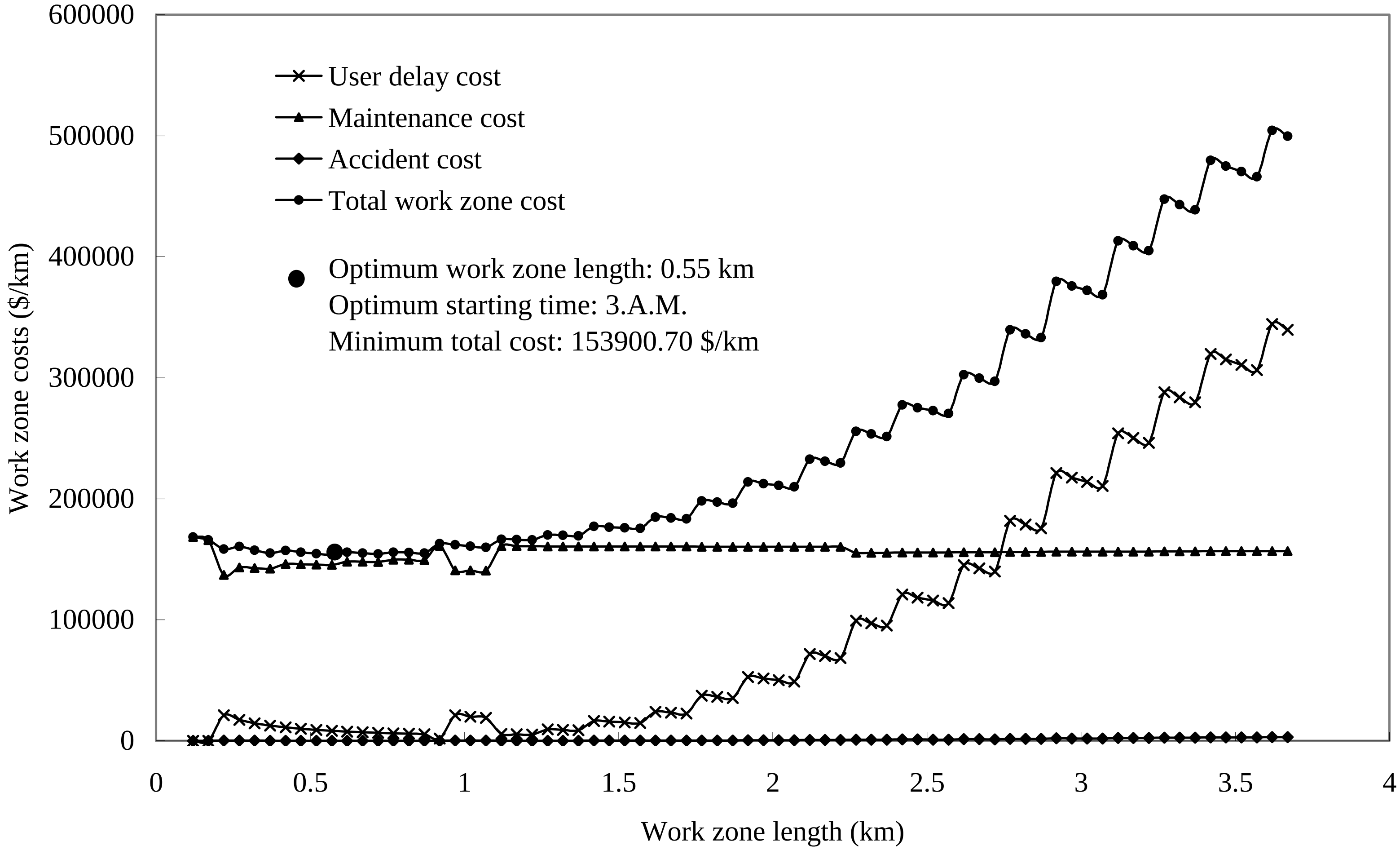


Figure 8 Variation of the work zone costs versus the work zone segment length for example 2B
(Six-lane freeway with two-lane closures)

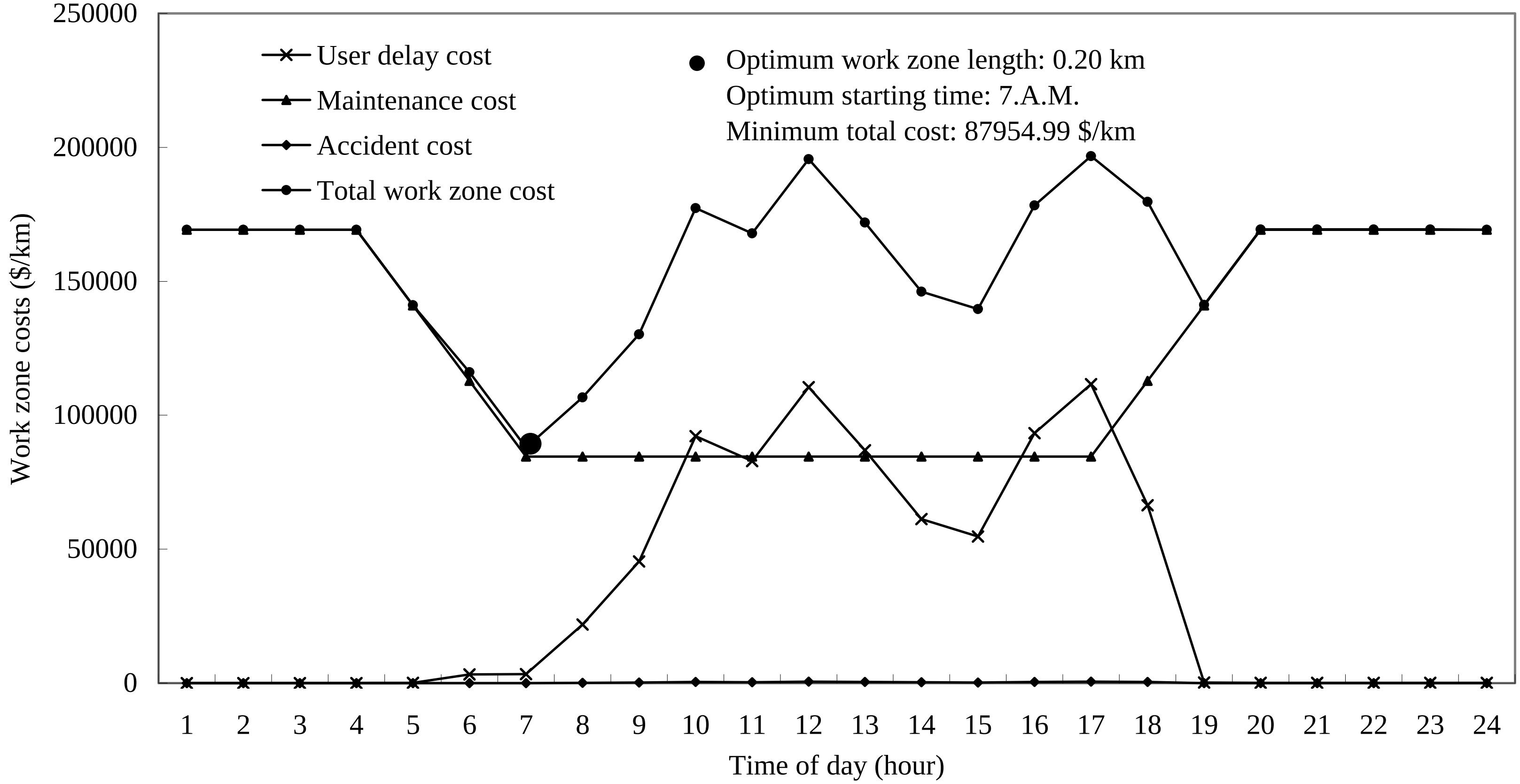


Figure 9 Variation of work zone costs versus the starting time of the day for
the global optimum solution of 0.20 km for the work zone segment length and 7 A.M. for the starting time for example 3

Part III

Radial Basis Function Neural Network for Work Zone Capacity and Queue Estimation

RADIAL BASIS FUNCTION NEURAL NETWORK FOR WORK ZONE CAPACITY AND QUEUE ESTIMATION

Asim Karim[5] and Hojjat Adeli[6], Fellow, ASCE

ABSTRACT. An adaptive computational model is presented for estimating the work zone capacity and queue length and delay taking into account the following factors: number of lanes, number of open lanes, work zone layout, length, lane width, percentage trucks, grade, speed, work intensity, darkness factor, and proximity of ramps. The model integrates judiciously the mathematical rigor of traffic flow theory with the adaptability of neural network analysis. A radial-basis function neural network model is developed to learn the mapping from quantifiable and non-quantifiable factors describing the work zone traffic control problem to the associated work zone capacity. This model exhibits good generalization properties from small set of training data, a specially attractive feature for estimating the work zone capacity where only limited data is available. Queue delays and lengths are computed using a deterministic traffic flow model based on the estimated work zone capacity. The result of this research is being used to develop an intelligent decision support system to help work zone engineers perform scenario analysis and create traffic management plans consistently, reliably, and efficiently.

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INTRODUCTION

Recognizing the need for serving the public's present and future transportation needs the Transportation Equity Act for the 21st Century (FHWA, 1998) has earmarked increased funding for maintenance, rehabilitation, and reconstruction of the nation's aging highway system. It is therefore expected that the number of work zones would increase in the future impacting further the normal operation of the highway system. The primary goal of the various departments of transportation (DOTs or traffic agencies) is to enhance mobility and safety at all times on the highway system. Over the years the quality and uniformity of traffic control devices and procedures have improved. However, the numbers of work zone related fatalities and injuries have remained practically the same and the traveling public has become increasingly frustrated with additional mobility restrictions (FHWA, 2000). A large population is exposed to work zones and their negative impacts. This in turn generates widespread negative sentiments towards the public agencies responsible for providing efficient and safe transportation services to the public.

As work zones on today's highways are becoming an increasingly frequent and unavoidable reality traffic agencies are faced with the challenging problem of effectively planning and managing work zones in their jurisdictions. This is a complex multifaceted problem that requires life cycle cost analyses at the system level. An analysis at the system level, however, will only be useful when a reliable model for the impact of a given work zone on traffic flow is available. In current practice, work zone engineers rely on their judgment based on previous experiences to quantify work zone traffic impacts and to make decisions. Work zone engineers have to consider a large number of factors such as work zone layout, work intensity, diversion of traffic, and driver behavior.

The effectiveness of a work zone traffic management plan (TMP) may be measured by the delay experienced by motorists and/or the length of queue formed on the upstream side. To improve the objectivity and reliability of a work zone TMP a reliable model is needed that maps traffic flow and work zone characteristics to delay time and queue length. For such a model to be useful in practice it must have the following characteristics:

- It should be based on a simple underlying principle of traffic flow. Complicated physical and/or psychological models of traffic flow are unrealizable and intractable for practical purposes. Also, the data input needed for some of these models are not readily available thus introducing a source of error. A simple model, on the other hand, can be reasoned with and 'calibrated' to produce reliable results for different work zone scenarios.
- It should consider the major factors that affect traffic flow through work zones. For example, work zone capacity should not be an input but rather should be determined from an input of work zone characteristics. Consequently, the model should be able to process both quantifiable and non-quantifiable (or linguistic) variables involved in the analysis.
- It should be flexible in the sense that it can be adapted and extended for the analysis of different work zone traffic control scenarios. In particular, its applicability should not be restricted to a single roadway geometry and/or work zone layout. To accomplish this the model should be capable of learning from input/output data and not be based solely on a physical/psychological model of traffic flow. This is essential because real world behavior under all situations can not be modeled satisfactorily by conventional mathematics only.

With these guidelines in mind, a new adaptive computational model is developed for estimating the work zone capacity as well as queue delay and length based on the conservation principle of traffic flow. The model integrates judiciously the mathematical rigor of traffic flow theory with the adaptability of neural network analysis. A radial-basis function neural network (RBFNN) model is developed to learn the mapping from quantifiable and non-quantifiable factors describing the work zone traffic control problem to the associated work zone capacity. Queue delays and lengths are computed using a deterministic traffic flow model based on the estimated work zone capacity. The goal of this research is to help create an intelligent decision support system to help work zone traffic engineers create TMPs consistently and efficiently.

REVIEW OF WORK ZONE TRAFFIC CONTROL PLANNING

A work zone is a region within an existing highway's roadway where active maintenance, rehabilitation, and/or reconstruction work is carried out. The highway is not closed and traffic flow and highway work exists in close proximity to each other. A work zone thus imposes a spatial and temporal restriction on a highway's roadway that negatively impacts the normal flow of traffic. These impacts appear as increased congestion, travel times, accidents, and a greater level of dissatisfaction among the traveling public. Work zones are planned and managed to minimize these impacts and the overall cost. A primary concern of traffic agencies is creation of TMPs for long-term stationary work zones (with duration of more than one day) because they are of high impact and visibility with a lot at stake for all parties involved. Development of such plans requires a careful analysis of traffic flow through the work zone to determine the best work phasing and work zone layout. As mentioned earlier, the overall problem of planning and managing of work zones in a highway system is complex requiring life cycle cost analyses. Nowadays, however, the primary focus of traffic agencies is the creation of a TMP for a given work zone that minimizes queue delays and lengths.

Construction and maintenance work zones on highways have been studied for more than 30 years in an effort to develop safer and effective TMPs. A survey of the literature that specifically deals with mobility of traffic through work zones reveals a mix of empirical studies and mathematical analyses. Empirical studies collect and analyze data from work zones in an effort to develop an understanding of traffic demand, work zone capacity, work zone layout, traffic mitigation strategies, and traffic congestion.

By analyzing data from 161 observations of freeway queuing Cottrell (2001) presents an empirical model of queuing delay using linear regression analyses. Equations are presented that relate traffic flow and capacity variables to queue delay variables. The model, however, is for recurrent congestion only and does not consider congestion caused by work zones and their associated variables. Cassidy and Mauch (2001) also study recurrent congestion using cumulative plots of traffic count and show that the density in long queues that span several interchanges decreases in the upstream direction. In an earlier study Cassidy and Bertini (1999) analyze discharge patterns from freeway bottlenecks and conclude that discharge rates are nearly constant when taken cumulatively. These two articles provide general insights into queuing behavior caused by bottlenecks that may be applicable to work zones also. By analyzing data from 24 work zones Dixon et al. (1996) present capacity values of work zones for both urban and rural freeways. They found that work zone capacity is affected significantly by work intensity, rural and urban location, and darkness. The presence of a work zone forces many regular motorists to choose alternative routes even when a diversion is not specified explicitly. This phenomenon, called natural diversion, can play a significant role in work zone traffic flow analysis. Natural diversion is studied by Ullman (1996) for the particular situation where the freeway has continuous frontage roads. Krames and Lopez (1994) provide recommendations for work zone capacity after analyzing data from 33 work zones. They present a single base work zone capacity for different work zone configurations. This base value can be modified to reflect the effects of work intensity, traffic composition (percentage of trucks), and the presence of ramps just upstream of the work zone. The Highway Capacity Manual (FHWA, 2000) represents the current state of practice in traffic analyses summarizing the results of empirical studies in the past 20 years. Its coverage of work zone capacity, however, is brief and limited to a few general recommendations.

Empirical studies are generally limited in scope and not readily applicable to decision-making where different scenarios have to be analyzed objectively. They do provide valuable insights but such insights are case-specific and have to be captured in a generalized computational model to be of value to traffic agencies in the development of TMPs. Several models have been proposed in the literature for the determination of queue lengths and delay times associated with work zones. In general, these models are based on one of two approaches of traffic flow theory: shock wave analysis and queuing analysis (May, 1990). Shock wave analysis traces shock waves, or boundaries demarcating different flow regimes, in time and space to determine regions of queued (congested) and uncongested flow. Shock wave analysis is deterministic in nature and uses only two macroscopic traffic flow parameters, traffic demand and roadway capacity, as input. It does not take into account the dependence of traffic demand and work zone capacity on many other parameters and therefore is not very reliable for work zone traffic flow analysis. In queuing analysis, a work zone is modeled as a service process where vehicles arriving at the work zone experience some delay (queue delay) before they are able to continue along the highway. Queuing analysis can be deterministic or stochastic, and it may use either macroscopic or microscopic traffic flow parameters. Deterministic queuing analysis suffers from the same shortcoming as shock wave analysis while stochastic analysis requires traffic distribution information that is often not available in practice. A microscopic stochastic model of traffic flow provides the most detailed analysis possible. The accuracy of such a model, however, depends on the accuracy of human-vehicle-environment behavior models, which are still not well understood and are an area of research.

Chien and Schonfeld (2001) present an optimization model for the optimal length of a work zone on a four-lane divided highway (2-lanes in each direction) with one lane in each direction closed. The objective function is the total cost including user cost, accident cost, and agency maintenance cost. The model assumes that work zone capacity is constant and independent of work zone characteristics. Islam and Seneviratne (1993) evaluate the suitability and effectiveness of four traffic planning software tools for the evaluation of TMPs, while Sadegh et al. (1988) present a simulation model for work zones on arterials. The computer program called QUEWZ (queue and user cost evaluation at work zone) evaluates queue lengths and additional user costs for work zones on freeways (Memmott and Dudek, 1984; Krammes et al., 1987). This model uses the conservation of flow principle to calculate the queue lengths and user costs for different lane closure configurations and work schedules. The capacity of the work zone is calculated from empirical speed-flow-density relationships and is independent of the work zone characteristics such as work zone layout and work intensity.

Recently, an initiative at the Federal Highway Administration (FHWA) was launched to develop strategic tools for work zone traffic analysis and decision support. As part of this program, a spreadsheet based tool called QuickZone has been developed to quantify work zone queue delays and lengths given work zone capacity, traffic demand, and work phasing (Mitretek, 2000). The QuickZone software takes as input hourly values of traffic demand and work zone capacity. Queue lengths and delays are computed by the deterministic input-output conservation principle of traffic flow. The software does not take into account work zone layout, lane widths, driver behavior, work intensity, and proximity of ramps in the computation of work zone queue delays and lengths.

DETERMINISTIC QUEUING MODEL FOR WORK ZONE TRAFFIC ANALYSIS

A deterministic macroscopic queuing model is used to calculate queue lengths and delays produced by bottlenecks on highways such as work zones. This model is based on the principle of conservation of flow which states that under homogeneous roadway conditions the number of vehicles entering a segment in a given time period must be equal to the number of vehicles exiting the segment in the same time period. If the road segment is inhomogeneous with a bottleneck such as a capacity reducing work zone existing on a portion of the segment, then the number of vehicles exiting may be fewer than the number of vehicles entering the segment. The difference in such a situation represents the queue formed in the upstream direction.

This model is an adaptation of the theory of incompressible fluid flow to vehicular traffic streams. It only requires as input traffic demand (or flow rate), highway capacity, and their variation over time. If conservation of flow is evaluated over a reasonable time period (say greater than 15 minutes) the model produces practically accurate estimates for queue lengths and delay times that can be used for planning, assuming that the demand and capacity values represent the actual conditions on the highway accurately. In the following paragraphs, the model is formulated for a single link or segment of freeway containing a capacity reducing work zone.

Figure 1 shows the layout of a freeway segment with a construction work zone. The work zone acts like a metered on-ramp that allows only a certain number of vehicles to pass through in a given amount of time. Major freeway repair, rehabilitation, and reconstruction projects are multi-day repetitive operations where work zone layout and phasing is often identical from day to day. Therefore, it is sufficient to analyze a typical day (or at most a few typical days) of work for their traffic impact. If a 1-hour evaluation time period (Δt = 1 hour) is considered twenty four values of traffic demand or anticipated hourly traffic flow approaching the work zone (f_t) and highway capacity (c) are needed as input to cover a period of one day. Let these values be denoted by f_t (t=0,..,23) and $c(t)$ (t=0,..,23), respectively, where the index t indicates the time period. Then, for time periods t = 1, 2, 3,…, 23, using the conservation principle the number of vehicles in the queue in time period t is given by

$$Q(t) = \max\left[f_t(t) - c(t) + Q(t-1), 0\right] \qquad t = 1, 2, 3, \ldots, 23 \qquad (1)$$

The term $Q(t-1)$ on the right hand side of recursive Eq. (1) represents the number of vehicles in the queue for the previous time period. When t = 1 the queued vehicles at the previous time period $Q(t-1)$ can be taken equal to zero if the beginning of evaluation period is chosen at a time when demand is less than the capacity. The highway capacity $c(t)$ is equal to the work zone capacity, c_W, when the work zone exists and equal to c_0, the capacity of the freeway in the absence of the work zone (Figure 1).

If k is the jam density (the number of queued vehicles that occupy a given length of highway), then the average length of queue at time period t is given by

$$Q_L(t) = \frac{Q(t)}{k} \qquad t = 0, 1, 2, \ldots, 23 \qquad (2)$$

The expected daily queue delay (in vehicle-hours) experienced by motorists is given by

$$Q_D = \sum_{t=1}^{23} \frac{Q(t)+Q(t-1)}{2} \Delta t \qquad (3)$$

where Δt = 1 hour is the evaluation time period. Equations (1)-(3) define the primary parameters needed by the work zone engineer to assess the impact of a work zone on traffic in creating a TMP. Using these values the user delay cost can be estimated provided that the average cost per vehicle hour expressed in dollars per vehicle hour is known. The accuracy of this analysis depends on the accuracy of the demand and capacity values used.

ESTIMATION OF TRAFFIC DEMAND AT WORK ZONES

To accurately predict the temporal development and extent of queues and delays created in work zones it is necessary to have a reasonably accurate estimate of the traffic demand, that is the anticipated hourly traffic flow of the freeway approaching the work zone. The annual average daily traffic (AADT), which is the daily traffic demand averaged over all days of the year, is unsuitable for this purpose. Shorter time estimates of traffic demand can be obtained from the AADT when daily, weekly and seasonal demand factors (α_S) are known for the freeway. Many traffic agencies maintain values for daily, weekly, and seasonal demand factors. For example, ODOT specifies values for α_S in the range of 0.76 and 1.72 (http://www.dot.state.oh.us/techservsite/). Many traffic agencies also maintain hourly vehicle counts on major highways, in which case α_S = 1.

These traffic demand values reflect the behavior and usage pattern of the public under normal and unrestricted freeway conditions. The usage patterns usually change after the establishment of the work zone impacting analyses of work zone traffic congestion.Once a work zone is set up on a freeway, traffic demand for that segment of the freeway reduces in reaction to increased travel times and availability of alternate routes. Therefore, the traffic flow approaching a work zone can be expressed as

$$f_t(t) = \alpha_D(t)\alpha_S f_t'(t) \qquad (4)$$

where f_t' is the average traffic demand on the highway prior to the establishment of the work zone, α_S is the seasonal demand factor, and $\alpha_D(t)$ $(0 < \alpha_D \leq 1)$ is the demand reduction factor (or diversion factor). The value of the latter factor depends on the number of motorists: (1) choosing alternate routes, (2) changing their schedules to avoid the work zone, (3) canceling their trips because of the work zone, and (4) changing transportation mode, for example, opting to use public transportation. Diversion of traffic through alternate routes may be signed or advised by an advanced traveler information system (ATIS). Or, it may occur naturally where motorists familiar with the highway corridor select alternate paths to their destinations. The magnitude of $\alpha_D(t)$ is determined from traffic demand studies carried out for similar freeway work zone scenarios. Alternatively, or in addition to traffic demand studies, the demand reduction factor can be determined from a traffic network analysis of the freeway corridor that includes the work zone and alternate origin-destination routes. This factor can change from one time period to another as the congestion caused by the work zone changes. This is because long queues and delays dissuade motorists from continuing on the freeway and force them to seek alternate routes.

NEURAL NETWORK MODEL FOR ESTIMATING WORK ZONE CAPACITY

Factors Affecting the Work Zone Capacity and Included in the Model

Accurate estimates of work zone capacity are critical for reliable and accurate computation of queue delays and lengths at work zones. Work zone capacities and, in general, freeway capacities depend on the prevailing roadway, traffic, and control conditions. As these conditions within a work zone are significantly different from those in an unrestricted segment of the freeway, work zone capacities have to be estimated separately for each work zone scenario by taking into consideration the unique characteristics of the work zone TMP that impact capacity. For example, work zone layouts may contain uncommon geometries such as lane drop-offs and sharp horizontal alignment changes that cannot support high speeds thus reducing the freeway capacity.

The primary factors impacting the work zone capacity and considered in this research are: number of lanes (x_1), number of open lanes (x_2), work zone layout (x_3), work zone length (x_4), lane width (x_5), percentage of trucks (x_6), grade (x_7), work zone speed (x_8), work intensity (x_9), darkness factor (x_{10}), and proximity of ramps or interchange effects (x_{11}). Theoretically, work zone capacity can be expressed as a function of these parameters:

$$c_W = f(x_i, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}) \tag{5}$$

The number of open lanes can vary from 1 to the maximum number of existing lanes in each direction. Some work zone layouts do not involve a reduction in the number of open lanes after the creation of the work zone (Figure 2b). The work zone layout parameter identifies one of the three common work zone layouts used in practice known as lane merging, lane shifting, and crossover (shifting a diverted lane onto the right-of-way of the opposing traffic) (Figure 2). For computational modeling, these three layouts are identified by numbers 0.1, 0.5, and 0.9, respectively. The lane width parameter is the minimum width of a traveled lane within the work zone. The standard highway lane width in the U.S. is 12 ft. A width less than 12 ft will negatively impact the lane's capacity. The percentage of trucks parameter represents the percentage of trucks, buses, and heavy vehicles in the traffic stream. A greater percentage of trucks tends to reduce mean speeds through the work zone and consequently reduce freeway capacity. Freeway grade impacts the mean speed of traffic through the work zone, especially when the percentage of trucks is large.

As part of a TMP a lower speed limit may be imposed and enforced through the work zone to enhance safety. A lower work zone speed, however, decreases the capacity of the work zone. The work intensity parameter describes the intensity of work activity carried out in the work zone. This is a readily non-quantifiable parameter. In this research, the work intensity is broadly categorized into low, medium, or high depending on the size and number of the equipment and labor at the site, the noise and dust created, and the proximity of work to the traveled lanes. For example, pavement marking operation is a low intensity work, pavement resurfacing is a medium intensity work, and pavement rehabilitation/lane addition is a high intensity work. For computational modeling, these three work intensity categories are identified by 0.1, 0.5, and 0.9, respectively. Low-visibility and darkness reduces capacity as motorists become more cautious under such conditions. The darkness factor can vary from greater than 0 to 1 where 1 indicates adequate illumination that does not reduce capacity.

The interchange effects (proximity of ramps) parameter indicates the presence of an on- or off-ramp within 1500 ft upstream of the work zone taper, or 500 ft downstream of the work zone. The proximity of ramps produces turbulence in traffic flow reducing the number of vehicles moving through the work zone. This parameter is modeled as a binary two-valued parameter with values of 0 (no ramps) or 1 (ramps exist in proximity to the work zone).

The Case for Neural networks

There is no mathematical function for the work zone capacity function represented by Eq. (5). In other words, the work zone capacity problem is too complicated to be amenable to classical mathematical solutions. The widely used *Highway Capacity Manual* (HCM) (TRB, 2000) provides scant information on the work zone capacity based on empirical data measurements. It provides a base capacity value for ideal unrestricted highway segments. This value can be modified to take into account certain deviations from the ideal conditions by applying reduction factors. Conditions within work zones are far from ideal and the values and reduction factors given for the ideal highway segments are generally not applicable to work zone analysis. The HCM provides a base capacity of 1600 vehicles per hour per lane (vphpl) for short-term work zones of any layout. Guidelines are also given on how to modify the base value to take into consideration work intensity, percentage trucks, proximity of ramps, and lane widths. Other factors considered in this research and described in connection with Eq. (5) such as work zone layout are not considered. Furthermore, it is important to consider the interaction of various factors on the work zone capacity. For example, darkness has a significant impact when the work is of high intensity.

Artificial neural networks have been used to solve complicated pattern recognition and estimation problems not amenable to conventional mathematical modeling (Adeli and Hung, 1995; Adeli and Park, 1998; Adeli and Karim 2001). Most civil engineering applications of the neural networks are based on the simple backpropagation (BP) algorithm (Adeli, 2001). But, the BP algorithm has shortcomings including very slow convergence rate and problem-dependent trial-and-error selection of the learning and momentum ratios. In the next section, a radial-basis function neural network (RBFNN) is developed for estimating the freeway work zone capacity.

The RBFNN has a simple topology consisting of an input layer, a hidden layer of nodes with radial basis transfer functions, and an output layer of nodes with linear transfer functions. Using the training data, the RBFNN creates clusters for similar patterns. Each cluster has a center (represented by a hidden layer node). Similarity of any new pattern to the training patterns is measured by its proximity to the centers of the clusters. As such, the RBFNN is a regularization or generalization network (Moody and Darken, 1989; Poggio and Girosi, 1990). It is most suitable for estimation problems where limited data is available and overfitting needs to be avoided. The danger of overfitting is reduced by the local nature of the transfer functions that allow only a fraction of the nodes to participate in the mapping of a given pattern. When data are limited the effect of noise becomes significant and some patterns may not be sufficiently represented in the training. Generalization in the vicinity of cluster centers is maintained by the graded nature of the transfer functions. The generalization properties of RBFNNs are discussed in detail by Poggio and Girosi (1990) and Adeli and Wu (1998). In contrast, the multilayer feedforward neural network trained by the BP algorithm has a large number of global transfer functions making it susceptible to the overfitting problem when training data are limited and noisy.

Another advantage of the RBFNN over the multilayer feedforward neural network and BP algorithm is its rapid training. Information in a RBFNN is locally distributed. As such, only a few weights have to be modified in each iteration during the training process. Because of these reasons, the RBFNN is found to be suitable for learning the work zone capacity function for which only limited data is available.

Radial-Basis Function Neural Network for Estimating Work Zone Capacity

The architecture of the proposed RBFNN for estimating the work zone capacity is shown in Figure 3 schematically. It has an input layer with eleven nodes representing the eleven parameters included in the work zone capacity function defined by Eq. (5), a hidden layer with

N_h nodes with radial-basis transfer functions, and an output layer with one node representing work zone capacity.

Some of the variables in Eq. (5), such as the work intensity, are in linguistic terms. Such linguistic variables are pre-processed first by converting them to numerical values normalized between zero and one. The numerical parameters are normalized between 0 and 1 as well. The normalization is done so that no single factor dominates the training process. The number of nodes in the hidden layer, N_h, is equal to the number of cluster centers used to characterize the training data. It is chosen as a fraction of the total number of training instances. This choice is based on numerical experimentation for the problem at hand to determine which number adequately covers the input space and produces the best mapping. A number within the range of 10 to 30% of the number of training instances is found to produce satisfactory results (Adeli and Karim, 2000). The cluster centers are represented by vectors $\boldsymbol{\mu}_j$ $(1 \le j \le N_h)$ obtained using the fuzzy c-means algorithm described in Adeli, and Karim (2000).

The weight of the link connecting the input node i to the hidden node j is set equal to μ_{ij} corresponding to the ith component of the vector $\boldsymbol{\mu}_j$. The output of a hidden node j is determined by the following Gaussian transfer function:

$$\phi_j = \exp\left(-\frac{\left\| \mathbf{x} - \boldsymbol{\mu}_j \right\|^2}{2\sigma_j^2} \right) \tag{6}$$

where $\mathbf{x}$ is the vector of input variables and the factor σ_j controls the spread or range of influence of the Gaussian function centered at $\boldsymbol{\mu}_j$. In this work σ_j is calculated as (Adeli and Karim, 2000)

$$\sigma_j = \frac{1}{3N_h}\sum_{i=1}^{N}\left\|\boldsymbol{\mu}_j - \boldsymbol{\mu}_i\right\| \quad 1 \le j \le N_h \tag{7}$$

where N is the total number of training instances. Equation (7) approximates the spread parameter σ_j as one third of the mean distance between cluster centers. The connection from the hidden node j to the output node is assigned the weight λ_j to be described shortly. The output y of the network is then given by

$$y = \sum_{j=1}^{N_h}\phi_j\lambda_j \tag{8}$$

The weights λ_j are calculated by minimizing the error between the network computed output y and the desired output y_d based on training examples. In other words, to train the network for λ_j's we solve the following unconstrained optimization problem:

$$\text{Minimize } E(\boldsymbol{\lambda}) = \sum_{i=1}^{N}\left|y^i - y_d^i\right| \tag{9}$$

The gradient descent optimization algorithm is used to solve this optimization problem. The output y of the system represents the work zone capacity, c_W.

COMPUTATION OF WORK ZONE QUEUE DELAYS AND LENGTHS

Figure 4 shows the inter-relation of work zone capacity, traffic demand, and delay estimation models schematically. The work zone capacity estimation model takes as input the eleven parameters affecting work zone capacity. These values are passed through the trained RBFNN model to determine the work zone capacity for the given work zone scenario. The traffic demand estimation model takes as input the hourly traffic demand prior to the establishment of the work zone, the queue delay and length, if any, and the driver behavior characteristics. The latter two factors are used to estimate the demand reduction factor. The estimates of queue delay and length are obtained from the work zone queue delay and length estimation model. This model takes as input the outputs from the traffic demand and work zone capacity estimation models. The work zone capacity and the modified traffic demand are used to estimate the work zone queue delay and length using Eqs. (3) and (2), respectively.

The model is evaluated for each time period Δt (for example, every hour). If the work zone scenario does not change during the construction then the work zone capacity remains constant during the analysis. Otherwise, different work zone capacity values are determined for different times of the construction reflecting the changing work zone scenario. Similarly, if the traffic flow approaching the work zone is known and the demand reduction factor is one, the traffic demand model is evaluated once. Otherwise, it is evaluated at every time step.

TRAINING AND TESTING THE NETWORK

The RBFNN model for work zone capacity estimation is trained using forty examples of work zone capacity (Table 1). These examples are created from the work zone capacity table provided by ODOT, the guidelines presented in the Highway Capacity Manual (TRB, 2000) for different highway and work zone capacities, and the experience and judgment of the authors. The ODOT lookup tables provide work zone capacity values for lane closure configurations of 3 to 2, 3 to 1, and 2 to 1, lane widths of 10, 11, and 12 ft, truck percentages from 0 to 25, work zone lengths from 0 to greater than 8 miles, and roadwy upgrades from 0 to 6 percent. Guidelines from the HCM, in the form of recommended ranges of adjustments, are used in conjunction with the judgement of the authors to adjust the capacity values for work zone layout, work zone speed, work intensity, and proximity of ramps. The training examples represent as many possible combinations of work zone scenarios to ensure that the boundaries of the input space are adequately covered for effective generalization by the RBFNN model. Training of the network took less than 10 seconds on a Pentium 4 PC with a root mean square error of 165. The purpose of the training was to achieve a generalized mapping rather than a perfect fit to the training data. A perfect fit would be of little practical value considering the noisy nature of the training data and the complexity of the problem that depend on many factors in addition to the eight primary factors modeled in this research.

The network is tested using 27 work zone capacity values observed in the field and reported in the literature (denoted by scenarios 1 to 27 in Figure 5). Nine samples are taken from Dixon et al. (1995) (scenarios 1 to 9 in Figure 5). These samples are for two-lane (in each direction) rural freeways in North Carolina with one lane closed and one lane open to traffic. The North Carolina data contain eight of the eleven parameters needed for the work zone capacity estimation model. Values of zero are used for the unavailable parameters. Twelve samples are taken from Jiang (1999) for work zones on four-lane freeways in Indiana (scenarios 10 to 21 in Figure 5). These samples are also for work zones with one open and one closed lane. They contain values for only seven of the eleven parameters. Six samples are taken from Kim et al. (2001) for work zones on freeways in Maryland (scenarios 22 to 27) in Figure 5). These samples are for work zones with two open lanes. The Maryland data also contain seven of the eleven parameters used in the new work zone capacity estimation model.

The RBFNN is used to estimate the work zone capacity for these real work zone scenarios from a variety of sites with different traffic and geometric characteristics. The work zone capacity values estimated by the RBFNN model are compared with the observed values in Figure 5.The error is mostly in the range of 0.4% to 11% while for 10 samples the errors range from 20 to 71% (samples 4 to 9, 12 to 14, and 25). One reason for the large errors in the estimated work zone capacity values is the large percentage of trucks in these samples' scenarios (19 to 27% for samples 4 to 9, 22 to 32% for samples 12 to 14, and 28% for sample 25). The percentage of trucks parameter significantly impacts work zone capacity by reducing mean speeds through work zones. The impact is compounded when the work zone is on an upgrade, a parameter not reported in the sample data used to train the neural network model. Furthermore, the maximum value for the percentage of trucks in the training data set is 25, thus forcing the RBFNN model to extrapolate for scenarios with higher values. It should also be noted that the data used for testing the RBFNN model suffered from several problems including missing values for several key parameters affecting work zone capacity and differing and/or unknown procedures for data collection and analysis. Nevertheless, considering the very limited amount of training data available to the authors, the model yields reasonably accurate results for most scenarios.

The RBFNN model presented is general and is expected to perform much better when tested with a larger and more reliable data set. This observation is based on the fact that the training root mean square error is 165 vehicles per hour, which is acceptable for most practical purposes.

EXAMPLES

Example 1

This example demonstrates the use of the new work zone capacity and delay estimation model as an intelligent decision support system for the creation of a work zone TMP. It also highlights the significance of accurately estimating the work zone capacity for reliable estimation of queue delay and length. A work zone needs to be established on a six-lane freeway (three lanes in each direction) for lane resurfacing. The work will start at 6 AM each day and terminate 8 hours later. The capacity of the unrestricted freeway (in one direction) is 5400 vph.

Six work zone scenarios are evaluated for this work, described in Table 2. Each scenario represents a different work zone geometry and management option. It is desired that at least two lanes be kept open through the work zone. The impact of work zone layout, lane width, length, speed, and proximity of ramps are investigated. A work zone scenario with one open lane (scenario 6) is also considered for situations where it becomes unavoidable. The RBFNN model for estimating work zone capacity is used to determine capacity values for these scenarios. The results, given in Table 2, clearly show the significant dependence of work zone capacity on parameters such as length, lane width and proximity of ramps. By increasing the work zone length from 1 to 5 miles, the work zone capacity is reduced from 2785 to 2705 vph (scenarios 1 and 2). The width of lanes has a more significant effect, as seen from the estimated capacity values for scenarios 3, 4, and 5. The proximity of a ramp reduces capacity by only 22 vph (scenarios 4 and 5). Comparing scenarios 1 and 2 with scenarios 3, 4 and 5 it is seen that the lane merging layout produces slightly better capacity values as compared to the crossover layout.

Table 3 gives the number of vehicles in queue at each hour (or queue delay in vehicle-hours) for the six work zone scenarios. The hourly traffic flow approaching the work zone (traffic demand) is given in column two. In this example, it is assumed that the traffic demand reduction factor is 1. The maximum vehicles in queue produced by the six scenarios varies from 115 (scenario 3) to 10193 (scenario 6). Assuming the jam density (k) is 200 vehicles per mile per lane and queue is evenly distribution among the 3 lanes, the maximum queue lengths produced by these scenarios varies from 0.19 to 17 miles. The maximum determined for scenario 6 may not be attained in practice because motorists would react to the delay and change their behavior.

In any case, scenario 6 should not be adopted except for emergency situations. Work zone scenario 3 provides the best solution for this example. This scenario satisfies ODOT's requirement that queue lengths should be less than 0.75 miles long at all times (ODOT, 2000).

The significance of accurate work zone capacity estimation is evident from Table 3. Comparing scenarios 3 and 4, a slight increase in work zone capacity caused by modifying the work zone characteristic has drastically reduced the queue delay. Scenario 4 causes a daily queue delay of 7097 vehicle-hours as compared to only 250 vehicle-hours for scenario 3.

Example 2

This example illustrates the use of the demand reduction factor and its impact on the computation of work zone queue delay and length. Hourly traffic demand is often measured on or estimated for unrestricted freeways. However, when a work zone is established the traffic flow approaching the work zone often reduces as motorists change behavior in reaction to delays or delay information. Data for the six-lane freeway presented in Example 1 is used in this example. Work zone scenario 1 is analyzed. The traffic demand on the freeway and the demand reduction factors are given in Table 4. Up to 6 percent of motorists change their behavior and reduce the flow approaching the work zone. The results of the capacity and delay estimation model are given in Table 4. It is seen that the number of vehicles in queue decreases sharply as compared to the case when no reduction in demand is considered in the analysis. This example highlights the importance of warning motorists in advance and providing them with alternate routes to the reduction of queue delays and lengths. It also shows that using traffic demand on unrestricted freeways for the computation of work zone queue delays and lengths will overestimate these values.

Example 3

This example illustrates the impact of work scheduling on work zone delays and queue lengths. A work zone on a four-lane (two lanes in each direction) freeway is analyzed. The work zone has a lane merging layout with one lane open having a width of 11 ft. Ten percent of the traffic stream is composed of heavy vehicles. The speed limit through the work zone is 45 mph. The work is of medium intensity with a duration of 6 hours, and no ramps exist in the proximity of the work zone. Using the RBFNN model for work zone capacity estimation, the capacity of this work zone scenario is found to be 1581 vph. The unrestricted freeway capacity is 3800 vph. The hourly traffic flow approaching the work zone (traffic demand) is given in Table 5. Three work zone starting times (or phasing) are analyzed. In phasing 1, work starts at 12 noon and ends 6 hours later. In phasing 2, work starts at 4 AM, while in phasing 3 work starts at 12 midnight. The results computed using the work zone capacity and delay estimation model are given in Table 5 and shown in Figure 6. It is seen that by scheduling work when traffic demand is low one can reduce or even eliminate work zone queue delays and lengths..

CONCLUSION

In this article, a new model for work zone capacity and delay estimation is presented. The model considers 11 parameters in the estimation of work zone capacity: number of lanes, number of open lanes, layout, length, lane width, percentage trucks, grade, speed, work intensity, darkness factor, and proximity of ramps. A RBFNN model is developed to map a work zone scenario to its capacity. The model also considers reduction in traffic flow approaching the work zone in the computation of queue delays and lengths. Accurate estimation of work zone capacity and demand are essential for the accurate and reliable determination of work zone queue delays and lengths. Three examples are presented to illustrate the use of the new model and to highlight the significance of capacity and demand values in the analysis of work zones.

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Table 1 Training data for the RBFNN model for estimating work zone capacity

No. of lanes	No. of open lanes	Layout	Length (miles)	Lane width (ft)	Percentage trucks	Grade (%)	Work zone speed (mph)	Work intensity	Darkness factor	Inter-change effects	Work zone capacity (vph)
2	1	M	1	10	5	0	45	Low	1	No	1450
3	1	M	2	11	5	1	45	Low	1	No	1430
2	2	S	8	11	10	0	55	Low	0.95	No	2900
2	2	S	1	11	3	1	55	Medium	1	Yes	2850
3	1	C	5	11	8	5	50	High	1	No	1350
3	2	M	2	11	15	0	40	Low	0.9	Yes	2750
3	3	S	10	12	5	0	40	Medium	1	No	4650
2	1	M	1	12	25	2	45	Low	1	Yes	1300
2	1	C	2	12	15	2	35	Medium	1	Yes	1250
3	2	C	5	12	10	0	45	High	0.9	No	2920
4	3	M	1	10	5	5	35	High	1	Yes	4000
3	2	M	15	10	7	0	40	High	1	No	2750
2	2	S	20	11	3	1	50	Medium	0.95	No	2950
2	2	S	3	12	10	0	55	Low	1	Yes	3000
2	1	M	5	11.5	0	5	40	Medium	1	Yes	1450
2	1	C	2	10	10	0	40	Low	0.95	No	1400
3	2	M	4	11.5	15	1	45	Medium	1	No	2980
3	2	M	2	12	25	1	45	High	1	No	2650
2	1	C	2	10	5	0	35	Medium	0.9	Yes	1250
2	1	M	2	10.5	8	0	45	Medium	1	No	1375

Table 1 – continued

No. of lanes	No. of open lanes	Layout	Length (miles)	Lane width (ft)	Percentage trucks	Grade (%)	Work zone speed (mph)	Work intensity	Darkness factor	Inter-change effects	Work zone capacity (vph)
2	1	M	1	12	3	2	55	High	1	No	1550
3	2	C	5	12	10	1	45	Low	1	Yes	2950
4	3	M	5	11	15	1	45	Low	1	Yes	4100
3	1	M	1	10.5	20	0	35	Medium	1	No	1310
2	2	S	5	10	10	0	40	Low	0.9	Yes	2700
3	2	M	4	10	10	0	50	Medium	1	No	2750
2	1	M	1	11	5	2	50	High	0.85	No	1300
2	2	S	2	11	5	0	45	High	1	No	2980
2	1	C	10	12	20	0	55	Medium	1	Yes	1400
2	2	S	5	11.5	5	0	45	Medium	0.95	Yes	3000
2	1	M	2	11.5	10	1	40	Low	1	No	1450
2	1	M	1	10	5	0	35	Medium	1	Yes	1300
2	2	S	2	11	5	5	50	Low	1	No	2950
2	1	C	1	10.5	3	2	45	Low	0.9	Yes	1420
3	1	M	1	11	20	0	45	Medium	1	No	1380
3	2	M	1	12	25	1	45	Medium	1	No	2750
2	2	C	5	11	5	1	35	Low	0.95	Yes	4400
3	2	C	3	11	0	5	35	High	1	Yes	2850
2	1	M	1	10	5	3	40	Low	1	No	1350
3	1	M	1	11.5	7	0	55	Low	1	Yes	1450

M = Lane merging; S = Lane shifting; C = lane rossover

Table 2 Description of work zone scenarios and their capacities estimated by the RBFNN model

Sce-nario	No. of open lanes	Layout	Lane width (ft)	Length (miles)	Work zone speed (mph)	Inter-change effects	Work zone capacity (vph)
1	2	M	11	1	45	No	2785
2	2	M	11	5	45	No	2705
3	2	C	12	5	55	No	2952
4	2	C	10.5	10	45	No	2625
5	2	C	11	10	45	Yes	2603
6	1	C	12	5	50	No	1478

M = Lane merging; C = Lane crossover

Table 3 Queue delay results for Example 1

Hour of day	Traffic demand (vph)	No. of vehicles in queue					
		Work zone scenarios (defined in Table 2)					
		1	2	3	4	5	6
0	682	0	0	0	0	0	0
1	431	0	0	0	0	0	0
2	304	0	0	0	0	0	0
3	323	0	0	0	0	0	0
4	312	0	0	0	0	0	0
5	580	0	0	0	0	0	0
6	1934	0	0	0	0	0	456
7	2986	201	281	34	361	383	1964
8	2666	82	242	0	402	446	3152
9	3067	364	604	115	844	910	4741
10	2681	260	580	0	900	988	5944
11	3035	510	910	83	1310	1420	7501
12	2887	612	1092	18	1572	1704	8910
13	2761	588	1148	0	1708	1862	10193
14	3133	0	0	0	0	0	7926
15	3503	0	0	0	0	0	6029
16	3586	0	0	0	0	0	4215
17	4027	0	0	0	0	0	2842
18	2609	0	0	0	0	0	51
19	1895	0	0	0	0	0	0
20	1591	0	0	0	0	0	0
21	1492	0	0	0	0	0	0
22	1423	0	0	0	0	0	0
23	833	0	0	0	0	0	0
Max. queue length (miles)		1.0	1.9	0.19	2.8	3.1	17.0

Table 4 Queue delay results for Example 2

Hour of day	Demand reduction factor	No. of vehicles in queue (with demand reduction)	No. vehicles in queue (from Table 3, Scenario 1)
0	1	0	0
1	1	0	0
2	1	0	0
3	1	0	0
4	1	0	0
5	0.99	0	0
6	0.98	0	0
7	0.95	52	201
8	0.95	0	82
9	0.97	190	364
10	0.97	6	260
11	0.95	104	510
12	0.94	33	612
13	0.96	0	588
14	1	0	0
15	1	0	0
16	1	0	0
17	1	0	0
18	1	0	0
19	1	0	0
20	1	0	0
21	1	0	0
22	1	0	0
23	1	0	0

Table 5 Queue delay results for Example 3

Hour of day	Traffic demand (vph)	No. of vehicles in queue		
		Phasing 1	Phasing 2	Phasing 3
0	180	0	0	0
1	50	0	0	0
2	117	0	0	0
3	420	0	0	0
4	833	0	0	0
5	1145	0	0	0
6	2161	0	580	0
7	821	0	0	0
8	1020	0	0	0
9	930	0	0	0
10	910	0	0	0
11	1320	0	0	0
12	1620	39	0	0
13	1728	186	0	0
14	2154	759	0	0
15	2420	1509	0	0
16	2021	2038	0	0
17	1460	1917	0	0
18	850	0	0	0
19	700	0	0	0
20	400	0	0	0
21	280	0	0	0
22	240	0	0	0
23	210	0	0	0

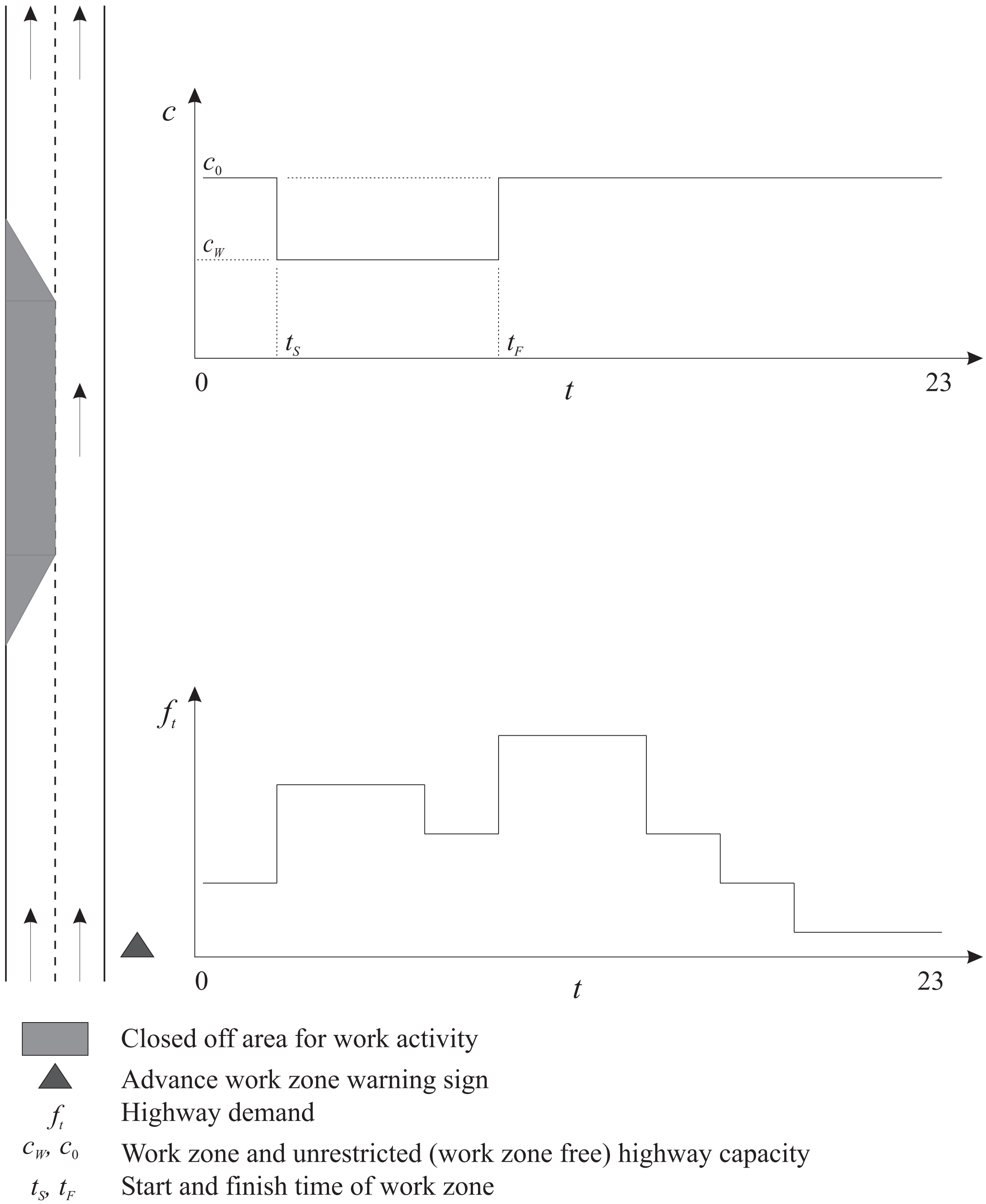

Figure 1 Schematic description of traffic demand and capacity through work zones

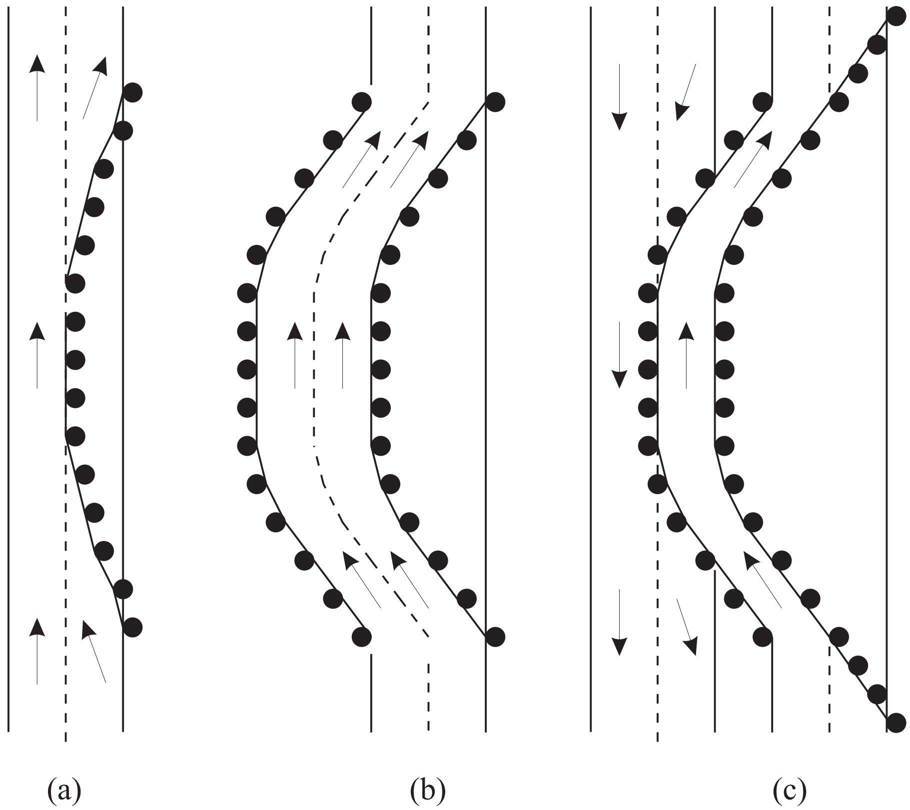

Figure 2 Common work zone layouts (a) Lane merging, (b) Lane shifting, and (c) Crossover

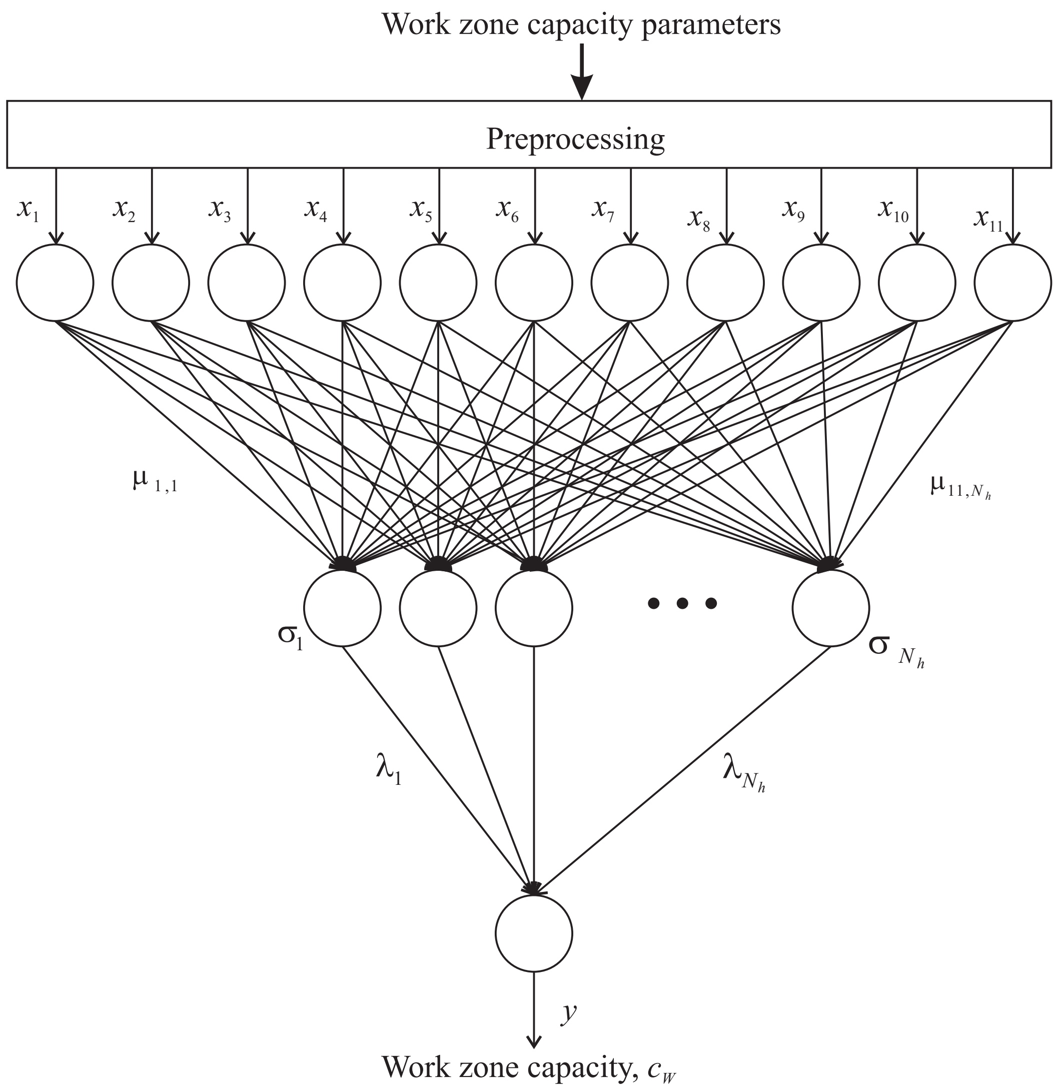

Figure 3 RBFNN model for work zone capacity estimation

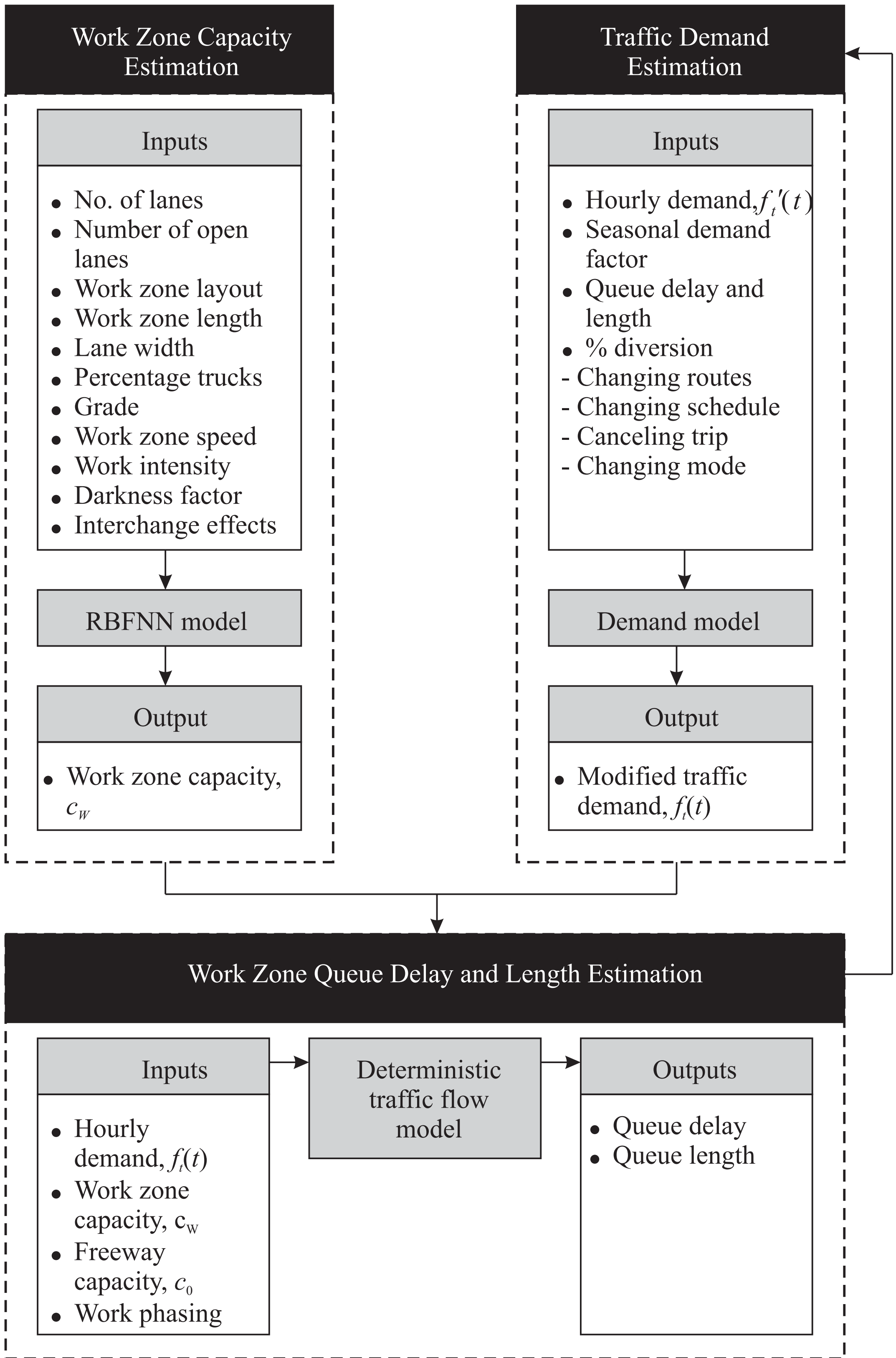

Figure 4 Inter-relation of work zone capacity and delay estimation models

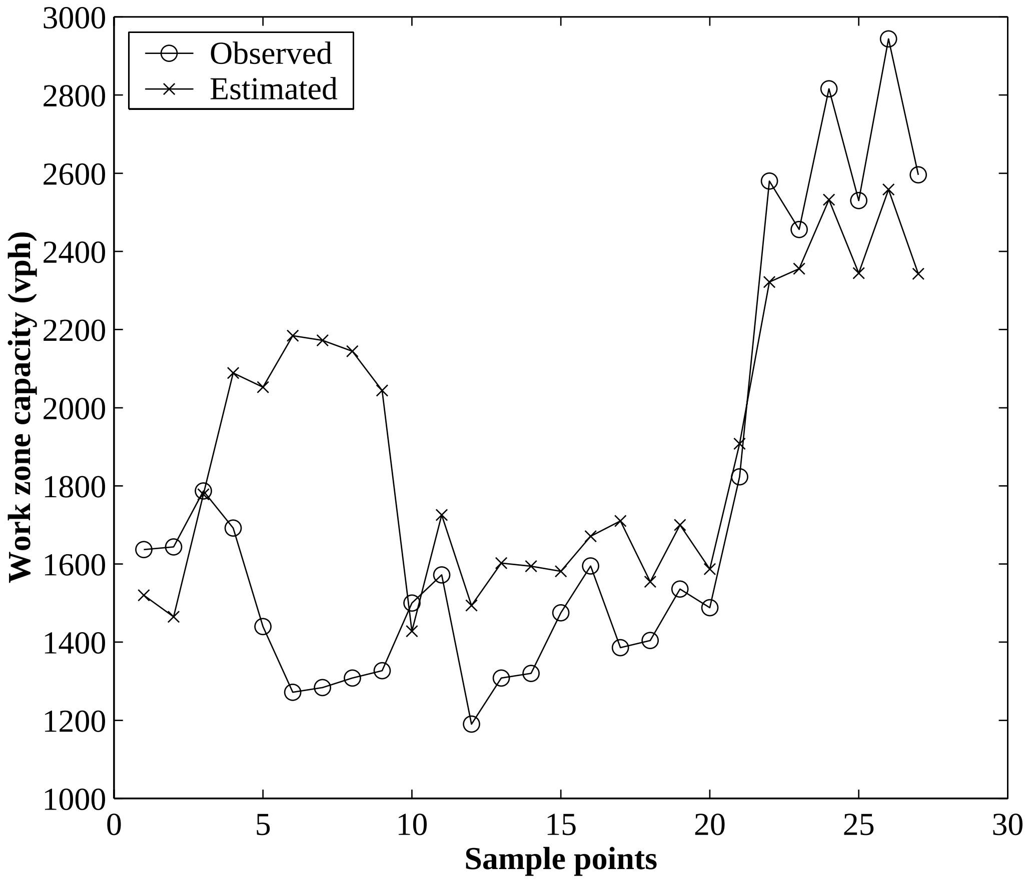

Figure 5 Comparison of observed and RBFNN estimated capacity values

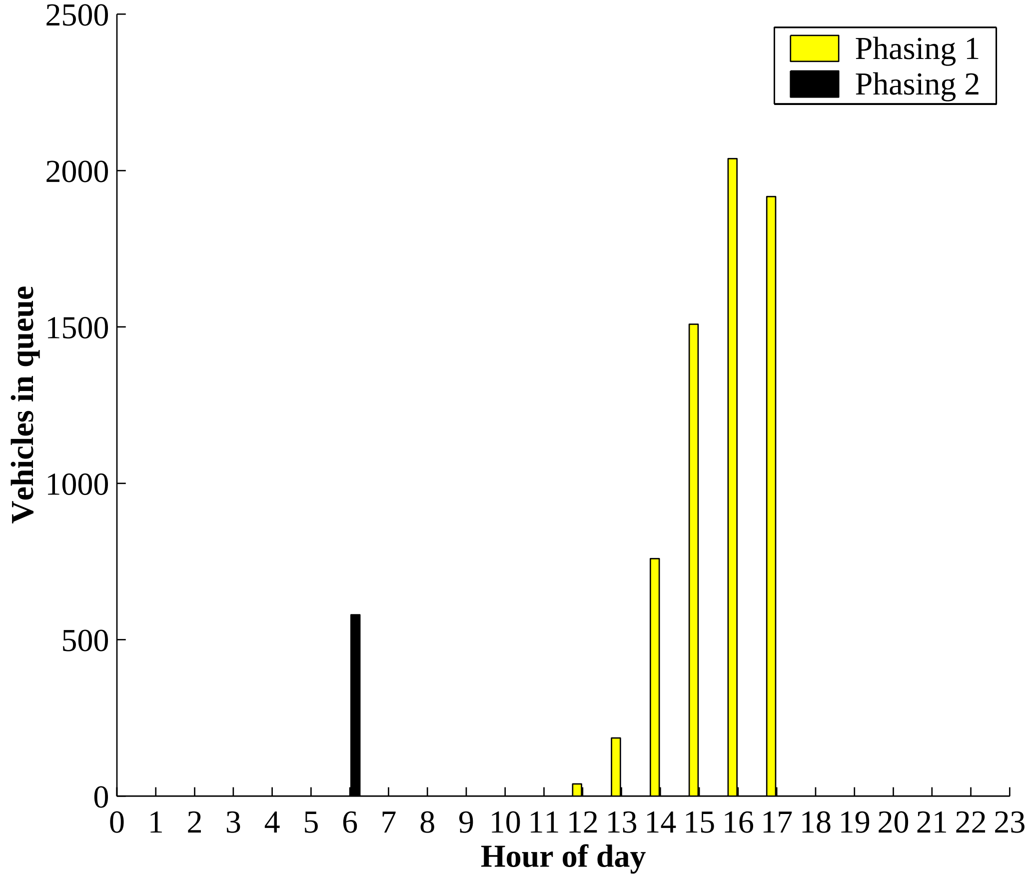

Figure 6 Number of vehicles in queue for different work phasing (Example 3)

Part IV

Neuro-Fuzzy Logic Model for Freeway Work Zone Capacity Estimation

NEURO-FUZZY LOGIC MODEL FOR FREEWAY WORK ZONE CAPACITY ESTIMATION

Hojjat Adeli, Fellow, ASCE[7] and Xiaomo Jiang[8]

ABSTRACT: The work zone capacity cannot be described by any mathematical function because it is a complicated function of a large number of interacting variables. In this article, a novel adaptive neuro-fuzzy logic model is presented for estimation of the freeway work zone capacity. Seventeen different factors impacting the work zone capacity are included in the model. A neural network is employed to estimate the parameters associated with the bell-shaped Gaussian membership functions used in the fuzzy inference mechanism. An optimum generalization strategy is used in order to avoid over-generalization and achieve accurate results. Comparisons with two empirical equations demonstrate that the new model in general provides a more accurate estimate of the work zone capacity, especially when the data for factors impacting the work zone capacity are only partially available. Further, it provides two additional advantages over the existing empirical equations. First, it incorporates a large number of factors impacting the work zone capacity. Second, unlike the empirical equations, the new model does not require selection of various adjustment factors or values by the work zone engineers based on prior experience.

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INTRODUCTION

Work zone capacity has a significant impact on the congestion and traffic queue delays which result in increased driver frustration, increased traffic accident, increased road user delay cost, and increased fuel consumption and vehicle emissions. Highway agencies often use the empirical and highly approximate method described in the *Highway Capacity Manual* (HCM) (HCM 2000) to determine the freeway work zone capacity with lane closures. The HCM provides a base capacity of 1600 vehicles per hour per lane (vphpl) for short-term ideal unrestricted highway work zones. Guidelines are given on how to modify the base value to take into account percentage of trucks, work intensity, proximity of ramps, and lane widths. However, a large number of additional factors affect the freeway work zone capacity estimation which are neglected in the HCM guidelines.

The earlier field measurements and investigations can be traced to the work done at Texas Transportation Institute (TTI) from the late 1970s to the mid-1980s. TTI's work provided the basis for the empirical freeway work zone capacity estimation guidelines included in the previous *Highway Capacity Manual* (HCM, 1985). Recently, a few studies have been conducted for estimation of the work zone capacity based on measured field data (Krammes and Lopez, 1994; Dixon and Hummer, 1995; Dixon et al. 1997; Jiang 1999; Al-Kaisy et al. 2000; Al-Kaisy and Hall, 2001; Kim et al. 2001).

The work zone capacity cannot be described by any mathematical function because it is a complicated function of a large number of interacting variables. That explains the dearth of scientific work on mathematical modeling of the freeway work zone capacity. In this article, a novel adaptive neuro-fuzzy logic model is presented for estimating the freeway work zone capacity. Seventeen different factors impacting the work zone capacity are included in the model. A neural network is employed to estimate the parameters associated with the bell-shaped Gaussian membership functions used in the fuzzy inference mechanism.

FACTORS IMPACTING THE WORK ZONE CAPACITY AND INCLUDED IN THE MODEL

In this article, a computational model is presented for estimating the work zone capacity under a variety of possible work zone scenarios. A large number of factors impacting the work zone capacity are included as inputs to the model. They are 1) percentage of truck (x_1), 2) pavement grade (x_2), 3) number of lanes (x_3), 4) number of lane closures (x_4), 5) lane width (x_5), 6) work zone layout (lane merging, lane shifting, and crossover) (x_6), 7) work intensity (work zone type) (x_7), 8) length of closure (x_8), 9) work zone speed (x_9), 10) interchange effects (proximity of ramps) (x_{10}), 11) work zone location (urban or rural) (x_{11}), 12) work zone duration (long-term or short-term) (x_{12}), 13) work time (daytime or night) (x_{13}), 14) work day (weekday or weekend) (x_{14}), 15) weather condition (sunny, rainy or snowy) (x_{15}), 16) pavement conditions (dry, wet, or icy) (x_{16}), and 17) driver composition (commuters or non-commuters such as tourists) (x_{17}).

Since heavy vehicles such as truck occupy more space on the roadway and move slower than passenger cars, a higher percentage of trucks tends to reduce the work zone capacity. Kramme and Lopez (1994) study the work zone capacity and conclude that a high percentage of heavy trucks has a significant impact on the work zone capacity. The HCM (2000) suggests a heavy-vehicle adjustment factor given as a function of two parameters: proportion of heavy vehicles and the passenger-car equivalent for heavy vehicles. Kim et al (2001) conduct a regression analysis of the interaction between the work zone grade and percentage of heavy trucks. The presence of grades may exacerbate the flow constriction in work zones particularly in the presence of heavy vehicles.

Measurements made at freeway work zones in Texas (Dudek and Richards, 1981; Krammes and Lopez, 1994) and North Carolina freeways (Dixon and Hummar, 1995; Dixon at el, 1997) show clearly that the work zone capacity varies significantly with the number of freeway lanes as well as number of lane closures. Among three commonly used work zone layouts, known as lane merging, lane shifting, and crossover, the lane shifting does not reduce the number of open lanes in the work zone but may affect the work zone capacity. The capacity value recommended for long-term work zone by HCM (2000) indicates that work zones with lane merging have a higher average capacity value than those with a crossover. A work zone with a lane width of less than the U.S. standard lane width of 12 feet may reduce the work zone capacity significantly. The HCM (2000) suggests a reduction factor up to 14% to account for the effect of lane width on work zone capacity.

Work zone capacity may decrease as the work intensity increases from the lightest (e.g. guardrail installation) to the heaviest (e.g. bridge repair). The intensity of work activities depends on a number of factors such as the type of work activities, the number of crews, the number and size of equipments, and the proximity of work activities to the open lane. The work zone intensity is classified into three levels (low, medium, or high) in Karim and Adeli (2003) and six levels in Dudek and Richard (1981). The HCM (2000) suggests a modification of the base capacity value of the work zone to account for the intensity of work activity without actually providing any modification factors or guidelines. This important issue is left for the work zone engineer to decide subjectively based on his/her experience or professional judgment.

Work intensity is a qualitative and subjective concept without any standard classification scheme. In this article, the work intensity is divided into six categories as defined in Table 1.

The length of the closure affects the work zone capacity. Longer work zones often indicate more intensive work activity and display more traffic signs causing travelers to drive more cautiously. A lower speed limit is often enforced in the work zone to improve safety which decreases the work zone capacity.

Ramps proximity to the work zone, especially the entrance ramps inside the work zone activity area, can create traffic turbulence resulting in a reduction in the work zone capacity. The HCM (2000) suggests an adjustment for ramps without actually providing any modification factors. Again, the issue is left for the work zone engineer to decide subjectively based on his/her experience. Al-Kaisy et al. (2000) suggest that both duration of work zone and driver composition can affect the work zone capacity. The average capacity at long-term freeway work zones is greater than that at short-term work zones because the commuters and frequent travelers become familiar with the configuration of the long-term work zone.

The workday (weekdays or weekends) and work time (daytime or night) also affect the work zone capacity. In all likelihood commuters and regular travelers during the weekdays are more familiar with the configuration of the work zone and the traffic control plans in the affected areas (e.g. route diversion) than non-commuters (e.g. tourists) traveling during the weekends. Night construction on the one hand can help increase the work zone capacity by avoiding traffic congestion during peak hours, and on the other hand can decrease the work zone capacity because of the reduced travelers' attention (Al-Kaisy and Hall 2001).

Weather (snowy, rainy, or sunny) and pavement conditions will have a significant impact on the work zone capacity. The HCM (2000) suggests 10 to 20 percent capacity reductions due to bad weather conditions without providing any specific guidelines. Again, the issue is left for the work zone engineer to decide subjectively based on his/her experience or professional judgment. Similarly, wet or icy pavement surface in the work zone forces the travelers to lower their speed in the work zone, which reduces the work zone capacity. The HCM (2000) provides no guidelines in this regard.

Symbolically, the work zone capacity can be expressed as a function of 17 variables defined in the previous paragraphs:

$$y = f(x_1, x_2, \ldots, x_{17}) \tag{1}$$

The work zone capacity cannot be described by any mathematical function because it is a complicated and non-quantifiable function of a large number of interacting variables some of which are linguistic.

VARIABLE QUANTIFICATION AND NORMALIZATION

In the new work zone capacity estimation model, some of the variables are linguistic such as work zone layout and weather conditions, some are binary two-valued parameters such as the interchange effect representing the existence of ramps near or within work zone, and others are numeric such as the work zone length. Spline-based nonlinear functions are used to quantify each linguistic as well as binary-valued variable mathematically. Spline-based nonlinear functions are also assigned to numeric variables in order to model the impact of their variations on the work zone capacity. These functions play another role, that is, to normalize the variables into the same range, 0 to 1. This normalization is desirable in the fuzzy inference mechanism developed in this work. The normalization prevents the undue domination of variables with large numerical values over the variables with small numerical values, thus improving the convergence of the network training. Compared with the conventional linear data normalization, the nonlinear normalization using spline-based functions represents the data variation more accurately.

Integer numbers are used to quantify the linguistic and binary-valued variables. Numbers 1, 2, and 3 are used to represent the three types of layouts (lane merging, lane shifting, and crossover), weather conditions (sunny, rainy, or heavy snowfall), and pavement conditions (dry, wet, or icy). Numbers 1 and 2 are used to represent the work zone location (urban or rural), work zone duration (short-term or long-term), work time (day or night), and day of week (weekday or weekend). Numbers 1 and 2 are also used to represent the binary-valued variables interchange effect (1 for no ramp and 2 for existence of ramp), driver composition (1 when it is not considered and 2 when it is considered), and pavement grade (1 when there is no grade and 2 for existence of grade). Numbers from 1 to 6 are used to represent the work intensity as defined in Table 1. Numbers from 1 to 7 are used to represent the seven localities where data are collected (Data used in this research are collected from six different states and the city of Toronto).

The normalized spline-based nonlinear functions for variables 1 to 17 are shown in Figure 1. The value of each normalized function varies from 0 to 1. For variables x_1 (percentage of truck), x_2 (pavement grade), x_3 (number of lanes), x_4 (number of lane closures), x_6 (work zone layout), x_7 (work intensity), x_{10} (interchange effects), x_{11} (work zone location), x_{12} (work zone duration), x_{13} (work time), x_{14} (work day), x_{15} (weather condition), x_{16} (pavement condition), x_{17} (driver composition), and x_{18} (data collection locality), an S-shaped spline-based nonlinear function is used, as defined by the following equation (Figure 1a):

$$q_i = \begin{cases} 2\left(\dfrac{x_i}{b_i}\right)^2 & \text{if } 0 \le x_i \le \dfrac{b_i}{2} \\ 1 - 2\left(\dfrac{b_i - x_i}{b_i}\right)^2 & \text{if } \dfrac{b_i}{2} < x_i < b_i \\ 1 & \text{if } x_i \ge b_i \end{cases} \qquad i = 1 \text{ to } 4,\ 6,\ 7,\ 10 \text{ to } 17 \qquad (2)$$

where b_i is the upper bound for variable x_i. The upper bound is different for various input variables. The values of the upper bound used in this work for various variables are summarized in Table 2. When no data are available for any particular variable x_i, the value of that variable is entered as zero in the S-shape spline function, Eq. (2), resulting in a corresponding value of zero for q_i.

For variables x_5 (lane width), x_8 (length of closure), and x_9 (work zone speed), a Z-shaped spline-based nonlinear function is used, as defined by the following equation (Figure 1b):

$$q_i = \begin{cases} 1 & \text{if } x_i \le a_i \\ 1 - 2\left(\dfrac{x_i - a_i}{a_i - b_i}\right)^2 & \text{if } a_i < x_i \le \dfrac{a_i + b_i}{2} \\ 2\left(\dfrac{b_i - x_i}{a_i - b_i}\right)^2 & \text{if } \dfrac{a_i + b_i}{2} < x_i < b_i \end{cases} \qquad i = 5,\ 8,\ 9 \qquad (3)$$

where a_i and b_i are the lower and upper bounds for variable x_i. Note that for the three variables lane width, length of closure, and work zone speed, a Z-shape spline function is used instead of an S-shape spline function to reflect the fact that an increase in the value of these variables increases the work zone capacity. Further, in contrast to the S-shape spline function, Eq. (2), the Z-shape spline function, Eq. (3), is a function of a non-zero lower limit. The lower and upper bound values used in this work for variables x_5, x_8, and x_9 are summarized in Table 2. When no data are available for variable x_i (i = 5, 8, 9), the corresponding upper bound is entered in the Z-shape spline function, Eq. (3), resulting in a value of zero for q_i.

The work zone capacity is also normalized to the range of zero to one using the following linear function:

$$C_n = (C - C_{\min})/(C_{\max} - C_{\min}) \tag{4}$$

where C_n is the normalized work zone capacity, and $C_{\min}$ and $C_{\max}$ are, respectively, the minimum and maximum work zone capacity values for all the training data set.

NEURO-FUZZY MODEL FOR WORK ZONE CAPACITY ESTIMATION

An adaptive neuro-fuzzy model is developed for the nonlinear mapping of the inputs described earlier and the output, the freeway work zone capacity, incorporating fuzzy logic and neurocomputing concepts. Fuzzy logic is an effective approach for representing a) imprecision and b) linguistic variables (Adeli and Hung, 1995; Adeli and Park, 1998; Zadeh, 1978). Neural network algorithms are powerful in providing solutions to complex pattern recognition problems where an analytical solution cannot be found (Adeli 2001; Adeli and Hung 1995; Adeli and Karim, 2001). In the neuro-fuzzy model for work zone capacity estimation, a backpropogation neural network is employed to estimate the parameters associated with the membership functions used in the fuzzy inference mechanism.

Fuzzy Inference Mechanism

A fuzzy logic inference mechanism is employed using a set of IF-THEN fuzzy implication rules in the following form (Sugeno and Kang, 1988):

IF $\mu_{i,1}: q_1$, AND $\mu_{i,2}: q_2$, AND, ..., AND $\mu_{i,18}:\ q_{18}$ THEN $C_i = C_n \sum_{j=1}^{18} \left(q_j \mu_{i,j}(q_j) \right) \ i = 1, \cdots, N$ (5)

where $q_1, \ldots, q_{18}$ are the 18 normalized input variables defined by Eqs. (2) and (3), $\mu_{i,j}$ is the membership function or the degree of membership of variable *j* in the *i*-th fuzzy implication rule, $\mu_{i,j}: q_j$ indicates the degree of membership of q_j is $\mu_{i,j}$, C_i is the value of the work zone capacity obtained from rule *i*, C_n is the normalized measured work zone capacity defined from Eq. (4), and *N* is the total number of fuzzy implication rules.

In this work, a bell-shaped Gaussian function is used for the membership function in the following form:

$$\mu_{i,j}(q_j) = \exp\left(-\frac{(q_j - c_{ij})^2}{2\sigma_{ij}^{\ 2}} \right) \quad \text{i = 1, …, N} \quad j = 1,\ldots,18 \qquad (6)$$

where c_{ij} and σ_{ij} represent the center and the half-width of the membership function for the *j*-th variable and *i*-th fuzzy implication rule. The former determines the position of the function and the latter determines its shape.

The total number of fuzzy implication rules, *N*, is equal to the number of *clustering centers* for any given training data set. We use a *subtractive clustering* approach to determine the number of clusters and clustering centers. In this approach, it is assumed that each data point belongs to a potential cluster based on the minimum value of a predefined objective function. The approach is explained pictorially for a two-dimensional (two-variable) case in Figure 2. In this work, an exponential data density measure is used as the objective function in the following form (Chiu 1994):

$$f(o_l) = \sum_{k=1}^{K} \exp\left(-4 \left\| \frac{\mathbf{q}_k - \mathbf{o}_l}{\mathbf{r}} \right\|^2 \right) \qquad l = 1,\ldots, \mathrm{N} \tag{7}$$

where $\|\mathbf{X}\| = \sqrt{\sum_{18} |X_i|^2}$ is the Euclidean distance, $\mathbf{q}_k$ is the 18×1 vector of the *k*-th input data set, $\mathbf{o_l}$ is the 18×1 vector of potential cluster data centers, and $\mathbf{r}$ is the 18×1 vector of predefined data cluster radii. Since all data have been normalized to the range 0 to 1, a constant value of *r*, in the range of 0 to 1, is chosen for all the radii corresponding to various variables. This is another advantage of normalizing the data. Without such normalization different values have to be chosen for various radii. At the beginning, *K* is equal to the total number of training data sets, M. In other words, we start with K cluster centers and compute *K* different values for the data intensity measure or the objective function defined by Eq. (7) (Figure 2a). The data set yielding the smallest objective function is selected as the first cluster and is excluded from further processing. Next, the subtractive clustering algorithm is applied to the remaining data points that do not belong to any cluster, or the *subtracted* set, and the second cluster is identified (Figure 2b). This process is continued, finally resulting in N clusters. The selection of the data cluster radius (a value between 0 and 1) is a trial-and-error process. A smaller value of the cluster radius leads to a larger number of clusters requiring more computational resources for training the network and vice versa. The number of clusters should be just large enough to provide accurate results.

In Eq. (6), the initial values of the membership function centers for the ith fuzzy implication rule, c_{i1} to c_{i18}, are set to the values of the clustering data centers o_1 to o_{18}, and the initial values of σ_{ij} are determined from

$$\sigma_{ij} = r\ (q_{j,\max} - q_{j,\min}) \quad i = 1,\ \ldots,\ N \quad j = 1,\ldots,18 \tag{8}$$

where *r*, the cluster center's radius, represents the influence range of the variable, and $q_{j,\max}$ and $q_{j,\min}$ are the maximum and minimum values of the *j*-th variable among all training data sets, respectively. The standard deviations of q_j in the membership function, Eq. (6), may be used to estimate the initial values of σ_{ij}. In this work, however, Eq. (8) is used instead in order to speed up the training convergence of the model.

For the fuzzy inference mechanism, any fuzzy implication rule *i* performs an AND operation, that is, multiplying the degrees of membership function of all the variables and finding the following output:

$$w_i = \prod_{j=1}^{18} \mu_{i,j}(q_j) \qquad i = 1, \ldots, N \tag{9}$$

This output represents the *firing strength* of the *i*-th fuzzy implication rule. The estimated work zone capacity, $\hat{C}$, is obtained from the fuzzy inference mechanism as the aggregation (or summation) of the outputs of N fuzzy implication rules as follows:

$$\hat{C} = \sum_{i=1}^{N} C_i \frac{w_i}{\sum_{i=1}^{N} w_i} \tag{10}$$

Topology of the Neuro-Fuzzy Model

Figure 3 shows the topology of the neuro-fuzzy inference model for estimating the work zone capacity. It consists of an input layer, a fuzzy implication layer, and an output layer. The input layer has 18 nodes representing the 17 variables defined in the previous section and an 18th node to indicate the data collection locality. The values of the variables in the input layer are quantified and normalized to values between 0 and 1, employing the S-shape and Z-shape Spline-based nonlinear functions described earlier.

The fuzzy implication layer consists of two sub-layers. The first (left) sub-layer represents the fuzzy membership function layer, where every node represents one Gaussian membership function ($\mu_{i,j}$). The number of nodes in this sub-layer is equal to 18N. Each membership function is used to map one normalized input variable to one cluster. The second (right) sub-layer consists of N nodes representing N fuzzy AND operations. The output layer has only one node that performs the fuzzy aggregation (summation) operation. The output of this node is the estimated work zone capacity.

Training the Neuro-Fuzzy Model

The fuzzy inference mechanism presented in a previous section requires estimation of the parameters c_{ij} and σ_{ij} associated with the membership functions. In this work, the parameters are adjusted using the backpropogation (BP) neural network-training algorithm.

A mean squared error function, $E(c_{ij},\sigma_{ij})$, is defined as the average of the squared differences between the measured and estimated work zone capacity values over all the training data sets:

$$E(c_{ij},\sigma_{ij}) = \frac{1}{M}\sum_{k=1}^{M}\left|C_n^k - \hat{C}^k\right|^2 \quad i = 1, \ldots, N \quad j = 1,\ldots,18 \tag{11}$$

where C_n^k and $\hat{C}^k$ are the k-th normalized measured and estimated work zone capacity values, respectively.

In this work, the parameters c_{ij} and σ_{ij} are updated after *all* the training data sets are applied. In other words, a training iteration or *epoch* is based on all the training data sets. The adjustment is given by the following equation:

$$W_{\text{ij, new}} = W_{\text{ij, old}} + \sum_{k=1}^{M} \eta (C_n^k - \hat{C}^k) q_j \quad \text{j = 1, …, 18} \tag{12}$$

where $W_{ij} = \{c_{ij}, \sigma_{ij}\}$ (i=1, …, N) represents the parameter set of the membership function, $\mu_{i,j}$, for the *j*-th variable and *i*-th fuzzy implication rule, and η is the learning ratio.

The generalization capability of the neuro-fuzzy model demonstrates how accurately it can estimate the work zone capacity with a new data set. In training the network, one has to be cognizant of the *over-generalization* problem, also known as *over-fitting* problem in the statistics literature. In this work, rather than simply minimizing the error as defined by Eq. (11) we employ an *optimum generalization* strategy in order to avoid over-generalization and achieve the most accurate results. This is done by dividing the available data sets for training into two groups: a training group and a checking group. The latter consists of only a fraction, in the order of 10-20%, of the total data sets available for training chosen randomly. The mean squared error term for the training set normally decreases with the number of iterations, as noted by convergence curve A in Figure 4. In each iteration of the training stage, the trained network is used to estimate the work zone capacity for each set of the checking data sets and their mean squared error is computed. The variation of this mean squared error with the iteration number of the training set is normally a concave curve with a minimum (curve B in Figure 4). The iteration number corresponding to the minimum point on this curve is where the training of the network is stopped; the values of the membership function parameters obtained at this iteration provide the optimum generalization results. As observed in Figure 4, at iterations beyond the minimum point of curve B, the mean squared error in the checking set increases indicating the over-generalization of the network.

After training of the neuro-fuzzy work zone capacity estimation model using the optimum generalization strategy, a third group of data sets, the testing data sets, are used to evaluate the model.

DATA COLLECTION FOR TRAINING, CHECKING, AND TESTING THE MODEL

Data for training, checking, and testing of the model were collected from the existing literature and augmented by four data sets provided by the Ohio Department of Transportation. A total of 168 data sets were collected including 9 sets from the state of North Carolina (Dixon and Hummer, 1995), 79 sets from Texas (Dudek and Rochards, 1981; Krammes and Lopez, 1994), 17 sets from California (Krammes and Lopez, 1994), 12 sets from Indiana (Jiang, 1999), 12 sets from Maryland (Kim et al., 2001), 4 sets from Ohio, and 35 sets from Toronto, Canada (Al-Kaisy and Hall, 2001), as summarized in Table 3. None of the data set includes all the 17 input variables used in the new computational model. The number of input variables provided ranged from four (number of lanes, number of lane closure, work zone intensity, and work zone duration) to fourteen (percentage of heavy trucks, grade of pavement, number of lanes, number of lane closure, work zone intensity, length of closure, work zone speed, proximity of ramps to work zone, work zone location, work zone duration, work time, work day, weather conditions, and driver composition). For those unavailable input variables, values of zero are obtained after variable quantification and normalization, as described earlier.

The 168 data sets summarized in Table 3 are divided into three parts: 133 sets are used for training, 21 sets are used for checking, and finally 14 sets are used for testing the neuro-fuzzy work zone capacity estimation model.

TRAINING AND TESTING THE NETWORK

After trying several different values, a value of 0.1 was selected for the learning ratio, η, and a constant value of 0.3 for the cluster center's radii, *r*, for various variables. The number of clusters resulting from the subtractive clustering approach is 11, which is set to the number of fuzzy implication rules, *N*. In other words, every input node in the network topology presented in Figure has 11 membership functions. Convergence results for training the network based on 133 training data sets and 21 checking data sets are displayed in Figure 5a.

Figures 6a and 6b show the normalized measured and estimated work zone capacity values for checking and testing data sets, respectively. There exist four and three *outliers* in the checking and testing data sets, respectively. In this work, an outlier is defined as any point with an error value 50% larger than the mean error for all the data points. There are three explanations for the existence of outliers: measurement error, inhomogeneity in the collected data (that is, data collected in one state may not be representative of data collected in another state), and lopsidedness of the data set (that is, some input variables are observed in a small number of data sets and other input variables are observed in a large number of data sets). Table 3 shows that a large number of training data sets are available from Texas (66), Toronto (29), and California (14), but only two training data sets are available from Ohio.

To improve the estimation accuracy of the new neuro-fuzzy model, the training data set are modified or de-noised to make them more representative of actual conditions. First, the data sets yielding outliers are deleted (in the example presented in Figure 6, the outliers are from the three localities with the most data, that is, Texas, Toronoto, and California). Next, roughly the same numbers of training and checking data sets are chosen from various localities randomly and the network is re-trained. If outliers are observed again after the second training the outlier data sets are replaced with new remaining data sets from the same locality and the network is trained again. This process is continued until there is no outlier. For the example presented in Table 3, the final de-noised data set are presented in Table 4 which includes roughly the same number of data sets for each locality except Ohio where only limited measured work zone data are available at the time of this writing. Convergence results for training the network based on the reduced and de-noised training data sets are displayed in Figure 5b, which indicates a substantial reduction in the error as well as a faster convergence. Figures 7a and 7b show the normalized measured and estimated work zone capacity values for checking and testing data sets, respectively, using the reduced data set. It is important to note that the mean squared values in Figure 7 using the reduced data set is more than an order of magnitude smaller than the values in Figure 6 using the raw data. This large reduction in the error indicates a significant improvement in the accuracy for estimating the work zone capacity.

After training of the neuro-fuzzy work zone capacity estimation network using the de-noised data sets, the parameters of the Gaussian membership functions corresponding to 18 variables and 11 clusters are obtained and the corresponding membership functions are computed. As an example, Figure 8 shows the eleven different bell-shape Gaussian membership functions for the normalized input variable q_1 (percentage of trucks).

MEASURING THE ACCURACY OF THE ESTIMATED WORK ZONE CAPACITY

In order to evaluate the accuracy of the new model, it is compared with two approximate empirical equations using the 10 sets of testing data given in Table 4. The input values for the 10 data sets are summarized in Table 5.

Krammes and Lopez's (1994) proposed the following empirical equation for estimating the work zone capacity:

$$C = (1600\text{pcphpl} + I - R) \times H \times N_o \tag{13}$$

where C = work zone capacity (vph), I = adjustment value for work intensity ranging from -160 to 160 passenger cars per hour per lane (pcphpl), R = adjustment value for presence of ramps, H = adjustment factor for heavy vehicles given as a function of two parameters: proportion of heavy vehicles and passenger-car equivalent for heavy vehicles given in HCM (2000), and N_o = number of open lanes in the work zone. Equation (13) adjusts a single base capacity value of 1,600pcphpl based on the effects of the intensity of the work activity, percentage of heavy vehicles, and presence of entrance ramps near the starting point of the lane closure. Similar to broad guidelines for work zone capacity estimation in HCM (2000), the values of various adjustment values are left for the work zone engineer to choose based on prior experience.

Kim et al. (2001) suggest the following empirical equation for work zone capacity based on multiple-variable regression analysis of 12 sets of measured work zone capacity values obtained in the state of Maryland:

$$C = 1857 - 168.1N_c - 37.0L_c - 9.0H_t + 92.7L_d - 34.3L_w - 106.1I_w - 2.3G_w \times H_t \tag{14}$$

where N_c =number of lane closures in the work zone, L_c = location of closed lanes (right = 1, otherwise =0), H_t = percentage of heavy vehicles, L_d = lateral distance to the open lane, L_w = work zone length, I_w = work intensity, and G_w = work zone grade.

The work zone capacity estimates obtained by the new adaptive neuro-fuzzy model as well as two empirical equations (13) and (14) are summarized in Table 6. The root mean squared (RMS) error value obtained for the new nuero-fuzzy model, 127, is substantially lower than the RMS values 267 and 358 obtained for Kim et al. (2001) and Krammes and Lopez (1994) equations, respectively. The error percentage between the estimated and measured work zone capacity values ranges from 0.9 to 13.5 for the new neuro-fuzzy model (less than 10% with the exception of one), compared with 0.2 to 21.8 for the empirical equation presented by Kim et al. (2001), and 0.1 to 23.1 for that of Krammes and Lopez (1994).

Figure 9 shows a comparison of the estimated ($\hat{C}$) and measured work zone capacity (C) values in terms of number of open lanes. The solid line represents $\hat{C}_i = C_i$, that is perfect correlation. The slight departure of the scattered dots representing the estimated work zone capacity from the ideal line indicates high estimation accuracy of the new neuro-fuzzy model.

CONCLUSION

A novel neuro-fuzzy freeway work zone capacity estimation model is presented in this article using fuzzy logic and neurocomputing concepts. A backpropogation neural network is employed to estimate the parameters associated with the bell-shaped Gaussian membership functions used in the fuzzy inference mechanism. The network has been trained using measured data obtained from six different states and city of Toronto in Canada.

Comparisons with two empirical equations demonstrate that the new model in general provides a more accurate estimate of the work zone capacity, specially when the data for factors impacting the work zone capacity are only partially available. The new model provides two important additional advantages over the existing empirical equations. First, it incorporates a large number of factors impacting the work zone capacity. Second, unlike the empirical equations, the new model does not require selection of various adjustment factors by the work zone engineers based on prior experience. The new model can be implemented into an intelligent decision support system a) to estimate the work zone capacity in a rational way, b) to perform scenario analysis, and c) to study the impact of various factors influencing the work zone capacity.

ACKNOWLEDGMENT

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Appendix I. References

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Table 1. Categories of work intensity in work zones used in the new model

Intensity level	Qualitative description	Work type examples
1	Lightest	Median barrier Installation or repair
2	Light	Pavement repair
3	Moderate	Resurfacing
4	Heavy	Stripping
5	Very heavy	Pavement marking
6	Heaviest	Bridge repair

Table 2 Upper and lower limit values used in this work for various variables q_i

Normalized Variable	Description	Variable type	Upper bound	Lower bound
q_1	Percentage of truck	Numeric	25%	
q_2	Pavement grade	Binary	2	
q_3	Number of lanes	Integer	6	
q_4	Number of lane closure	Integer	5	
q_5	Lane width	Numeric	12 m	8 m
q_6	Work zone layout	Linguistic/Integer	3	
q_7	Work intensity	Linguistic/Integer	6	
q_8	Length of closure	Numeric	5 km	0.5 km
q_9	Work zone speed	Numeric	60 km/hr	20 km/hr
q_{10}	Interchange effects	Binary	2	
q_{11}	Work zone location	Binary	2	
q_{12}	Work zone duration	Binary	2	
q_{13}	Work time	Binary	2	
q_{14}	Work day	Binary	2	
q_{15}	Weather condition	Linguistic/Integer	3	
q_{16}	Pavement condition	Linguistic/Integer	3	
q_{17}	Driver composition	Binary	2	
q_{18}	Data collection locality	Integer	7	

Table 3. Raw data for training, checking, and testing the model

State	Index	168 data sets		
		Training	Checking	Testing
California	1	14	2	1
Indiana	2	8	2	2
Maryland	3	8	2	2
North Carolina	4	6	2	1
Ohio	5	2	1	1
Texas	6	66	9	4
Toronto	7	29	3	3
Total		133	21	14

Table 4. De-noised data for training, checking, and testing the model

State	Index	67 data sets		
		Training	Checking	Testing
California	1	6	1	1
Indiana	2	8	2	2
Maryland	3	8	2	2
North Carolina	4	6	2	1
Ohio	5	2	1	1
Texas	6	8	2	2
Toronto	7	8	1	1
Total		46	11	10

Table 5 Input values for 10 work zone scenarios used to test the neuro-fuzzy work zone capacity estimation model

Var.	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}
Data set	Truck (%)	Grade (%)	No. of lanes	No. of Lane closures	Lane Width	Layout	Work Intensity	Length of closure (m)	Speed (mph)	Ramp	Location	Work dur.	Work time	Work day	Weather Cond.	Pave. Cond.	Driver comp.	State
1	-	-	3	1	-	-	3	-	-	-	-	Long	-	-	-	-	-	California
2	32	-	2	1	-	M	6	11.7	-	-	Rural	Long	Day	Weekday	-	-	-	Indiana
3	10	-	2	1	-	C	2	11.7	-	-	Rural	Long	Day	Weekday	-	-	-	Indiana
4	8	5	4	1	-	-	1	0.18	30	Yes	Urban	Short	Day	Weekday	Sunny	-	0	Maryland
5	8.5	0	4	2	-	-	6	2.2	21	Yes	Urban	Short	Night	Weekday	Sunny	-	0	Maryland
6	-	-	3	1	12	M	-	0.6	-	No	-	Short	Day	Weekend	Sunny	-	-	Ohio
7	26.2	-	2	1	-	-	6	-	-	-	Rural	Long	Day	Weekday	-	-	-	N. Carolina
8	-	-	4	1	-	-	1	-	-	-	-	Short	-	-	-	-	-	Texas
9	-	-	5	3	-	-	3	-	-	-	-	Short	-	-	-	-	-	Texas
10	-	3	3	1	-	-	-	-	-	-	Urban	Short	Day	-	Sunny	Dry	1	Toronto

M = Merging, C = Crossover, - Unavailable data

Table 6 Comparison of the work zone capacity estimates obtained from the new neuro-fuzzy model with two empirical equations

State	Data set number	Open lanes	Closed lanes	Measured values (C_i) (vph)	Krammes and Lopez (1994)		Kim et al. (2001)		Neuro-fuzzy model ($\hat{C}_i$) (vph)	
					Values (vph)	Error (%)	Values (vph)	Error (%)	Values (vph)	Error (%)
California	1	2	1	2600	3200	23.1	3166	21.8	2364.4	9.1
Indiana	2	1	1	1308	1307	0.1	1295	1.0	1395.7	6.7
	3	1	1	1595	1362	14.6	1464	8.2	1810.2	13.5
Maryland	4	3	1	5205	4545	12.7	4695	9.8	5342.6	2.6
	5	2	2	2456	3020	23.0	2451	0.2	2687.1	9.4
North Carolina	6	1	1	1284	1536	19.6	1471	14.6	1272.2	0.9
Ohio	7	2	1	3318	3200	3.6	3378	1.8	3414.8	2.9
Texas	8	3	1	4590	4800	4.6	5067	10.4	4644.5	1.2
	9	2	3	2680	3200	19.4	2705	0.9	2899.8	8.2
Toronto	10	2	1	3904	3200	18.0	3378	13.5	3779.4	3.2
Root mean square $\sqrt{\frac{\sum_{i=1}^{10}(\hat{C}_i - C_i)^2}{10}}$					358		267		127	

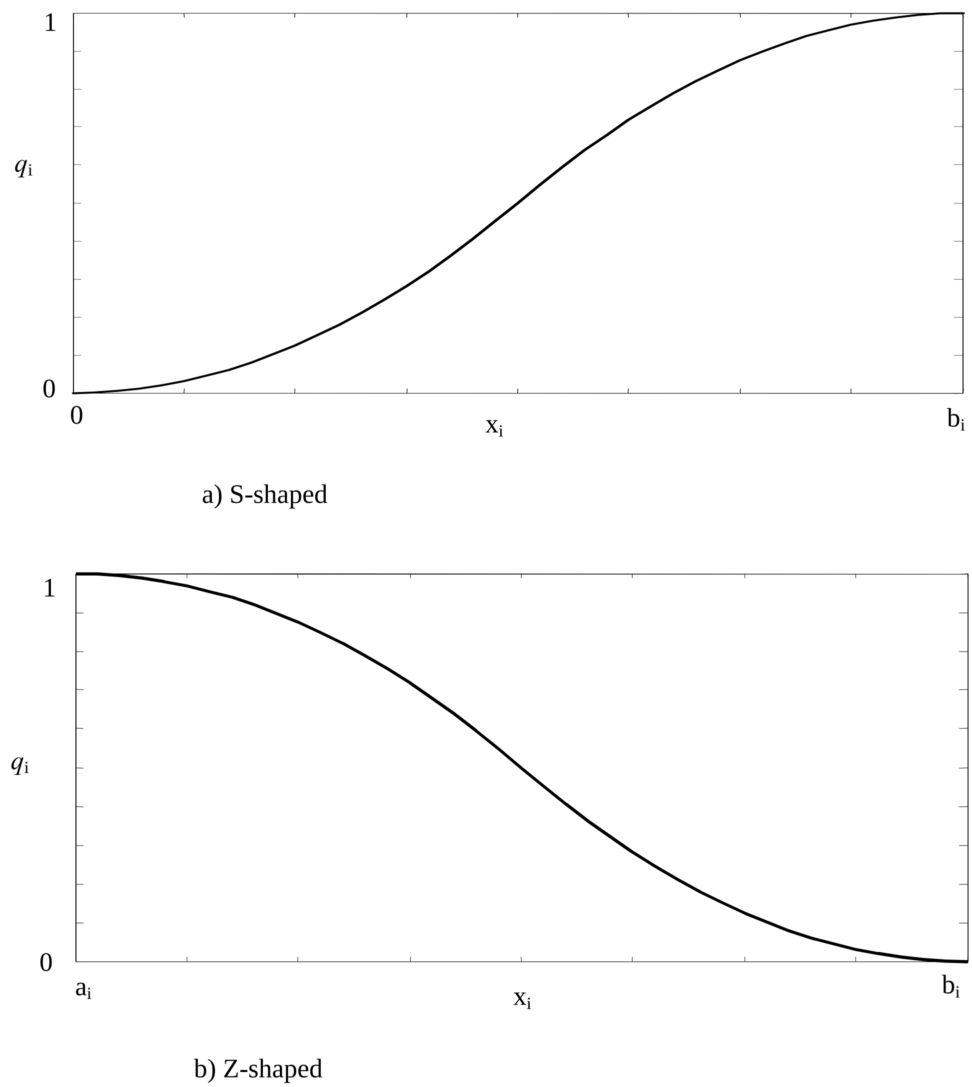


Figure 1 Spline-based nonlinear functions used to quantify and normalize the variables

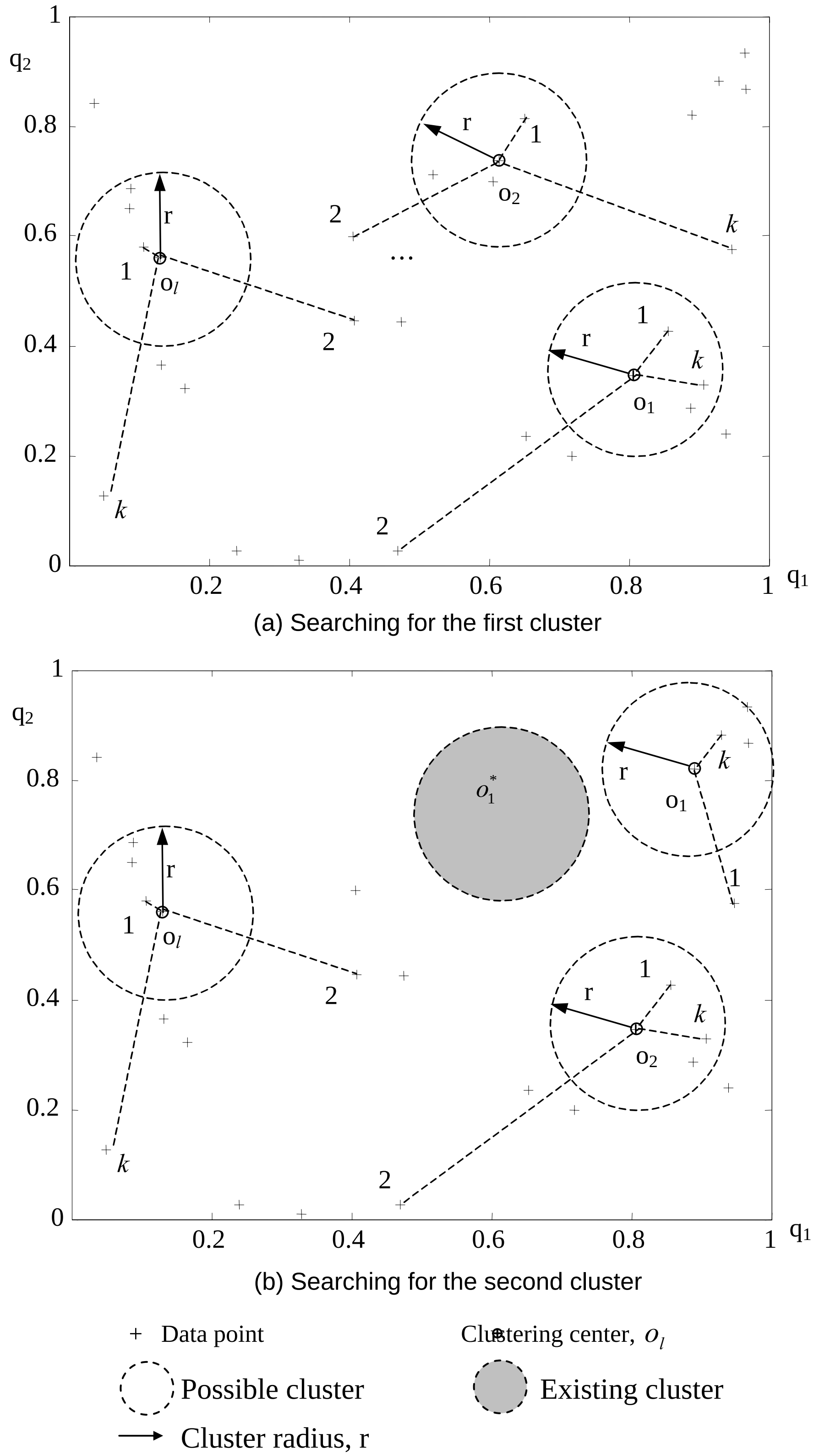


Figure 2 Illustration of subtractive clustering for a two-dimensional (two-variable) case

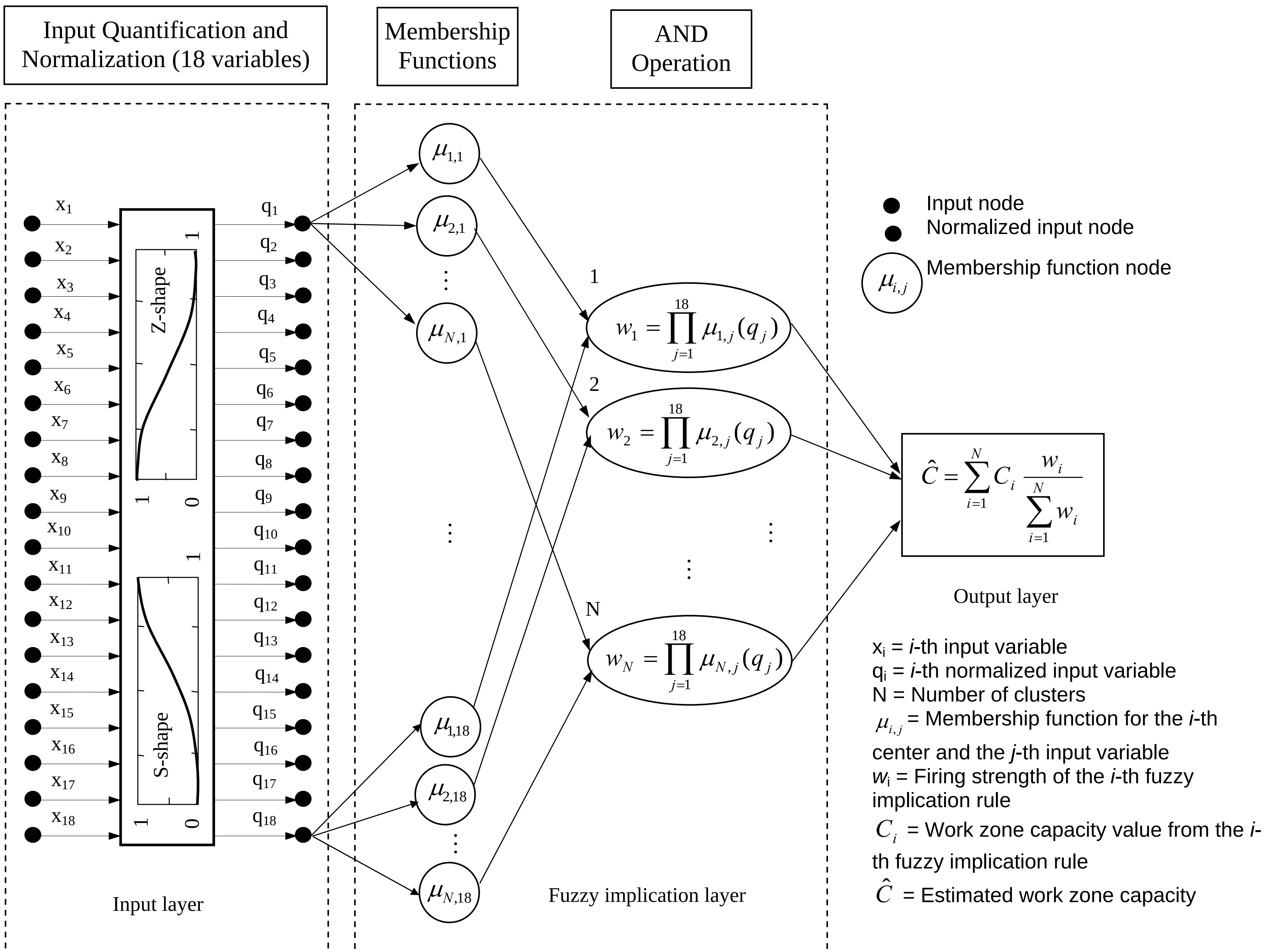


Figure 3 Topology of the neuro-fuzzy model for estimating the work zone capacity

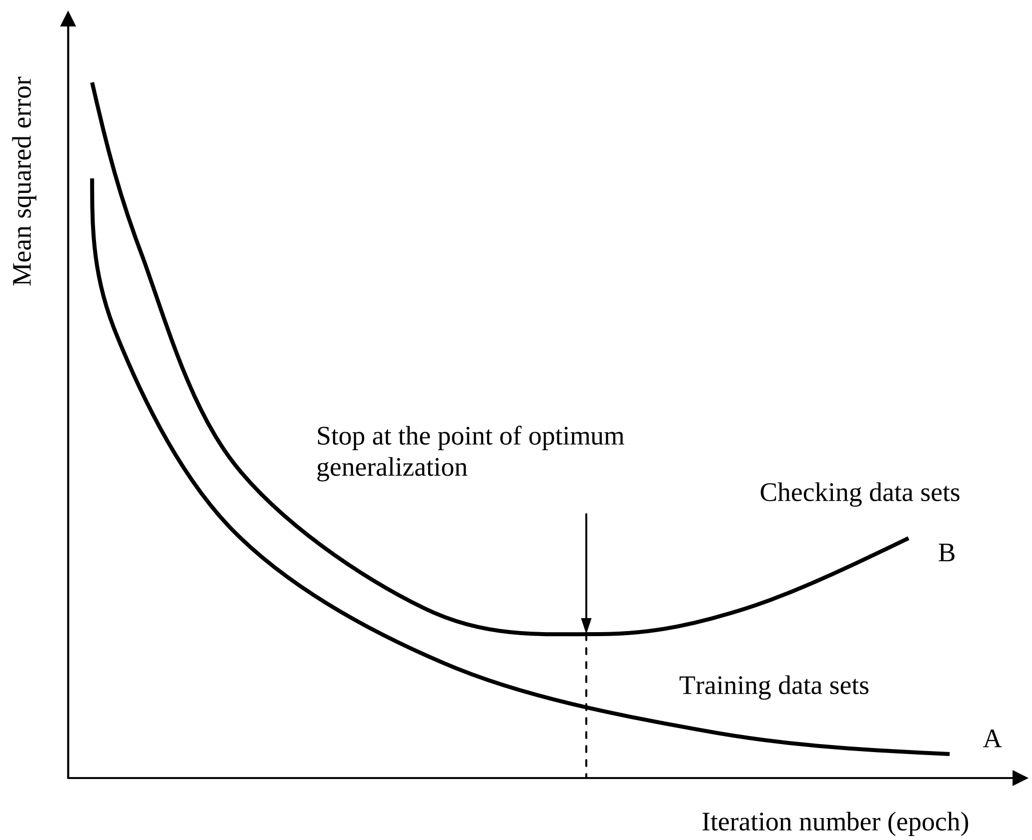
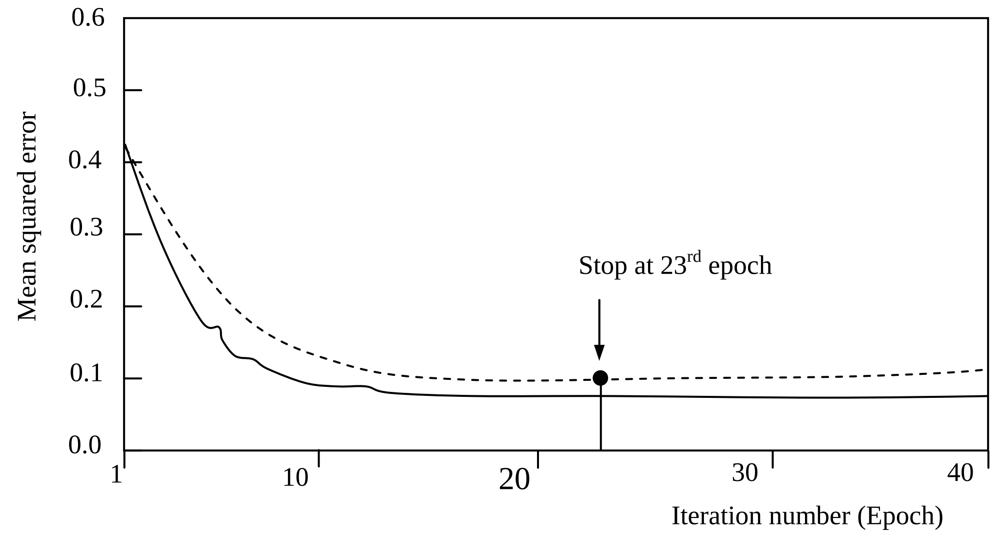
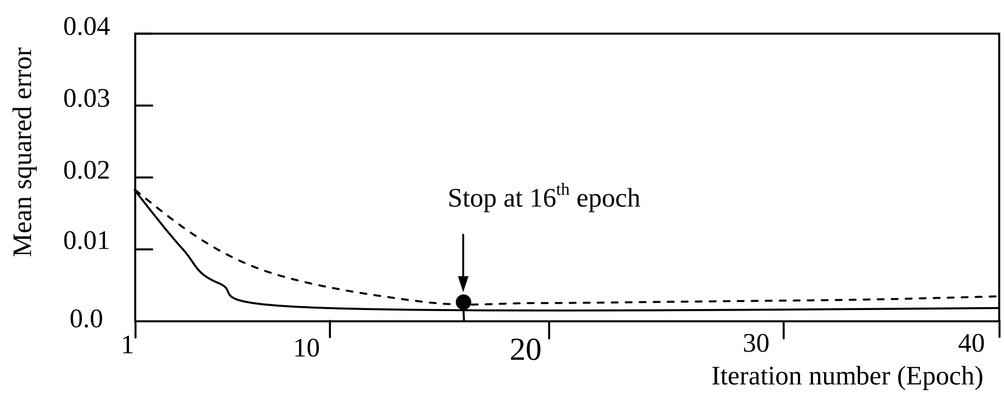


Figure 4 Procedure to find the point of optimum generalization

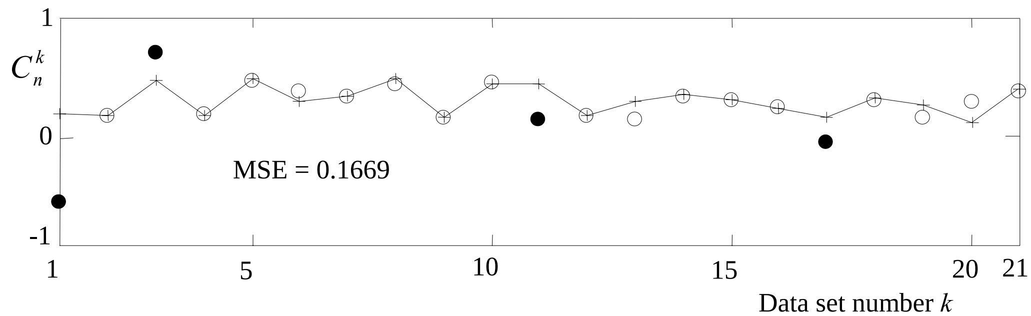


a) Raw data sets

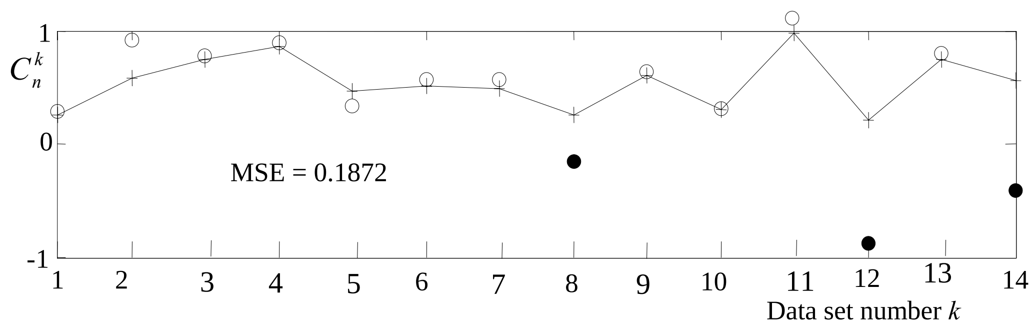


b) Improved data sets

Figure 5 Convergence curves for training the new neuro-fuzzy model



(a) Checking data sets

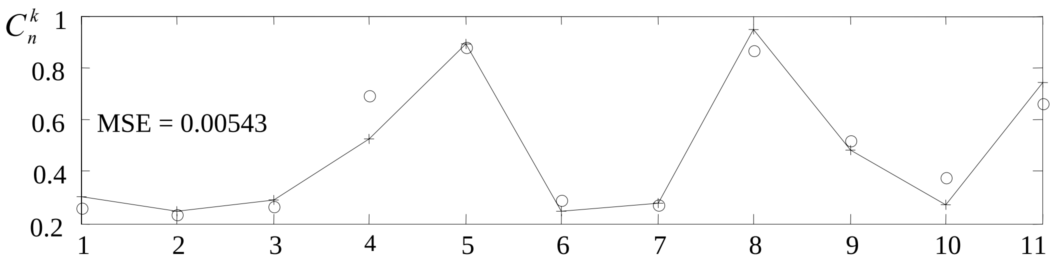


(b) Testing data sets

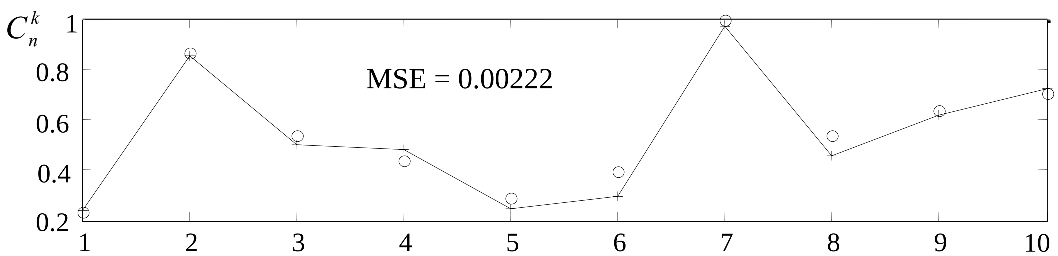
+ Measured value ○ Estimated value ● Outlier

C_n^k = Normalized work zone capacity for the k-th data set

Figure 6 Normalized measured and estimated work zone capacity values for checking and testing data sets using the raw data (MSE= mean squared error)



(a) Checking data sets



(b) Testing data sets

\+ Measured value ○ Estimated value

C_n^k = Normalized work zone capacity for the *k*-th data set

Figure 7 Normalized measured and estimated work zone capacity values for checking and testing data sets using the de-noised data (MSE= mean squared error)

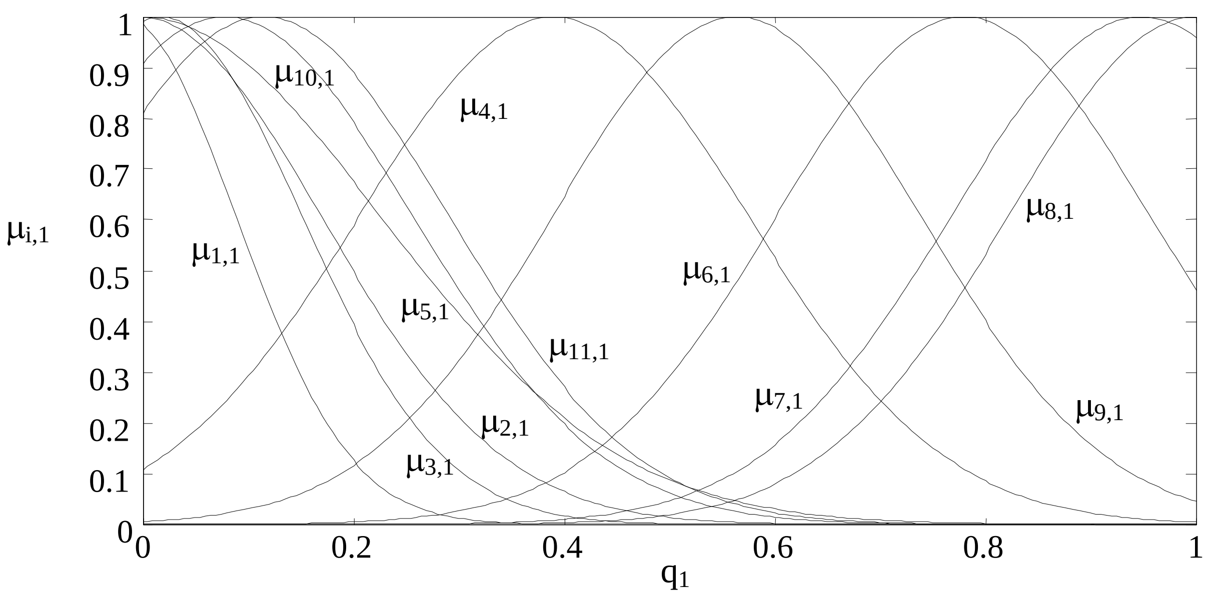


Figure 8. Bell-shape Gaussian membership functions for the normalized input variable q_1 (percentage of trucks) after training the network with the de-noised data

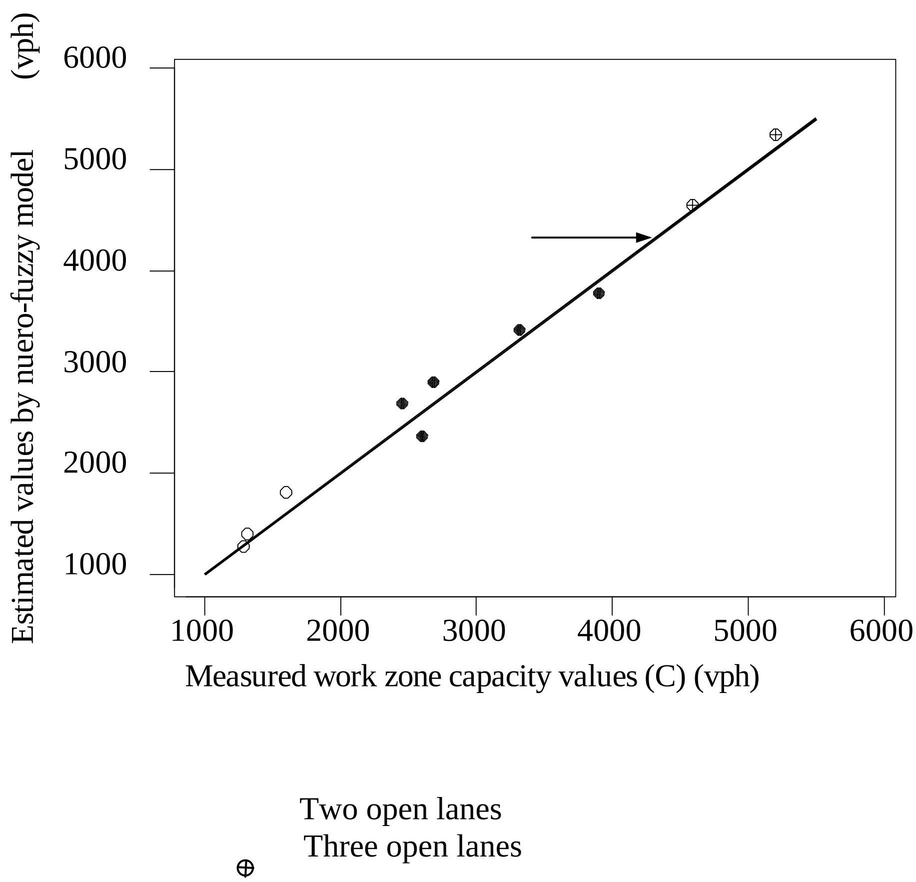


Figure 9 Comparison of the estimated ($\hat{C}$) and measured work zone capacity (C) values

Part V

INTELLIZONE: An Object-Oriented Model for Freeway Work Zone Capacity and Queue Delay Estimation

INTELLIZONE: AN OBJECT-ORIENTED MODEL FOR FREEWAY WORK ZONE CAPACITY AND QUEUE DELAY ESTIMATION

Xiaomo Jiang[9] and Hojjat Adeli[10]

ABSTRACT: Existing computer models used to estimate queue delay upstream of the work zone have a number of shortcomings. They do not provide any model to estimate work zone capacity, which has a significant impact on the congestion and traffic queue delays. They cannot be used to perform scenario analysis for work zones with various characteristics such as work zone layout, number of closed lanes, work intensity and work time. In this article, an object-oriented (OO) model is presented for freeway work zone capacity and queue delay and length estimation. The model is implemented into a interactive software system, called *IntelliZone*, using Microsoft Foundation Classes (MFC) and a hierarchy of multiple specialized *frameworks*. A three-layer application architecture is created to separate the application functions and classes from MFC classes. The high-level application domain layer is divided into *packages*. *IntelliZone*'s capacity estimation engine is based on pattern recognition and neural network models incorporating a large number of factors impacting the work zone capacity. This research provides the foundation for a new

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generation of advanced decision support systems for effective management of traffic at work zones.

INTRODUCTION

Highway agencies are increasingly focusing attention on reconstruction and improvement of the existing highway systems in the United States due to the aging highway infrastructure. Freeway work zones have become a major source of traffic congestion and travelers' delays which result in reduced freeway capacity, increased driver frustration, increased traffic accident, increased road user delay cost, and increased fuel consumption and vehicle emissions. Thus, highway agencies are facing with the challenging problem of effectively planning and managing the work zone to ameliorate its effects on the vehicular traffic. They often use the empirical and highly approximate method described in the *Highway Capacity Manual* (HCM) (HCM, 2000) to determine the freeway work zone capacity and to estimate the travelers' queue delays with lane closures. The HCM provides a base capacity of 1600 vehicles per hour per lane (vphpl) for short-term ideal highway work zones. Guidelines are given on how to modify the base value to take into account percentage of trucks, work intensity, proximity of ramps, and lane widths. However, many other additional factors, neglected in the HCM guidelines, affect the freeway work zone capacity estimation (Adeli and Jiang, 2003)

To assist highway agencies to create an effective traffic management plan (TMP) for a given work zone, a few models have been proposed to estimate the queue length and travelers' delay associated with work zones. Memmott and Dudek (1984) estimate the road user delay costs based on the average speed and average daily traffic (ADT) in freeway work zones. Using the deterministic queuing analysis approach and the conservation principle of traffic flow, they developed a computer program named QUEWZ for Queue and User Cost Evaluation of Work Zones to estimate the user costs and queue length for a work zone in the state of Texas. However, the work zone capacity is estimated from empirical speed-flow-density relationships independent of the work zone characteristics such as work zone layout and work intensity.

A Microsoft Excel-based model has recently been developed for predicting the work zone delay, called QuickZone, based on the deterministic queuing model for each network link in the work zone (MITRETEK, 2001). QuickZone estimates the hourly delay taking into account the expected time-of-day utilization and seasonal variation in travel demand. QuickZone, however, does not have a work zone capacity estimation model. Rather, it requires the value of the work zone capacity as input. The accuracy of the traffic delay estimates by QuickZone depends heavily on an accurate estimation of the work zone capacity.

The ideal goal of an effective TMP is to minimize travelers' delays and construction and operation costs while enhancing the safety of the travelers and highway workers. As such, an accurate estimation of the work zone capacity and travelers' queue length is of paramount importance for creating an effective work zone TMP. However, the existing computer models such as QUEWZ and QuickZone used to estimate queue delay upstream of the work zone have a number of shortcomings. They do not provide any model to estimate work zone capacity, which has a significant impact on the congestion and traffic queue delays. They cannot be used to perform parametric or scenario analysis for work zones with various characteristics such as work zone layout, number of closed lanes, work intensity and work time.

To overcome these shortcomings, the senior author and his associates have recently developed a number of computational models for accurate estimation of work zone capacity and traffic queue delays using computational intelligence approaches such as neurocomputing (Adeli and Hung, 1995; Adeli and Park; Adeli and Karim, 2001), fuzzy logic, and case-based reasoning (CBR). Karim and Adeli (2002) present a CBR model for freeway work zone traffic management. The model considers work zone layout, traffic demand, work characteristics, traffic control measures, and mobility impacts. A four-set case base schema or domain theory is developed to represent the cases based on the above characteristics of the problem. Three examples are presented to show the practical utility of the CBR system for work zone traffic management. Jiang and Adeli (2002) present a new freeway work zone traffic delay and cost optimization model in terms of two variables: the length of the work zone segment and the starting time of the work zone using *average hourly traffic* data. The total work zone cost defined as the sum of user delay, accident, and maintenance costs is minimized. Number of lane closures, darkness factor, and seasonal variation in travel demand normally ignored in prior research are included. In order to find the global optimum solution, a Boltzmann-simulated annealing neural network is developed to solve the resulting mixed real variable-integer cost optimization problem for short-term work zones.

Karim and Adeli (2003) present an adaptive computational model for estimating the work zone capacity and queue length and delay taking into account the following factors: number of lanes, number of open lanes, work zone layout, length, lane width, percentage trucks, grade, speed, work intensity, darkness factor, and proximity of ramps. The model integrates judiciously the mathematical rigor of traffic flow theory with the adaptability of neural network analysis. A radial-basis function neural network model is developed to learn the mapping from quantifiable and non-quantifiable factors describing the work zone traffic control problem to the associated work zone capacity. Queue delays and lengths are computed using a deterministic traffic flow model based on the estimated work zone capacity.

In this article, an object-oriented (OO) model is presented for freeway work zone capacity and queue delay estimation. The model is implemented into a highly interactive software system, called *IntelliZone* (Intelligent decision support system for work zone traffic management). The integration of the modeling, control and decision support features is described.

FUNCTION ARCHITECTURE

Since 1991, the senior author and his associates have advanced the use of OO technology for development of flexible, maintainable, and reusable software systems for computer-aided engineering (CAE) applications (Yu and Adeli, 1991, 1993; Adeli and Yu, 1993; Adeli and Kao, 1996; Karim and Adeli, 1999a, b). The object in the OO technology is a "*black box*" which abstracts a real world entity by encapsulating its characteristics (data and functionality). *Abstraction* means identifying the distinguishing characteristics of an object without having to process all the information about the object. *Encapsulation* is an OOP mechanism that combines data into codes and prevents data and codes from outside interference and misuse. The additional two mechanisms provided by OOP languages (e.g., Visual C++), *inheritance* (the process by which the object of one class acquires the properties of another class) and *polymorphism* (a feature that allows one interface to be used for a general class of actions), allow easy extension and reusability of previously developed objects. The properly integrated application of polymorphism, encapsulation and inheritance provides efficient development and management of a complicated software system.

Figure 1 shows the function diagram of *IntelliZone*. It consists of four interaction stages: input, analysis, output, and TMP stages. In the input stage, the user can select up to seventeen input parameters for work zone capacity estimation (noted in the left-upper box of Figure 1). For traffic delay and queue estimation, up to four additional parameters may be identified in the input stage (noted in the left-lower box of Figure 1). Work zone capacity is estimated by *IntelliZone*. It is also included in the list of input parameters for the sake of generality and to allow the user to input any predefined number (e.g., based on actual measurements at a particular work zone) or modify the estimated value provided by *IntelliZone*.

The work zone capacity cannot be mathematically modeled because it is a complicated and non-quantifiable function of a large number of interacting variables some of which are linguistic (e.g. work intensity). The computational model for work zone capacity is the radial basis neural network model presented in Karim and Adeli (2003). However, the number of influencing factors considered is increased from eleven to seventeen. Further, the simple backpropagation (BP) neural network algorithm (Hagan et al., 1996) is also provided as a second alternative approach for estimation of work zone capacity. The queue delay and length estimation model is described in Jiang and Adeli (2003).

To improve the accuracy of estimation and accelerate the convergence speed of the neural network model, the values of the seventeen input variables for work zone capacity estimation are quantified and normalized to values between 0 and 1 employing the S-shape and Z-shape spline-based nonlinear functions described in Adeli and Jiang (2003). The normalization prevents the undue domination of variables with large numerical values over the variables with small numerical values, thus improving the convergence of the network training in estimating work zone capacity. Compared with the conventional linear data normalization, the nonlinear normalization using spline-based functions represents the data variation more accurately.

IntelliZone provides three different types of output (Figure 1). The convergence results of neural network training can be viewed graphically. Similarly, the hourly queue length is presented graphically. A report output can be created where the work zone input and output information is summarized along with the results of the queue delay and length estimation. The hourly queue length plot assists the work zone engineer to modify the work zone traffic management plan and perform scenario analysis efficiently. For example, if the queue length within a given period of the day exceeds the acceptable limit, the work zone engineer can improve the work zone TMP by changing the work zone schedule (e.g., by changing the work time to avoid the traffic peak), or changing the work zone layout to increase the work zone capacity.

Figure 2 shows how an effective TMP can be created for a particular work zone using *IntelliZone* interactively.

APPLICATION ARCHITECTURE

The prototype software system *IntelliZone* is based on the object-oriented software architecture using Visual C++ and the Microsoft Foundation Class (MFC) library. Design of a complex OOP software system usually requires the hierarchical use of multiple specialized *frameworks*. A *framework* is a collection of cooperating classes relevant to a specific domain (templates used to create multiple objects with similar features). Furthermore, the dependencies among the frameworks must be clearly delineated to avoid any conflicts. In this work, a layered approach (Baumer et al., 1997, and Karim and Adeli, 1999a, b) is used to separate the application functions and classes of *IntelliZone* from MFC classes, thus allowing for ease of development and maintenance.

The application architecture for constructing an object-oriented intelligent decision support system for work zone management is shown schematically in Figure 3. Three levels of abstractions are modeled in layers. The outermost layer is the MFC *shell* layer. It is a framework created from the standard MFC library which encapsulates the most common functionality of the Windows Application Programming Interface (API) into an OO interface. The other two layers depend on and use the services of this shell layer. Typically, the shell layer provides commonly used data structures, mathematical functions, client/server middleware (low-level transaction management software), and request brokers (software that manages cooperation and communication among heterogeneous software components). The shell layer is closely connected to the Windows operating system, and its implementation in the form of a framework is available on various Windows operating systems.

Depending on the shell layer is the productivity layer (the middle layer in Figure 3). In this work, it is subdivided into *database* and *user-interface* layers. The *database* layer provides an interface to the applications for data management, storage, and retrieval, including generating report document, processing data, and utilizing the existing databases. The frameworks in the *user-interface* layer aid in the design of user-friendly interactive interfaces. All input and output in the software are communicated through the user-interface layer. Depending on both the shell and productivity layers are the application domain layer. Generally, this layer contains algorithms and computational models for the solution of specific problems in the domain. It is usually subdivided to further categorize and generalize the application domain requirements. One or more frameworks may be used to implement this layer. In this work, four application frameworks are created in the domain layer to represent input variable quantification/normalization, traffic demand computation, work zone capacity estimation, and travelers' queue delay estimation.

Figure 4 shows the *IntelliZone* application architecture for freeway work zone traffic management in the form of a *package* diagram. This diagram shows the breakdown of the application into packages and their dependencies. Generally, a *package* is a collection of related software elements, which may be classes, components, or frameworks. In this work, the packages represent a collection of classes. In Figure 4, the dashed-line arrows indicate the dependency of a package on another. A software dependency exists if any change in a package requires a change in the dependent package.

The high-level application domain layer is divided into two packages: an *Application* package and a *Domain* package. The Application package consists of the *Model* package and the *User interface* package. The Model package in turn contains four packages for input variable quantification/normalization, work zone capacity estimation, traffic demand computation, and travelers' queue delay estimation. The *Domain* package contains two software packages, one for work zone scenario design and modification and the other for displaying queue length at various hours of the day. The Application and Domain software packages depend on the *Graphics* package, *File and database support* package, and *Miscellaneous support* package of the MFC library.

The execution of packages is controlled by an MFC class, *CObject*, which has global dependency.

CLASS DIAGRAM

IntelliZone is designed to run under all 32-bit Microsoft Windows environments such as Microsoft Windows 95/98/2000 and Windows NT 4.0 or above version. Figure 5 shows the main classes for the controlling class, CObject, used in *IntelliZone*. Five control classes are used for overall work zone project management (*CWzProject*), interface windows for user-friendly data input/modification (*CDialog*), operation action for performing various computations (*CAction*), document management (*CDocment*), and graphical view (*CView*). These classes are directly derived from the MFC class *CObject* to take advantage of the services provided for object storage and retrieval. Sub-classes are derived from the five control classes and inherit their properties. Functions of classes in Figure 5 are described briefly in Appendix I. Figures 6 and 7 show the classes, their inter-relationships, and the main methods used in each class for the work zone capacity estimation, and queue delay and length estimation parts of *IntelliZone*, respectively. Every box represents a class. The methods encapsulated in a class are listed in the box. The classes in boldface are derived directly from an MFC class and classes in italic represent non-MFC classes. Each one of the latter classes performs only a particular function and is therefore called a method class. The methods of classes in Figure 6 and 7 are described briefly in Appendix II.

Figure 8 shows the information flows and exchanges among various user interface windows. The sequence of user interactions with various interface windows is identified by shaded boxes from the bottom to top along the double-line arrows. The input/output information flow and exchanges are executed along the dashed line arrows. A freeway work zone project is divided into several work zone segments based on the construction schedule. Work zone capacity and traffic queues are estimated for every segment. The work zone capacity and traffic queue are re-estimated after any parameter change in any user-interface dialog.

USER INTERFACE FOR CAPACITY ESTIMATION

IntelliZone provides an interactive user-friendly interface for training and using the neural network models to estimate the work zone capacity. Figure 9 shows the introductory screen shot of *IntelliZone*. The menu bar in the top provides the options Capacity (for capacity estimation), Delay (for traffic queue delay estimation), and Result (for displaying the results). The Capacity option provides three dialog boxes: Project Information (Figure 10), Work Zone Scenarios (Figure 11), and Work Zone Capacity Estimation (Figure 12). All input data entry and modification for work zone capacity estimation are handled by these dialog boxes.

The dialog box in Figure 10 provides the interface for inputting the basic information about a given project, including project identification (ID) number, name, description, location and address as well as project length. With the exception of the project length, the information provided in this dialog box does not affect the work zone capacity estimation and queue length estimation. Figure 11 shows the main dialog box for inputting the values for up to seventeen input variables used in the capacity estimation model. The user provides numerical input values for 7 variables and chooses from a number of options for the remaining variables. For example, for the work zone intensity the user chooses from 6 different intensity levels. The user can input for up to 20 different scenarios. The data for various scenarios are summarized in a list box at the bottom of the dialog box. When a data item is not available the default value of N/A is used to indicate the lack of data.

The dialog box in Figure 12 provides the user-interface for capacity estimation of the work zone scenarios using either the backpropagation or fuzzy-radial basis function neural network model. Each neural network model has been trained using actual data. The results are saved as the weights of the links. The user can use each neural network model with saved values for the weights, or alternatively, ask for new network training with a new set of randomly initialized weights. The dialog box in Figure 12 also allows up to 20 different work zone capacity estimations using different scenarios, different neural network models, and with or without new training of the network.

The introductory screen of *IntelliZone* is divided into three windows (Figure 9). The Result option in the menu bar guides the user to two other multi-window screens. The first option, Training Curve, leads to the three-window screen shown in Figure 13. First, an option dialog is popped up asking for the capacity ID. Then, the results for training and testing of the network are displayed. The left window provides numerical results for the training and testing of the neural network. The upper right window displays the testing results graphically along with the desired results for the data used to train the network. It shows the accuracy of the trained neural network model for estimating the work zone capacity. The lower right window displays the training and checking curves. The lowest point in the checking curve (iteration number 23 in Figure 13) represents the iteration number for the network training with the best generalization (Adeli and Jiang, 2003). The results of training at this iteration are used in the neural network model.

USER INTERFACE FOR QUEUE ESTIMATION

The Delay option in the top menu bar (Figure 9) guides the user to three dialog boxes. The entry and modification of input information for work zone queue estimation is handled by three dialog boxes shown in Figs. 14 to 16. Figure 14 shows the Work Zone Segment input dialog box. For convenience of scheduling and construction, a work zone project is usually subdivided into several work zone segments. Each work zone segment is defined by a unique ID number. The start and finish dates and times (in increments of half an hour), length, and number of open lanes for each segment are also entered in this dialog box. The work zone segment duration is automatically calculated based on the start and finish dates and times. A summary of the input values for all the segment (up to 20) is displayed at the bottom of the dialog box.

Figure 15 shows the Work Zone Traffic Flow dialog box which is used to input the average hourly traffic flow from an existing hourly flow file. The flow file can include traffic flow data for multiple years. If the work zone project is for a future time the work zone engineer can modify the data by providing appropriate seasonal and diversion factors to be discussed in the next dialog box. A traffic flow ID number is used to uniquely identify the traffic flow set. For the same work zone segment, different traffic flow sets can be inputted. This is helpful for scenario analysis and studying the impact of various traffic flows on the work zone queue delay and length estimation. The values for other parameters such as work zone start and finish dates and times are inherited directly from the previous dialog box. Every set of hourly traffic flow data is also summarized in a box at the bottom of the dialog box where each line represents the traffic flow data for up to 24 hours in a day (when the duration of the work zone is more than one day, the flow data are presented in multiple lines).

Figure 16 shows the dialog box for work zone queue delay and length estimation. The results can be obtained for any combination of work zone segment, traffic flow, and work zone capacity. In this dialog box the user is asked to enter the traffic flow and work zone capacity ID numbers (every traffic flow is associated with a given work zone segment ID number described in the previous dialog box, Figure 15), seasonal demand factor, diversion factor (e.g., for a 10% diversion, the factor is 0.9), and average length for vehicle occupancy. If a value of zero is entered for the last item, only queue delay in vehicles per hour per lane for every hour of the day and its maximum value during the day are presented in the box at the bottom of the dialog box. Otherwise, the total queue length in km or mi in every hour of the day as well the maximum queue length during the day are presented.

If the existing flow data take into account the seasonal variation of the traffic the user (work zone engineer) shall enter a default value of one for the seasonal factor. Otherwise, the user will have the option to adjust the approaching traffic flow for seasonal variations by choosing a seasonal factor in the range of 0.5 to 2.0. The diversion factor is used to take into account the effect of an intersection close to the work zone or a residential street in an urban area. An intersection close to work zone creates traffic diversion and affects the anticipated hourly traffic flow approaching the work zone. If the traffic diversion is taken into account in the anticipated hourly traffic flows approaching the work zone then the user will enter a default value of one for the diversion factor. Otherwise, the user will have the option to adjust the approaching traffic flow by choosing a diversion factor in the range of 0.5 to 0.99. The work zone segment capacity is obtained from the capacity estimation model described in the previous section. But, the user is provided with the option of overriding the computed work zone capacity in case a more accurate number is available based on actual measurements in the particular locality.

As mentioned earlier, the Result option in the menu bar of the introductory screen of *IntelliZone* (Figure 9) guides the user to two other multi-window screens. The first option, Training Curve, was presented in Figure 13. The second option, Queue Graphs, leads to the three-window screen shown in Figure 17. First, a Graph Option dialog is popped up asking for the queue ID from dialog box shown in Figure 16. Then, the results for traffic flow and queue delay are displayed. The left window provides numerical values of the work zone traffic flow and queue delay (in vehicles per hour per lane) or length (in km or mi). The right-upper window displays the traffic flow graphically in the form of a bar diagram as a function of the hour of days. The maximum traffic flow in every day is noted in the display. The lower-right window displays the queue delay or length. The maximum queue value is also indicated in the display.

IntelliZone allows simultaneous execution of multiple work zone projects, each having different segments. The results for various projects are saved and may be displayed by toggling back and forth among various windows, as shown in the example of Figure 18. The Result option in the menu bar of the introductory screen of *IntelliZone* (Figure 9) creates a text file for input as well as output the results. It provides a report file for every project.

ILLUSTRATIVE EXAMPLE

The data used for training the neural networks were obtained from California, Indiana, Maryland, North Carolina, and Texas. They are described in Adeli and Jiang (2003) and will not be repeated here. As an illustrative example, *IntelliZone* is used to estimate the work zone capacity for an actual freeway work zone scenario with measured data provided by Dixon et al. (1997). The work zone site is a two-lane rural freeway on I-95 with one lane closure. Dixon et al. (1997) provide values for only nine out of seventeen input variables available in IntelliZone. The input values for the example are those used in Figure 11. Data are not provided for pavement grade, lane width, work zone length, work zone speed limit, proximity to a ramp, weather and pavement conditions, and the driver composition. No values are used for pavement grade, work zone length, and the driver composition in this example.

Two different groups of scenario analysis are performed for this example. The results are summarized in Table 1. In group a) seven different values are used for the lane width in the work zone ranging from 9 ft to 12 ft in increments of 0.5 ft along with two different truck percentages. In this case, for the percentage truck of 26.2, the estimated work zone capacity ranges from 820 vphpl (for lane width of 9) to 1312 vphpl (for lane width of 12 ft). The measured value provided by Dixon et al. (1997) for the same truck percentage of 26.2 is 1284 vphpl. When the truck percentage is decreased to 18.8, the estimated work zone capacity ranges from 858 vphpl (for lane width of 9) to 1339 vphpl (for lane width of 12 ft). The measured value provided by Dixon et al. (1997) for the same truck percentage of 18.8 is 1327 vphpl. A high truck percentage in the traffic flow reduces the work zone capacity value, as expected.

In group b), freeway work time (daytime or night) and workday (weekday and weekend) are considered while keeping the lane width constant at 12 ft and the truck percentages the same as those used in group a). The results are summarized in Table 1. The work zone capacity is the lowest when work is performed at night in the weekend.

Traffic flow data measured in a work zone in a two-lane freeway in the state of North Carolina with one lane closure are employed to illustrate the use of *IntelliZone* for estimating the work zone queue delay or length. The hourly traffic flows approaching a work zone on route NC 147, 0.1 miles south of SR 1171, are stored in a text file (*flow.txt*) and used in the input dialog box (Figure 15). The period of data collection is approximately one year (year 2000). For the illustrative example, the project is divided into two work zone segments as shown in Figure 14. A vehicle occupancy length of 10 ft is used. The work zone queue delays and lengths estimated by IntelliZone at various hours are shown in Figure 16. Only part of the result can be seen in Figure 16. To see the entire results the user has to scroll down and to the right in the list box. The estimated results are also shown graphically in Figures 17 and 18.

FINAL COMMENTS

An OO model is presented for freeway work zone capacity and queue delay and length estimation. The model is implemented into an advanced intelligent decision support system, called *IntelliZone*, for effective management of work zones. *IntelliZone* has the following features and advantages:

- Integrated work zone capacity and queue estimation model.
- Capability of handling multiple-segment and multiple-traffic flow strategies;
- A mechanism to handle varying work zone scenarios.
- *IntelliZone*'s capacity estimation engine is based on pattern recognition and neural networks models incorporating a large number of factors impacting the work zone capacity.
- *IntelliZone* provides a highly interactive user-interface with all the tools necessary for scenario analysis and effective control of work zone traffic.
- *IntelliZone* provides a context-sensitive help facility readily available at any point of execution of the software.

APPENDIX I. DESCRIPTIONS OF MAIN CLASSES SHOWN IN FIGURES 5 AND 6

- *CAction*: Provides an interface for managing actions (input quantification/normalization, traffic demand computation, and capacity and queue delay estimation).
- *CBPnetwork*: Encapsulates the backpropagation neural network model.
- *CCapacityDialog*: Provides an interface for estimating the work zone capacity.
- *CCapacityDoc*: Records the capacity estimation result for a work zone project.
- *CCapacityView*: Provides an interface for graphically viewing the neural network training results.

- *CFlowDialog*: Provides an interface for inputting/modifying multi-flows for a work zone segment.
- *CIntelliZoneDoc*: Controls the presentation of results in the form of texts or documents.
- *CIntelliZoneView*: Controls the graphic presentation of results.
- *CProjectDoc*: Provides an interface for a work zone project application document.
- *CQuantify*: Quantifies and normalizes input variables for work zone capacity estimation.
- *CQueueDelay*: Encapsulates work zone queue delay model.
- *CQueueDialog*: Provides an interface for inputting/modifying multi-queues by users.
- *CQueueDoc*: Records the queue results for a work zone project.
- *CQueueView*: Provides an interface for graphically viewing the queue results.
- *CRBFnetwork*: Encapsulates fuzzy-radial basis function neural network model.
- *CScenarioDialog*: Provides an interface for abstracting multi-scenarios provided by the user.
- *CSegmentDialog*: Provides an interface for abstracting multi-segments provided by the user.
- *CTrafficFlow*: Encapsulates multi-flows for a work zone segment.
- *CTrafficFlowDoc*: Records traffic flows for a work zone project.
- *CWzCapacity*: Provides an interface for estimating work zone capacity.
- *CWzProject*: Provides an interface for managing a work zone project.

- *CWzProjectDialog*: Provides an interface for abstracting a work zone project provided by the user.
- *CWzQueue*: Encapsulates multi-queues for a work zone project.
- *CWzScenario*: Abstracts a work zone segment scenario.
- *CWzScenarioDialog*: Provides an interface for abstracting multi-scenarios provided by the user.
- *CWzSegment*: Abstracts a segment of a work zone.
- *CWzSegmentDialog*: Provides an interface for abstracting multi-segments provided by the user.

APPENDIX II. DESCRIPTIONS OF MAIN METHODS IN FIGURES 6 AND 7

- *AdjustWeights*(): Adjusts the weights of the links in the neural network
- *BPnetwork*(): Executes the backpropagation neural network algorithm.
- *ClusterCenters*(): Creates cluster centers using fuzzy c-means algorithm.
- *ComputeFlow*(): Modifies the traffic flow using seasonal and diversion factor.
- *ConvertDate*(): Converts the value of date to hour.
- *ConvertUnits*(): Converts the value of an input provided in SI units to a value in the U.S. customary system of units.
- *GenerateNetwork*(): Generates a network for the neural network model.
- *GetLength*(): Sets the value of the length provided by an input dialog box.
- *NormalizeVariable*(): Normalizes variables to the range of 0 to 1 by using a nonlinear normalization function.
- *OnInitDialog*(): Initializes a dialog.

- *PropagateNet*(): Propagates the errors from the hidden layer to the output layer in the backpropagation neural network model.
- *QuantifyVariable*(): Quantifies the linguistic variables.
- *QueueEstimate*(): Executes traffic flow queue delay and length estimation.
- *RBFnetwork*(): Executes radial basis function neural network algorithm.
- *Sshape*(): Uses S-shape spline-based nonlinear normalization function.
- *TrainNet*(): Trains the neural network model using the normalized training data.
- *Zshape*(): Uses Z-shape spline-based nonlinear normalization function.

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Table 1 Scenario analysis and influence of input variables for work zone capacity determination

State: North Carolina	Location: Rural	Work duration: Long-term
Number of lanes: 2	Number of lane closures: 1	Truck percentage: 26.2 and 18.8
Work intensity: 6	Work time: day	Workday: weekday
Measured work zone capacity: 1284 and 1327 vphpl		Method: RBF network

Group	Scenario No.	Lane width (feet)	Estimated capacity (vphpl)	
			26.2% trucks	18.8% trucks
(a)	1	9.0	820	858
	2	9.5	943	986
	3	10.0	1093	1140
	4	10.5	1206	1257
	5	11.0	1259	1313
	6	11.5	1280	1334
	7	12.0	1312	1339
	Scenario No.	Work time	Workday	Estimated capacity (vphpl)
(b)	1	Daytime	Weekday	1265
	2	Night	Weekday	1183
	3	Daytime	Weekend	1008
	4	Night	Weekend	934

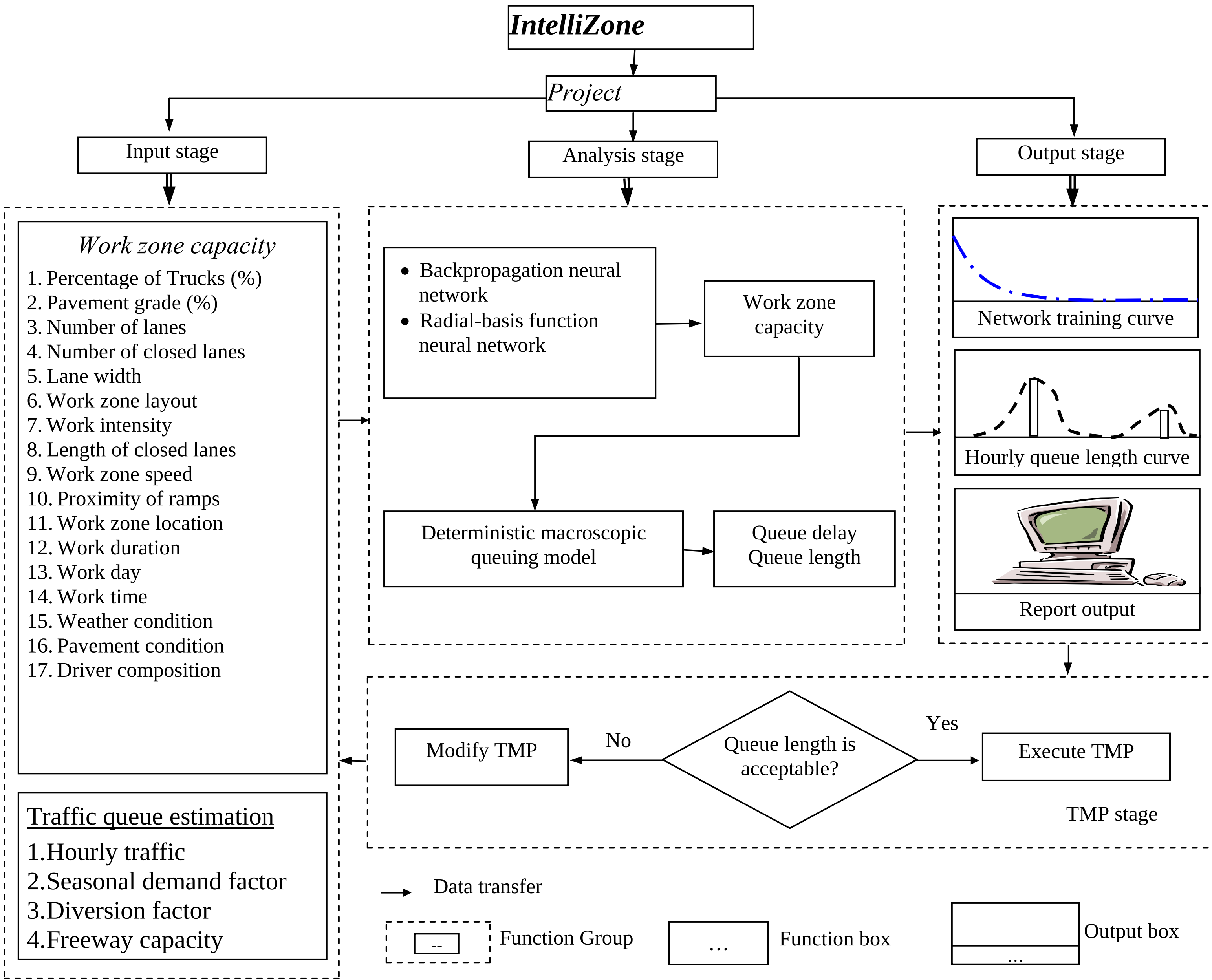


Figure 1 Function diagram of IntelliZone

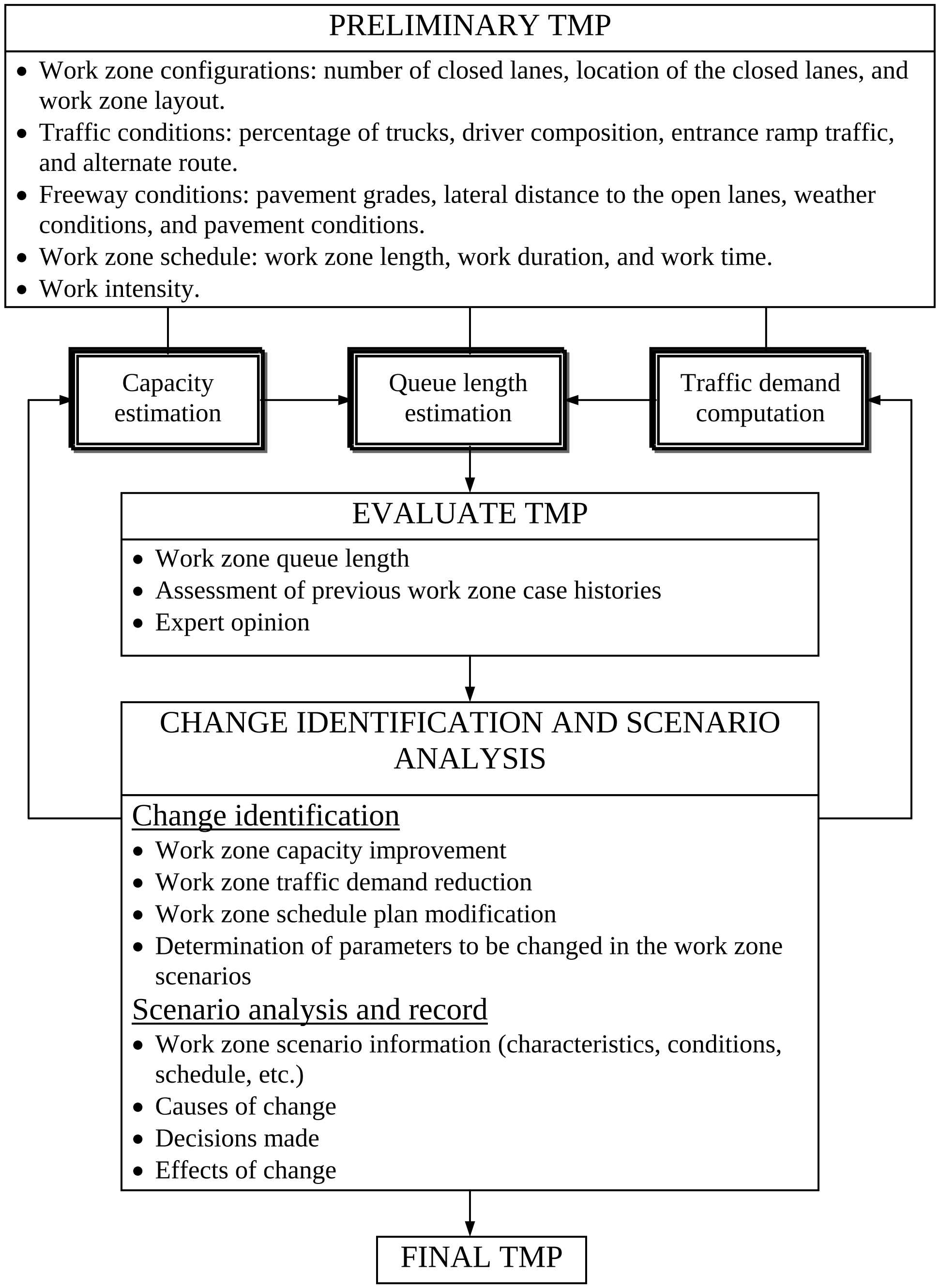


Figure 2 Intelligent decision support procedure for creating a freeway work zone TMP

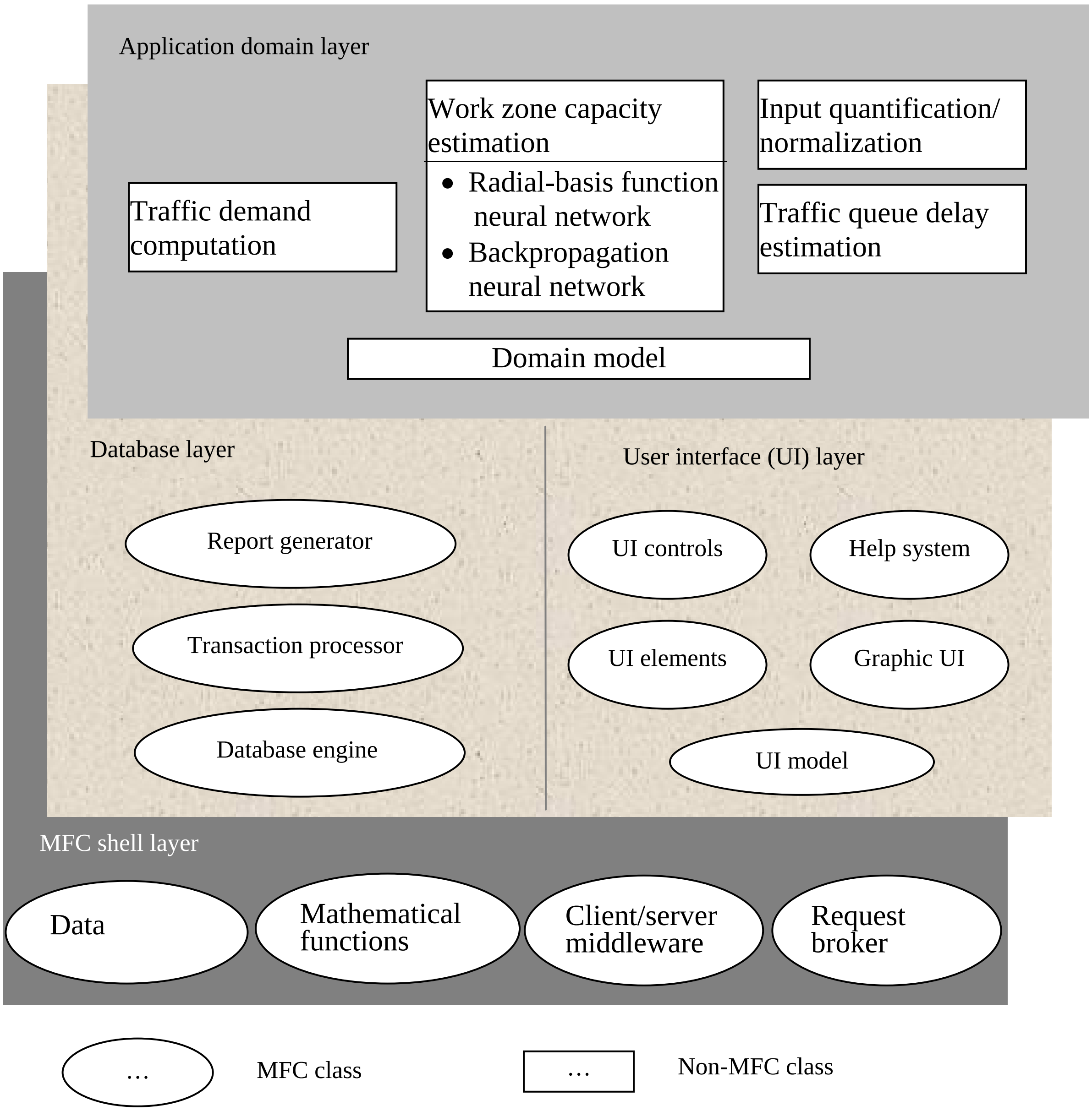


Figure 3 Schematic view of application architecture for constructing IntelliZone

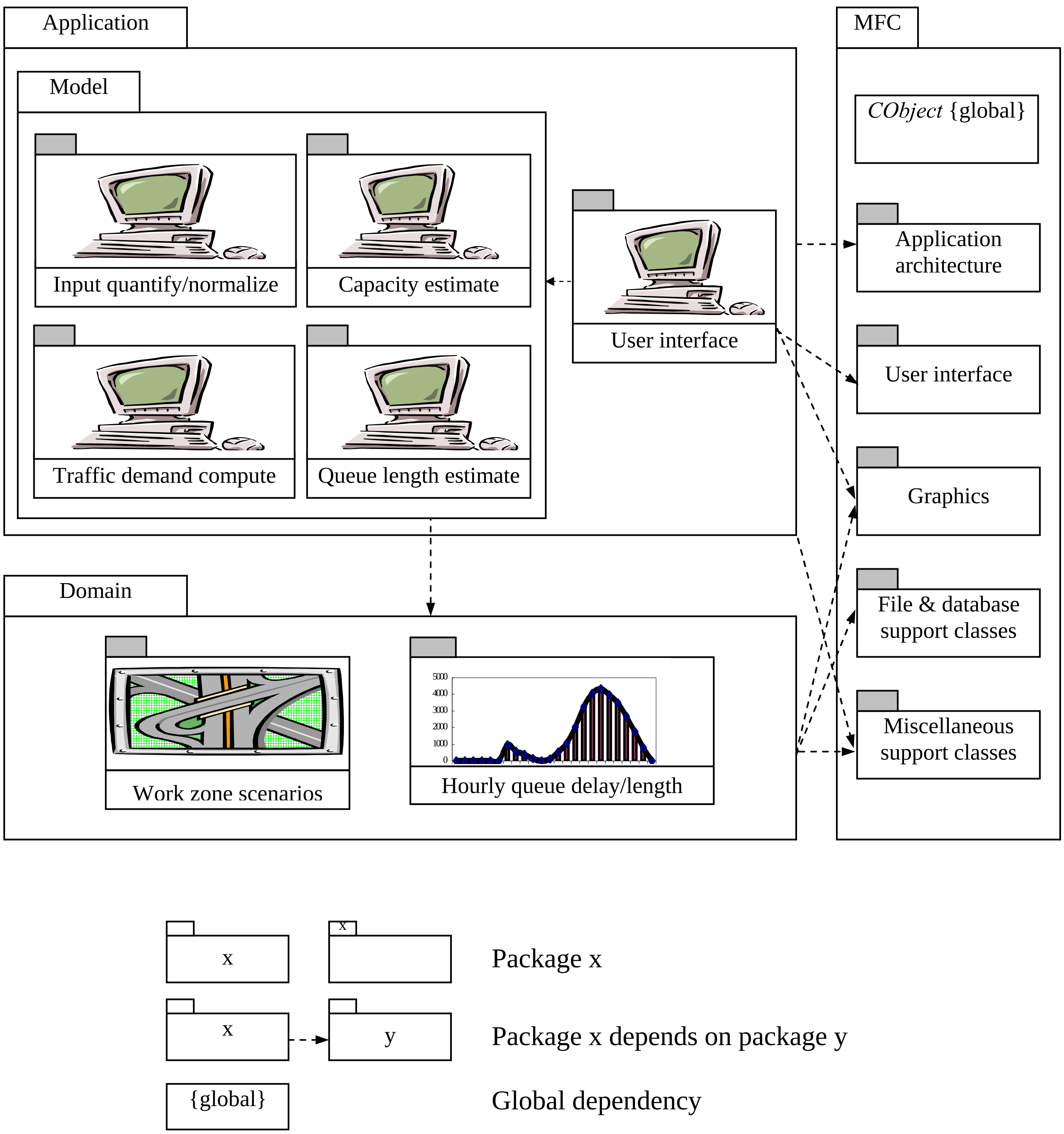


Figure 4 Package diagram of IntelliZone application architecture

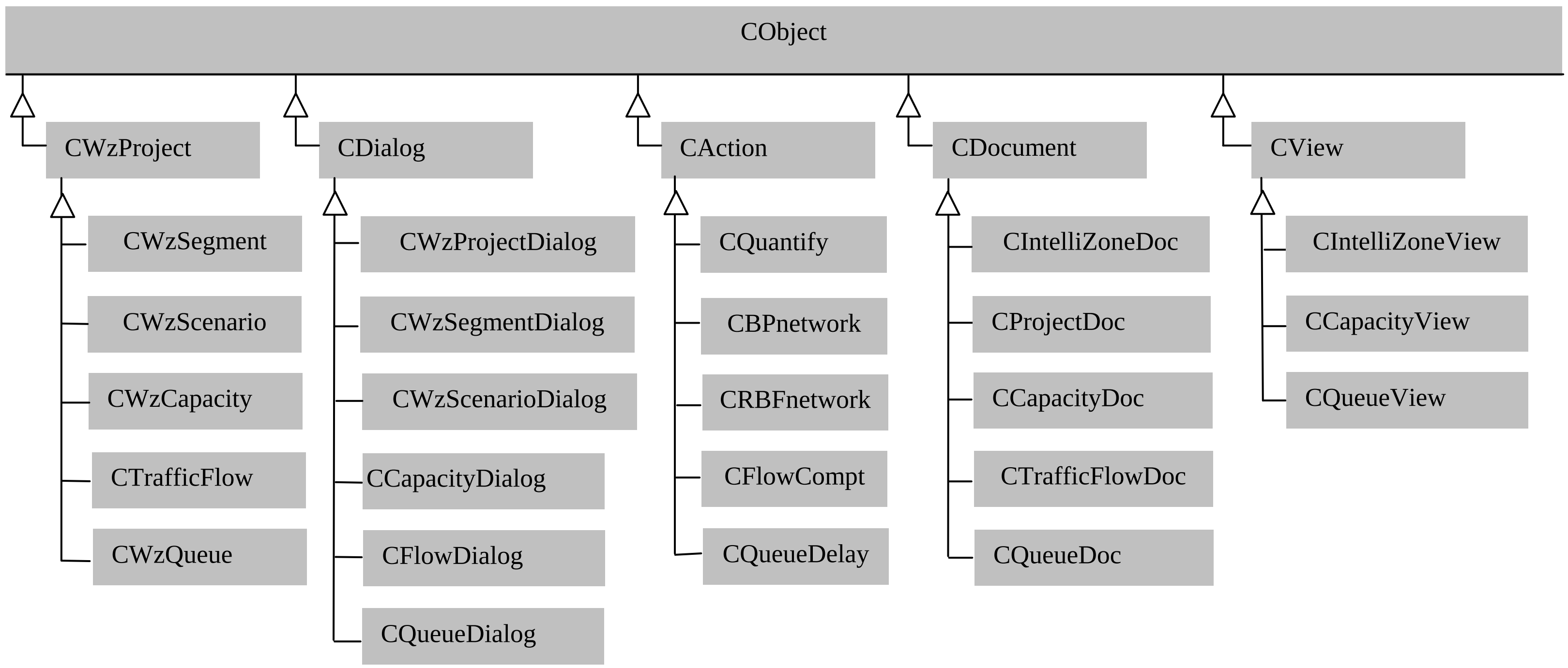


Figure 5 Main classes for the controlling class, CObject

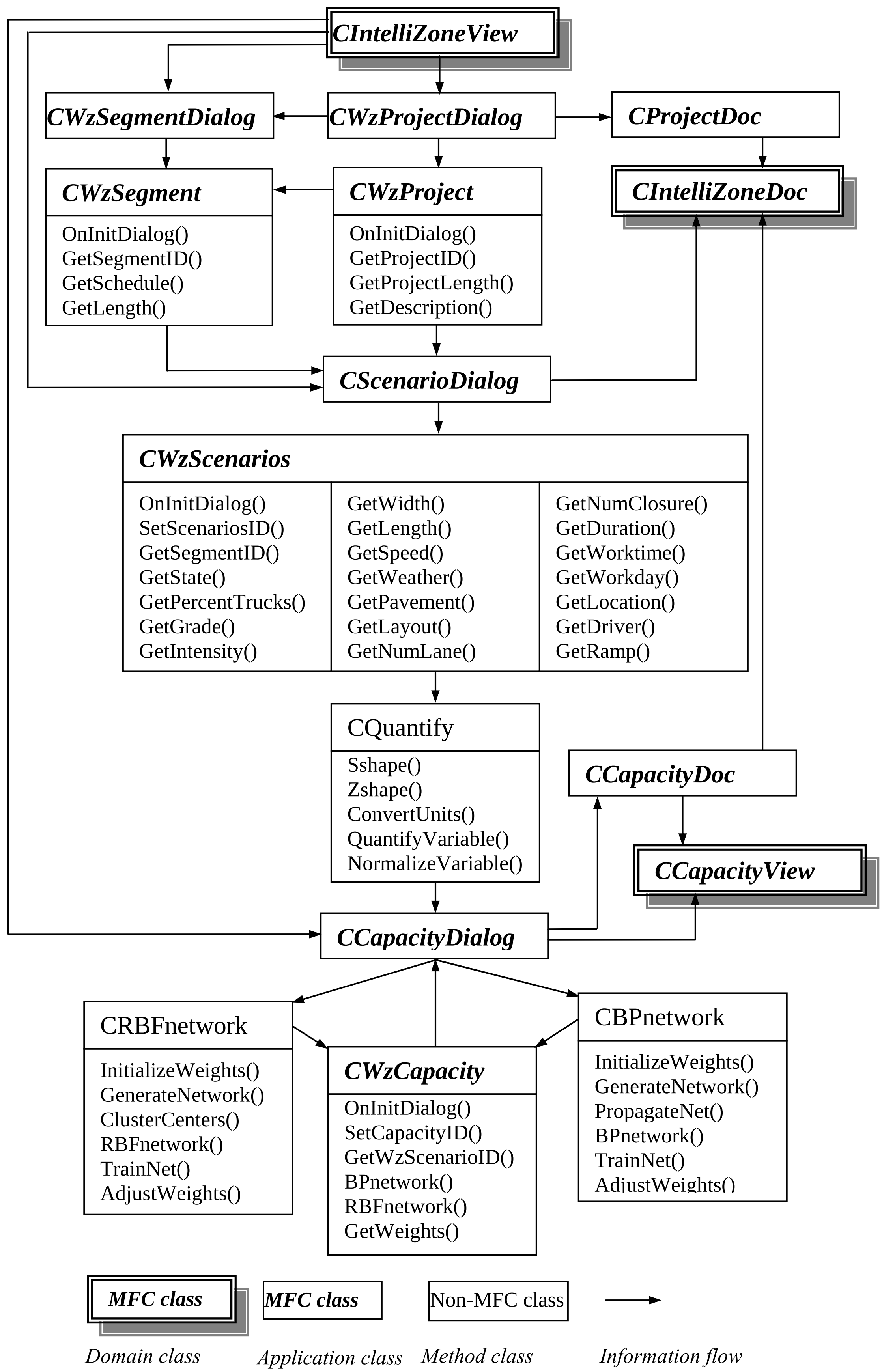


Figure 6 Classes, their inter-relationships, and the main methods used in each class for the work zone capacity estimation

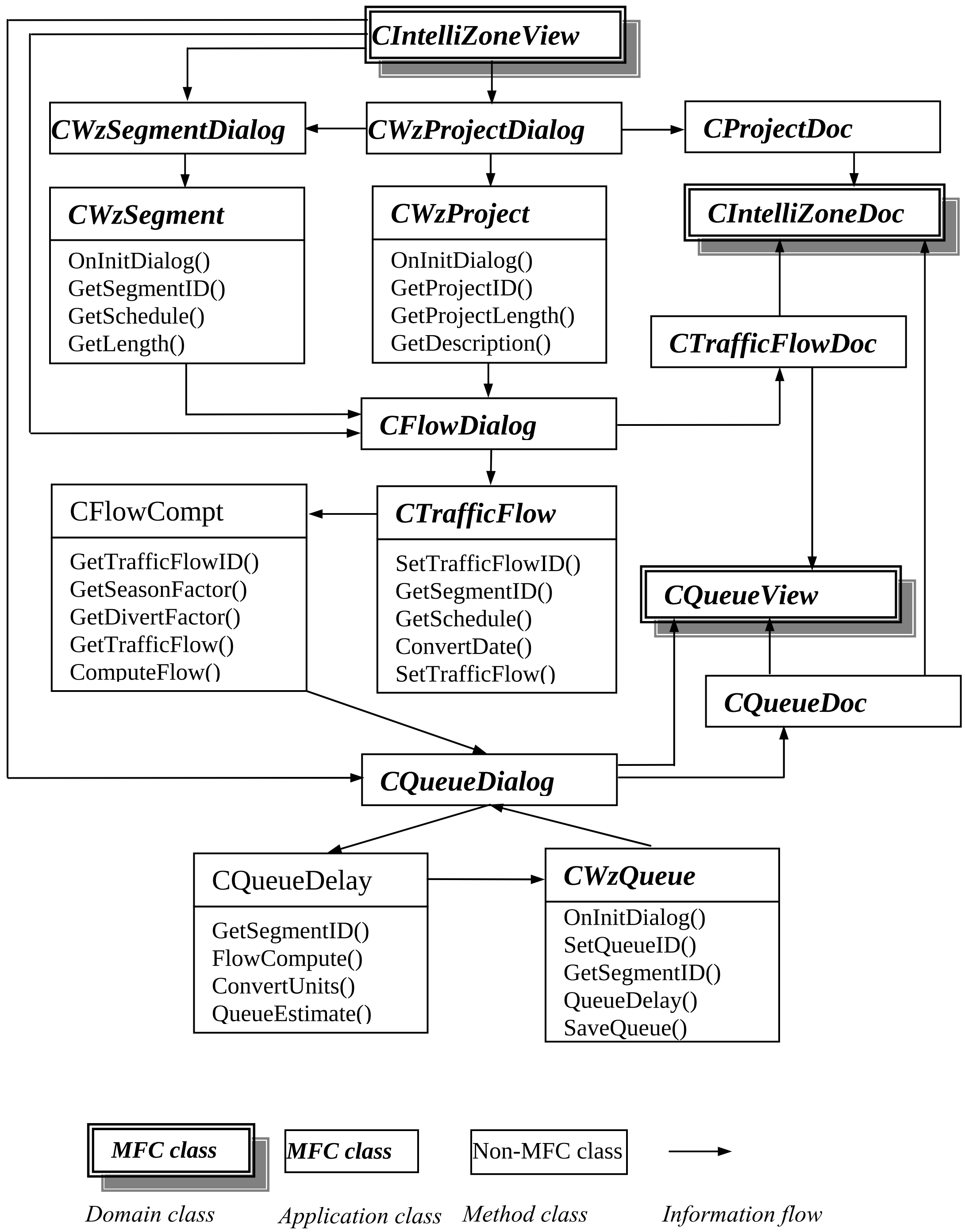


Figure 7 Classes, their inter-relationships, and the main methods used in each class for the traffic queue estimation

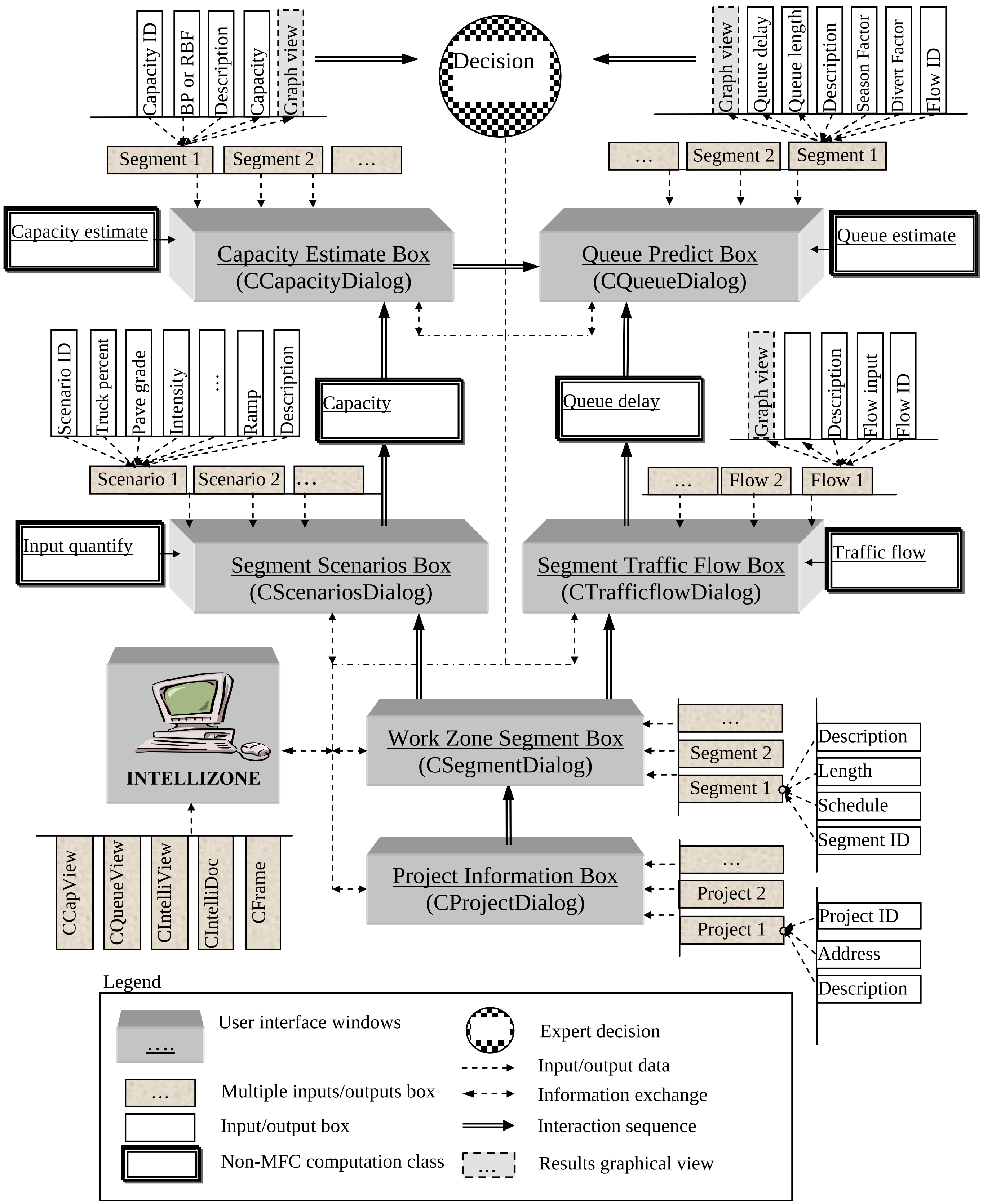


Figure 8 Information flows and exchanges among various user interface windows

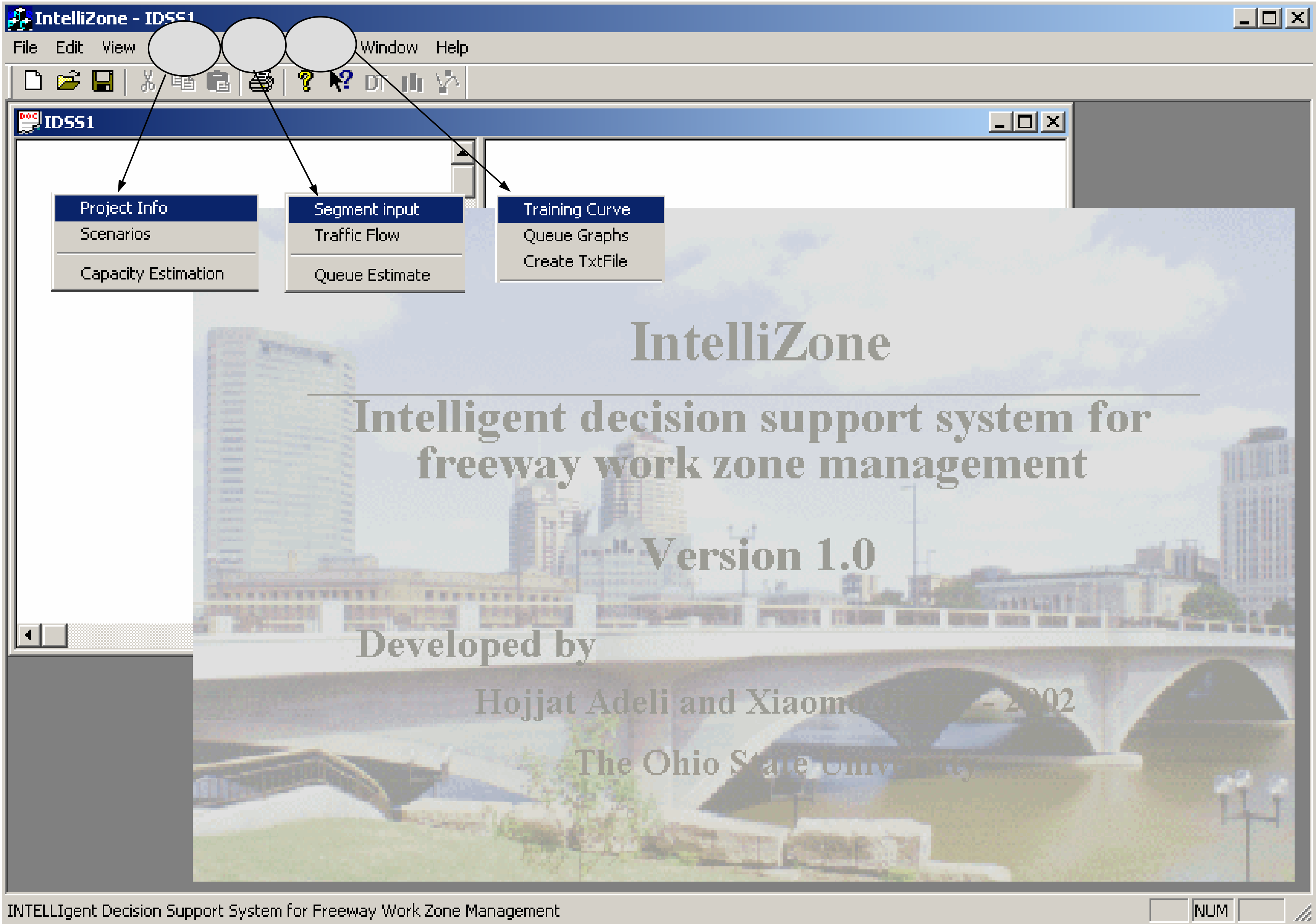


Figure 9 Introductory screen of *IntelliZone*

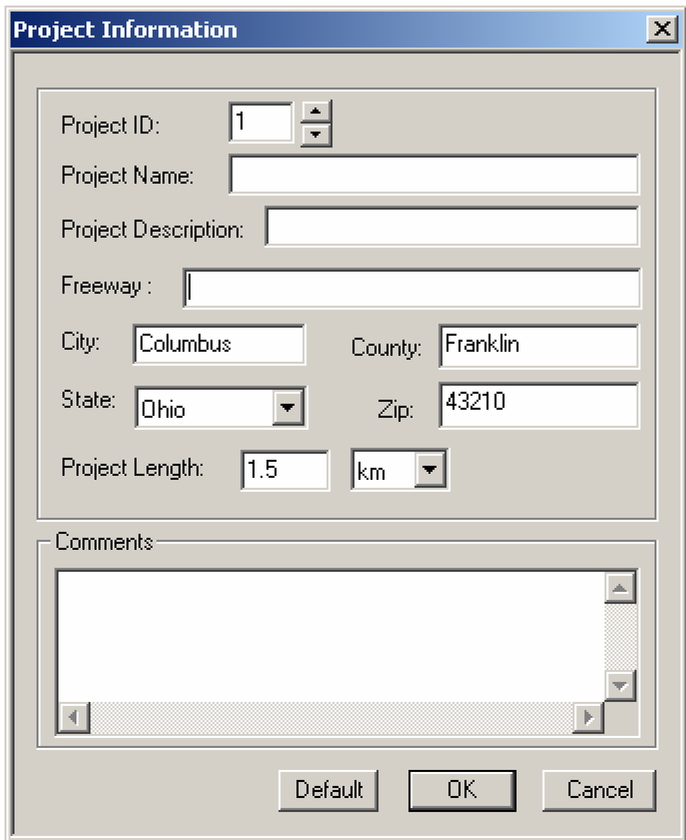
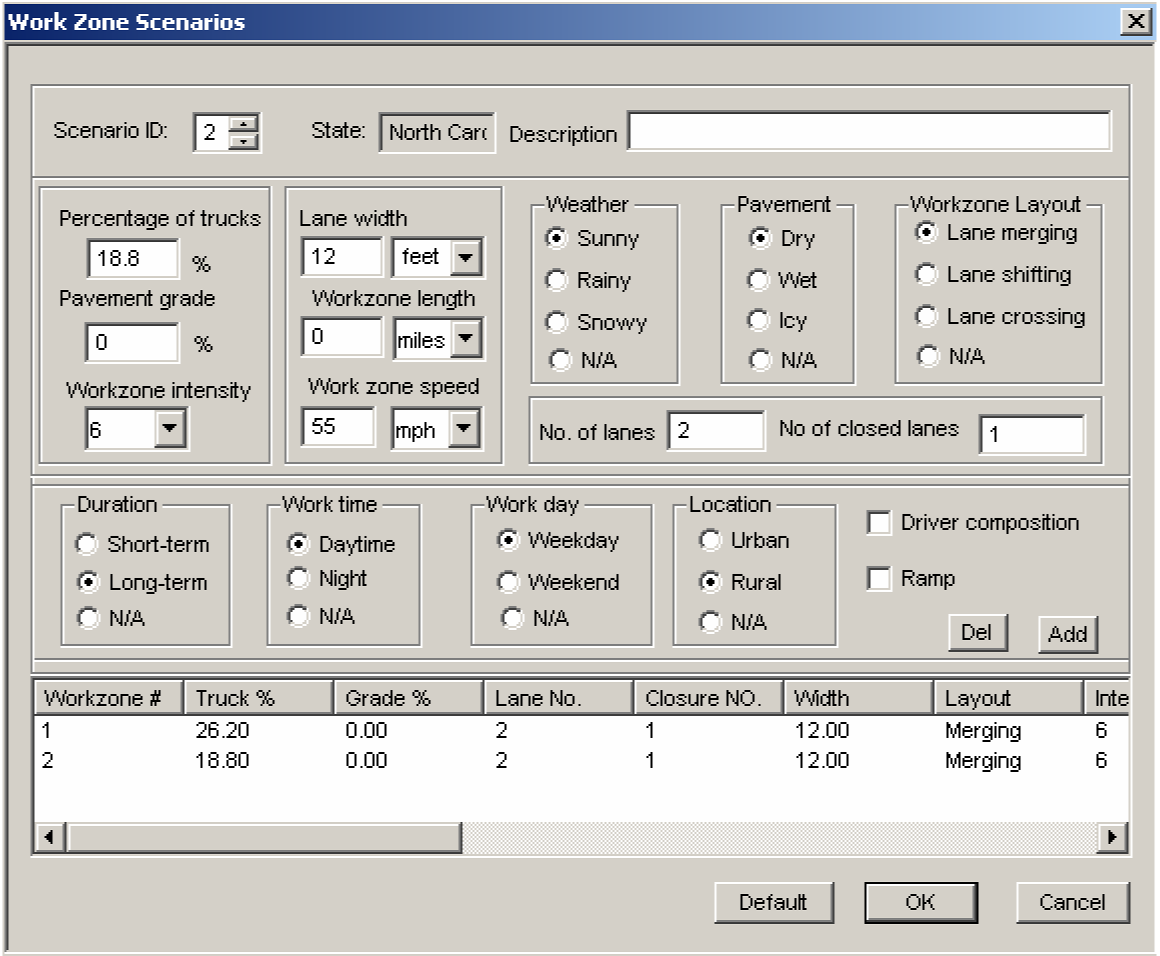
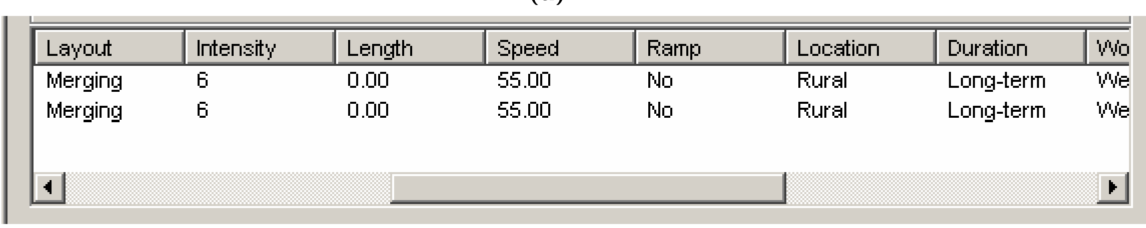


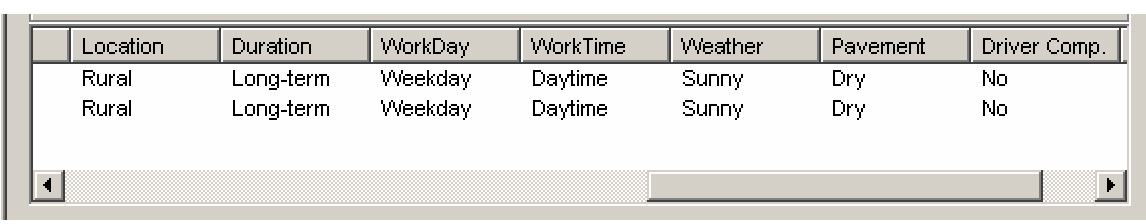
Figure 10 Project information dialog box



(a)



(b)



(c)

Figure 11 Work zone scenarios dialog box

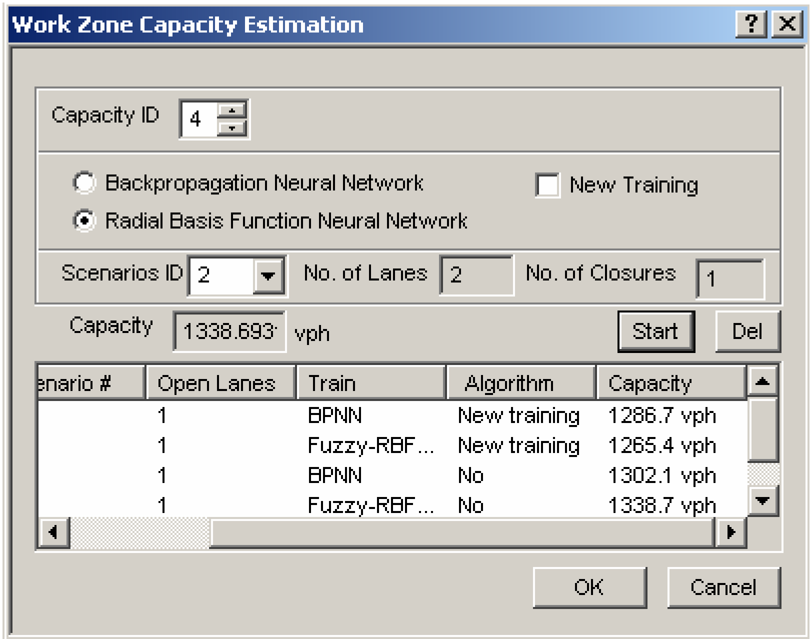


Figure 12 Work zone capacity estimation dialog box

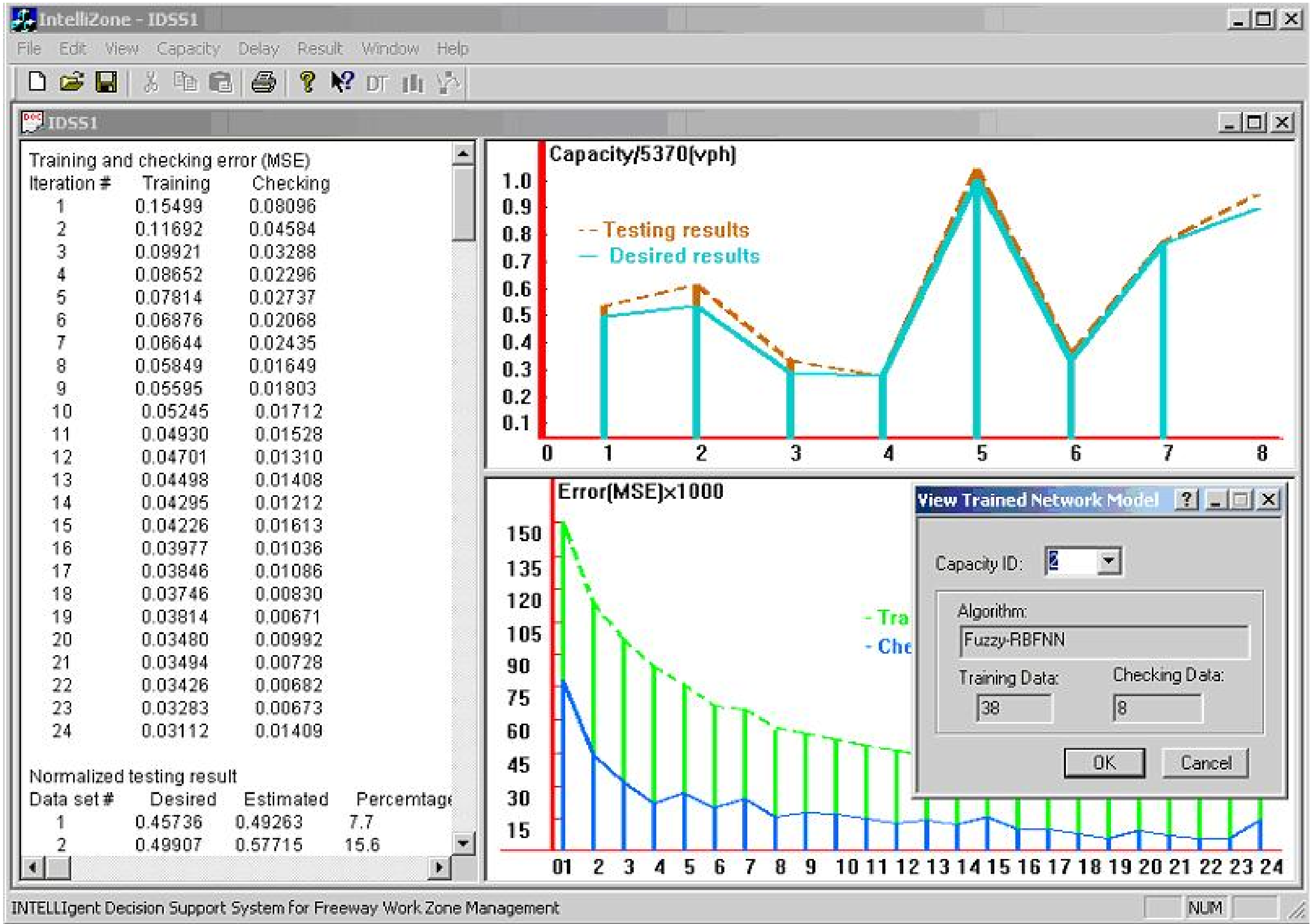
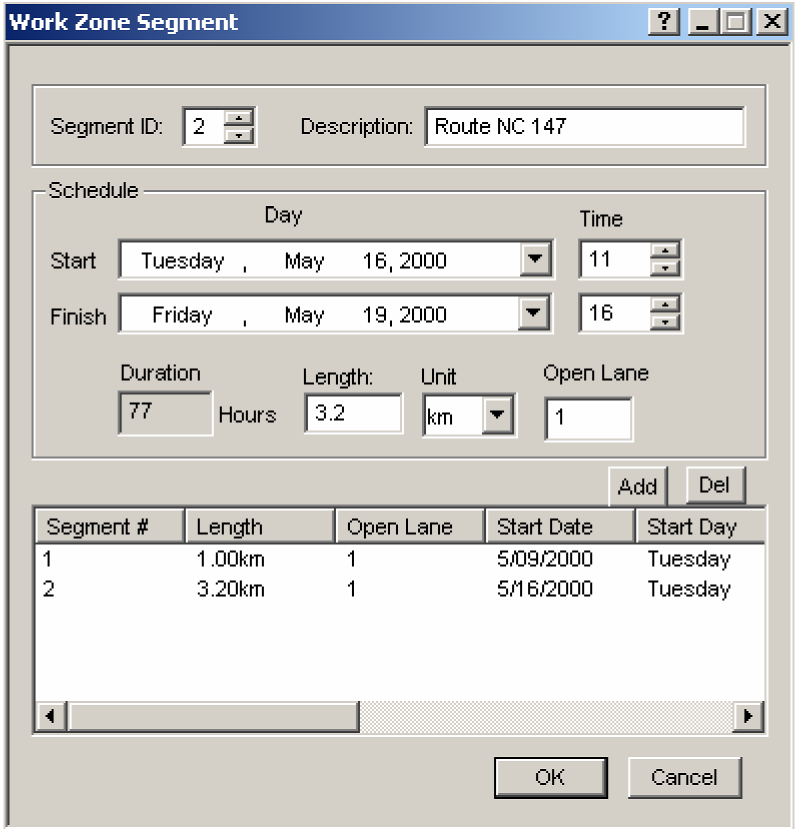
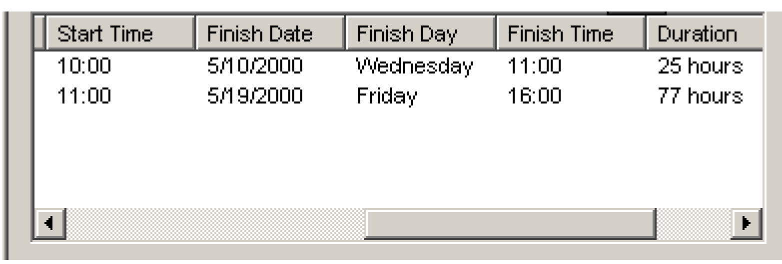


Figure 13 Multi-window interface for training the neural network

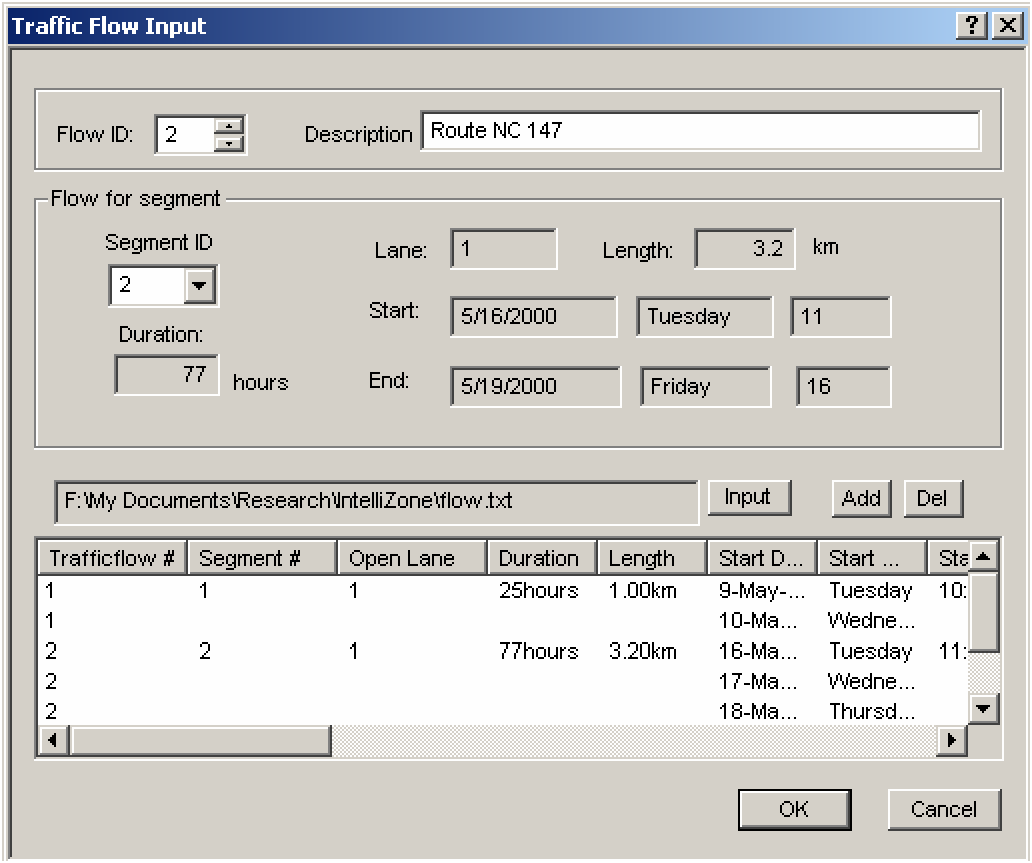


(a)

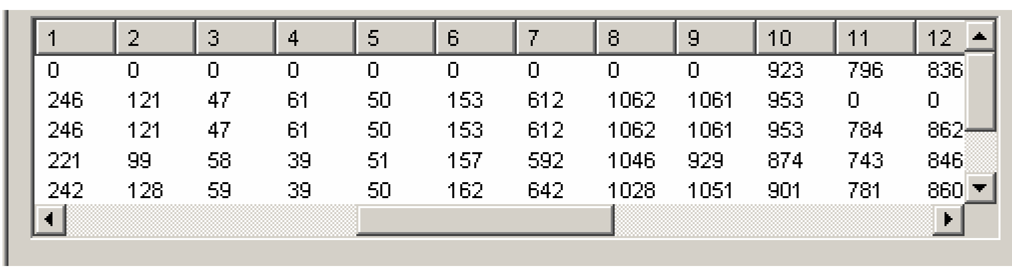


(b)

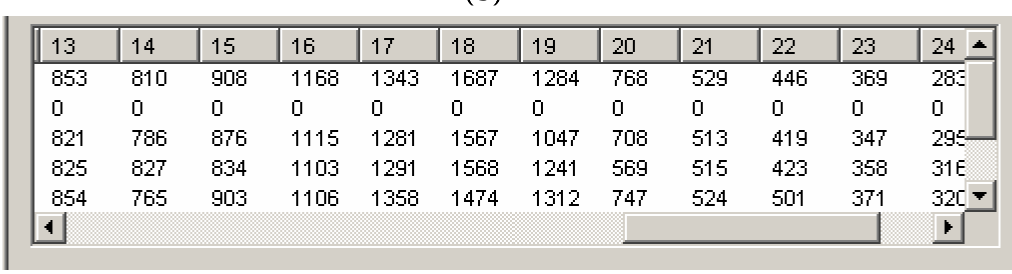
Figure 14 Work zone segment dialog box



(a)

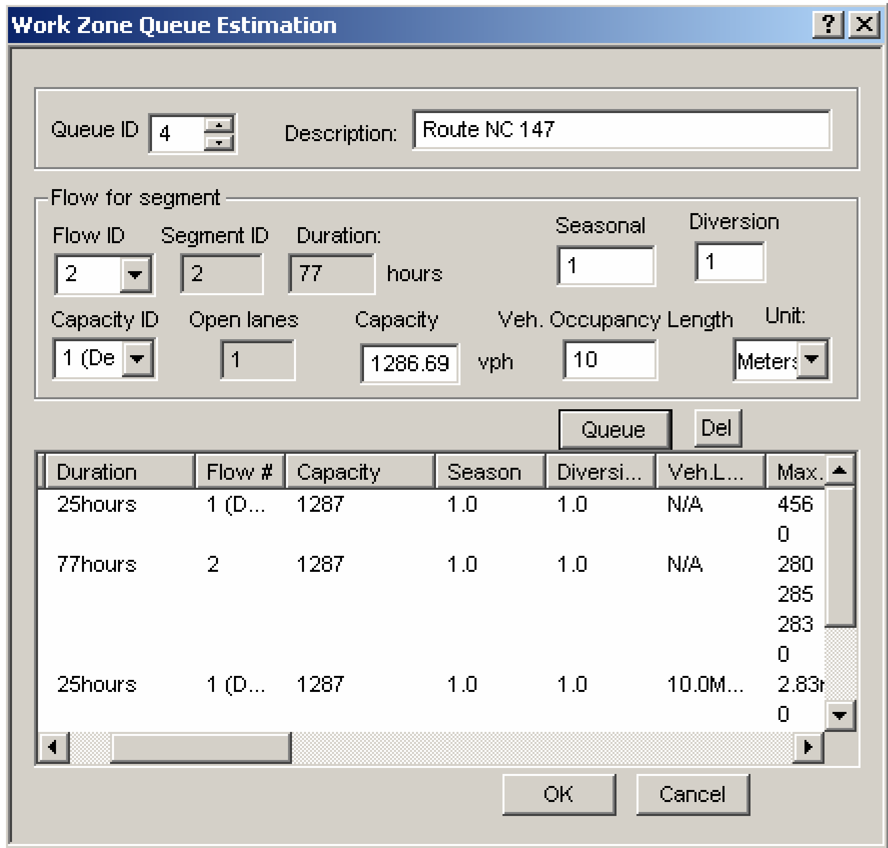


(b)

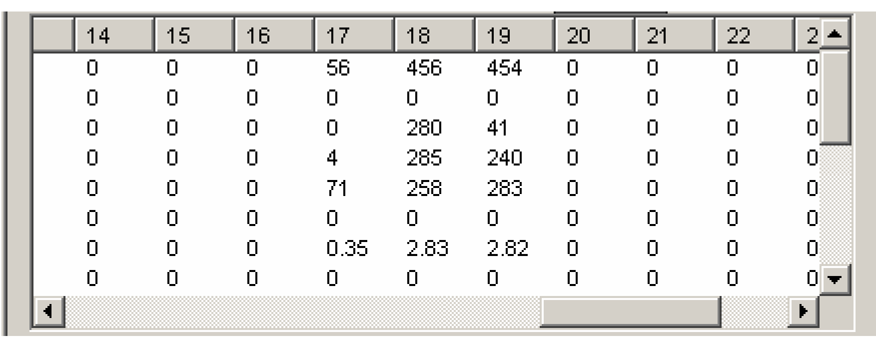


(c)

Figure 15 Traffic flow input dialog box



(a)



(b)

Figure 16 Queue delay estimation dialog box

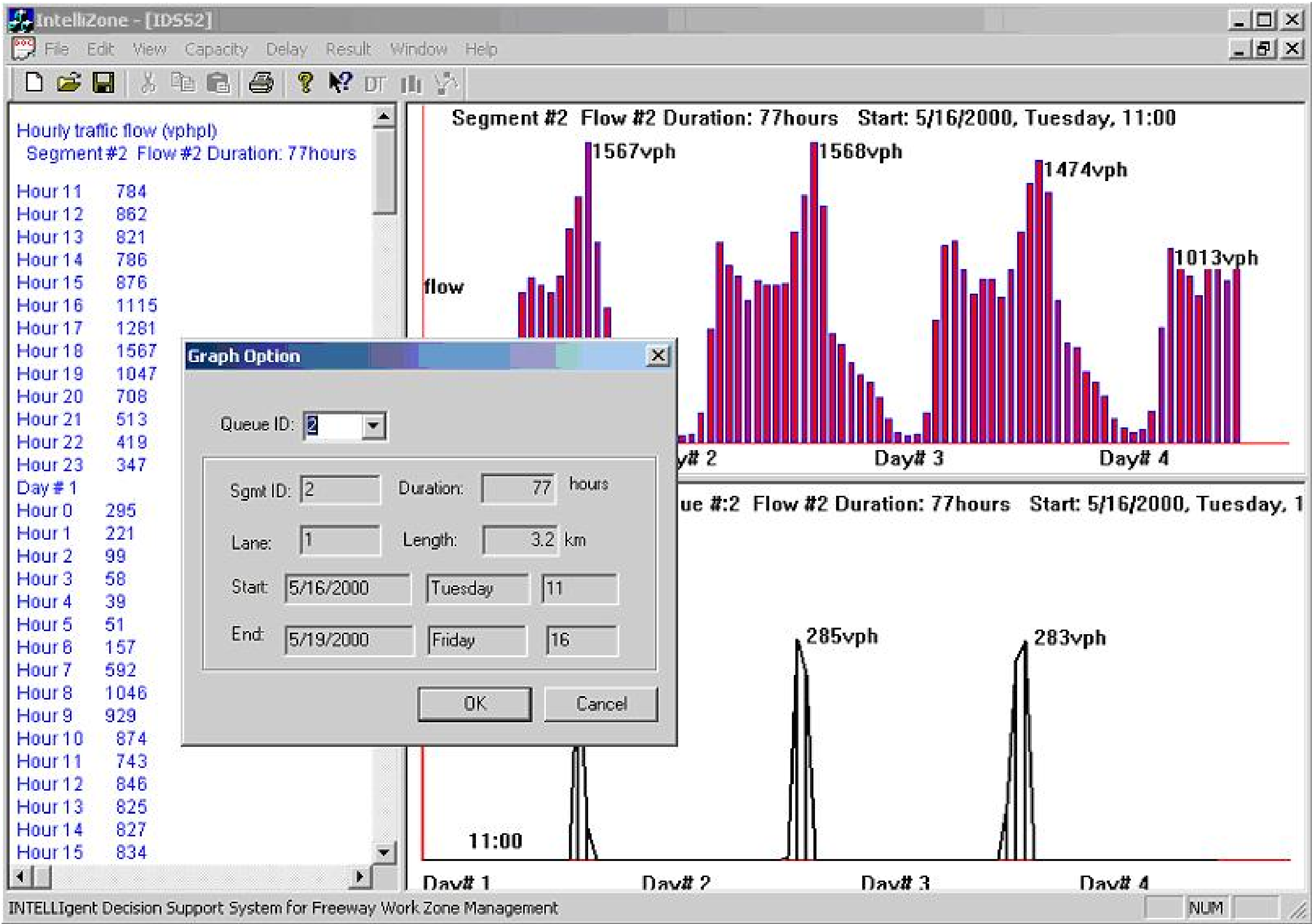


Figure 17 Multi-window interface for displaying the traffic flow and queue delay results

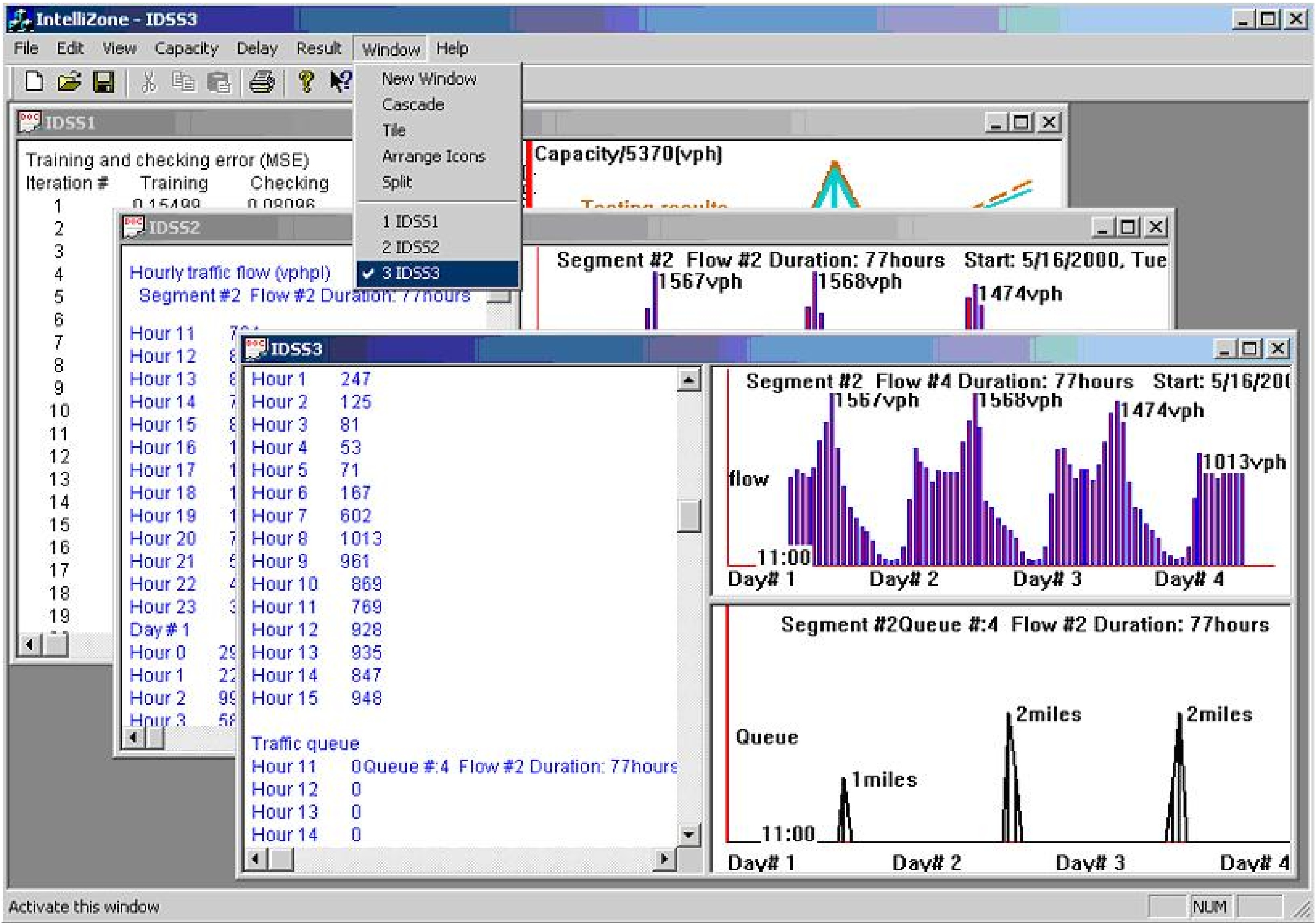


Figure 18 Toggling back and forth among traffic flow and queue delay windows

Part VI

Clustering-Neural Network Models and Parametric Study of Work Zone Capacity

CLUSTERING-NEURAL NETWORK MODELS AND PARAMETRIC STUDY OF WORK ZONE CAPACITY

Xiaomo Jiang[11] and Hojjat Adeli[12]

ABSTRACT: Two neural network models, called clustering-RBFNN and clustering-BPNN models, are created for estimating the work zone capacity in a freeway work zone as a function of seventeen different factors through judicious integration of the subtractive clustering approach with the radial basis function (RBF) and the backpropagation (BP) neural network models. The clustering-RBFNN model has the attractive characteristics of training stability, accuracy, and quick convergence. The results of validation indicate that the work zone capacity can be estimated by clustering-neural network models in general with an error of less than 10%, even with limited data available to train the models. The clustering-RBFNN model is used to study several main factors affecting work zone capacity. The results of such parametric studies can assist work zone engineers and highway agencies to create effective traffic management plans (TMP) for work zones quantitatively and objectively.

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INTRODUCTION

The work zone capacity in freeways is usually defined as the mean queue discharge flow rate at a freeway work zone *bottleneck* (any constricted location that restricts the flow of vehicles in a work zone) (HCM, 2000). The work zone capacity is a complicated and non-quantifiable function of a large number of interacting variables some of which are linguistic such as work zone layout and weather conditions, which explains the dearth of scientific work on mathematical modeling of the freeway work zone capacity. Karim and Adeli (2003) present an adaptive computational model for estimating the work zone capacity and queue length and delay taking into account the following factors: number of lanes, number of open lanes, work zone layout, length, lane width, percentage trucks, grade, speed, work intensity, darkness factor, and proximity of ramps. The model integrates judiciously the mathematical rigor of traffic flow theory with the adaptability of neural network analysis.

In a recent article, Adeli and Jiang (2003) present a new neuro-fuzzy model for estimating the work zone capacity taking into account seventeen different numeric and linguistic factors. A backpropagation neural network is employed to estimate the parameters associated with the bell-shaped Gaussian membership functions used in the fuzzy inference mechanism (Zadeh, 1978). An optimum generalization strategy is used in order to avoid over-generalization and achieve accurate results. Comparisons with two empirical equations demonstrate that the new neuro-fuzzy model has the following advantages: 1) it incorporates a large number of factors impacting the work zone capacity, 2) it provides a more accurate estimate of the work zone capacity, especially when the data for factors impacting the work zone capacity are only partially available, and 3) unlike the empirical equations, the new model does not require subjective selection of various adjustment factors or values by work zone engineers based on prior experience.

However, the existing models for freeway work zone capacity estimation cannot yield the required acc
create the clustering-RBF and clustering-BF neural network models. The two clustering-neural network models are developed for estimating the work zone capacity in a freeway work zone as a function of seventeen different factors.

The clustering-RBFNN model investigated in this research is a modification of the fuzzy-RBFNN model of Karim and Adeli (2003). Work zone patterns are first grouped into similar clusters using a data clustering approach. Similarity of any new work zone pattern to the training patterns is measured by its proximity to the centers of the clusters. Karim and Adeli (2003) use the fuzzy c-means algorithm (Adeli and Karim, 2000) to find the cluster centers. In this work, the *subtractive clustering* approach described in Adeli and Jiang (2003) is used to determine the optimum number of clusters and clustering centers where it is assumed that each data point belongs to a potential cluster based on the minimum value of a predefined objective function. Subtractive clustering is an effective approach for grouping data into clusters and discovering structures in data (Chiu, 1994; Yager and Filev, 1994). The clustering-BPNN model is similar to the clustering-RBFNN model except that the neural network classifier in the former is the simple BP algorithm and in the latter is the RBFNN.

FACTORS IMPACTING THE WORK ZONE CAPACITY

Seventeen different numeric and linguistic factors are used in the developed clustering-neural network models: 1) percentage of truck (x_1), 2) pavement grade (vertical slope in the longitudinal plane) (x_2), 3) number of lanes (x_3), 4) number of lane closures (x_4), 5) lane width (x_5), 6) work zone layout (x_6), 7) work intensity (x_7), 8) work zone length (length of closure) (x_8), 9) work zone speed (x_9), 10) proximity of ramps (x_{10}), 11) work zone location (x_{11}), 12) work zone duration (x_{12}), 13) work time (x_{13}), 14) work day (x_{14}), 15) weather condition (x_{15}), 16) pavement conditions (x_{16}), and 17) driver composition (x_{17}). A detailed discussion of impact of these factors is presented in Adeli and Jiang (2003).

Symbolically, the work zone capacity can be expressed as a function of 17 variables defined in the previous paragraphs:

$$y = f(x_1, x_2, \ldots, x_{17}) \tag{1}$$

Among the seventeen variables, some are linguistic such as work zone layout and weather conditions, some are binary two-valued parameters such as the interchange effect representing the existence of ramps near or within work zone, and others are numeric such as the work zone length. The variables are quantified and normalized using the methods described in Adeli and Jiang (2003). Spline-based nonlinear functions are used to quantify each linguistic as well as binary-valued variable mathematically. Spline-based nonlinear functions are also assigned to numeric variables in order to model the impact of their variations on the work zone capacity.

CLUSTERING-NEURAL NETWORK MODELS

General Topology of Neural Networks

Artificial neural networks have been shown as a powerful tool for solution of complicated problems not amenable to conventional mathematical approaches (Adeli and Hung; 1995; Adeli 2001; Adeli and Karim, 2001). The topology of the neural network models for estimating the work zone capacity is presented in Figure 1. It consists of an input layer, a hidden layer, and an output layer. The input layer has 18 nodes representing the 17 variables defined in the previous section and an 18^{th} node to indicate the data collection locality. The values of the variables in the input layer are normalized to values between 0 and 1 employing the S-shape and Z-shape spline-based nonlinear functions as explained in Adeli and Jiang (2003). The normalization prevents the undue domination of variables with large numerical values over the variables with small numerical values, thus improving the accuracy of estimating work zone capacity and accelerating the convergence of the network training. The normalized variables are denoted by q_1 to q_{18} in Figure 1. A bias node with the value of one ($q_0 = 1$) is added to the input layer. Without the bias, the hyperplane separating the patterns is constrained to pass through the origin of the hyperspace defined by the inputs, which limits the adaptability of the neural network model. The parameter w_{ij} represents the weight of the link connecting the normalized input node i to node j in the hidden layer

The number of nodes in the hidden layer, N+1, is equal to the number of cluster centers used to characterize and classify any given training data set. For the number of nodes in the hidden layer, instead of the trial-and-error approach commonly used in creating the neural network topology, the *subtractive clustering* method described in Adeli and Jiang (2003) is used. In Figure 1, the variables in the hidden layer are denoted by p_1 to p_N. A bias node with the value of one (p_0 = 1) is also added to the hidden layer for the same reason described earlier. The output layer has only one node for the estimated work zone capacity. The estimated work zone capacity, $\hat{C}$, is obtained from the clustering-neural network model as the aggregation of the weighted outputs of N+1 hidden nodes as follows:

$$\hat{C} = \sum_{j=0}^{N} w_j p_j \tag{2}$$

where the first term in the summation (for $j = 0$) represents the bias and w_j is the weight of the link connecting the jth node in the hidden layer to the output node.

Clustering-RBFNN

Adeli and Karim (2000) used the fuzzy c-means clustering algorithm to improve the performance of RBFNN for another pattern recognition problem, the freeway traffic incident detection problem. Karim and Adeli (2003) present a fuzzy-RBFNN model for mapping eleven quantifiable and non-quantifiable factors influencing the work zone capacity to the work zone capacity. In this work, the Gaussian function is used as basis in the hidden or the radial basis function (RBF) layer of the neural network model in the following form (Figure 2):

$$p_j = \exp\left(\frac{\left\| \mathbf{q} - \mathbf{c}_j \right\|^2}{2\sigma_j^2} \right) \qquad j = 1,2,\ldots, N \tag{3}$$

where $\|\mathbf{X}\| = \sqrt{\sum_{18} |\mathbf{X}_i|^2}$ is the Euclidean distance, p_j is the value of the *j*th node in the hidden layer, **q** is the 18×1 vector of the normalized input variables, $\mathbf{c}_j$ (j =1, …, N) is the 18×1 vector of the *j*th clustering data center, which are determined by the subtractive clustering approach, as are the optimum number of clusters, and N is the number of radial basis functions which is also equal to the optimum number of clusters.

In Eq. (3), the factor σ_j is the influencing range of the Gaussian function centered at $\mathbf{c}_j$, whose squared value in this research is approximated using the mean squared distance between cluster centers, as expressed by:

$$\sigma_j^2 = \frac{1}{N} \sum_{i=1}^{M} \left\| \mathbf{c}_j - \mathbf{c}_i \right\|^2 \quad j = 1, 2, \ldots, N \tag{4}$$

where M is the total number of training data sets. The work zone capacity estimated by the clustering-RBFNN model is obtained as the aggregation of the weighted outputs of N+1 hidden nodes from Eq. (2).

The weights of the links connecting the hidden nodes to the output node are updated by minimizing the mean squared error (MSE) of the normalized work zone capacity and using the gradient descent optimization algorithm described in Adeli and Jiang (2003). Two stopping criteria are used for convergence of the clustering-RBFNN model. One is the acceptable mean squared error value (0.001 used in this study) and the other is the maximum number of iterations (400 used in this study).

In a conventional RBFNN, the weights of the links connecting the input layer to the hidden layer (i.e. the RBF parameters $\mathbf{c}_j$ defining the cluster centers) have to be updated in every iteration, similar to a standard multiple-layer feed-forward neural network. In contrast, in the clustering-RBFNN model used in this research, the centers of RBF clusters (c_j) are determined in one step using the subtractive clustering approach, resulting in substantial speedup in the training convergence of the network and reduction of computer processing time for training the network.

Clustering-BPNN

The BP neural network (Hagan et al., 1996) has been popular because of its simplicity despite its slow convergence rate for complex pattern recognition problems (Adeli and Hung, 1994). It is based on the gradient descent unconstrained optimization approach where weights are modified in a direction corresponding to the negative gradient of a backward-propagated error measure. In this research, the simple BP neural network algorithm is integrated with the subtractive clustering technique and used as an alternative approach for estimation of work zone capacity. The output of the *j*th hidden node in the BP neural network, p_j, is determined by the sigmoid activation function (Figure 3):

$$p_j = 1/(1+\exp(-X_j)) \quad j = 1, 2, \ldots, N \tag{5}$$

where $X_j = \sum_{i=0}^{18} w_{ij} q_i$ is the aggregation of the 18 weighted normalized input variables plus the bias (for i = 0). The output value estimated by the clustering-BPNN model is obtained also using the sigmoid activation function as follows:

$$\hat{C} = 1/(1+\exp(-X)) \tag{6}$$

where $X = \sum_{j=0}^{N} w_j p_j$ is the aggregation of the weighted outputs of N nodes in the hidden layer plus the bias (for j = 0).

Figure 3 shows the architecture of the clustering-BPNN model for the work zone capacity estimation. There are a number of differences between this model and the clustering-RBFNN model shown in Figure 2. In the clustering-BPNN model: 1) weights of the links connecting the input layer to the hidden layer are required to be updated in each iteration of training the network, 2) aggregation is executed in both hidden and output layers, 3) a so-called *momentum* term is added to the weight modification equation or learning rule to help prevent the neural network getting trapped in a local minimum (Hagan et al., 1996), and 4) the *over-generalization* problem is avoided by employing an *optimum generalization* strategy (Adeli and Jiang 2003) for training the neural network. The resulting clustering-BPNN model requires more computation time for estimating the work zone capacity compared with the clustering-RBFNN model.

TRAINING AND VALIDATING THE NETWORKS

Training

The data used to train and validate the neural network models are collected primarily from the literature and complemented by data obtained directly from North Carolina Department of Transportation. The collected data sets from four different states and city of Toronto are divided randomly into training, checking, and validation data set, as summarized in Table 1. Limited data from California (from the late 1960's) and Ohio were also available to the authors but are not included in this study because those from

California are too old and those from Ohio are too few to represent typical work zones. None of the data set includes all the 17 input variables used in the new computational model. The number of input variables provided ranged from four (number of lanes, number of lane closure, work zone intensity, and work zone duration) to fourteen (percentage of heavy trucks, grade of pavement, number of lanes, number of lane closure, work zone intensity, length of closure, work zone speed, proximity of ramps to work zone, work zone location, work zone duration, work time, work day, weather conditions, and driver composition). For those unavailable input variables, values of zero are obtained after variable quantification and normalization, as described earlier.

Training of neural networks is performed similar to the approach used in Adeli and Jiang (2003) and skipped for the sake of brevity. Convergence results for training the networks based on the entire 39 training data sets in Table 1 are displayed in Figure 4. It is noted that the convergence rate for the clustering-RBFNN is substantially faster than the clustering-BPNN. On a 1.5GHz Intel Pentium 4 processor, the CPU time for training the former is 0.25 seconds and the latter 1.42 seconds.

Validation

Eight sets of validation data sets selected randomly from the collected data sets are used to validate the accuracy of the clustering-neural network models (Table 1). The input values for the 8 data sets are summarized in Table 2. There are two sets from the states of Indiana, Maryland and Texas each, and one set from North Carolina and Toronto each.

The work zone capacities estimated by three different models, the neuro-fuzzy logic (Adeli and Jiang, 2003), clustering-BPNN, and clustering-RBFNN models, are summarized in Table 3. The root of mean squared error (RMSE) values obtained for the three models are 229 vph, 215 vph, and 114 vph, respectively. As such, based on the limited training and validation data used, the clustering-RBFNN model provides the most accurate results. The error percentage for this model ranges from 0.1% to 8.7% (with one exception the error is generally under 5%). For the other two approaches, the error is in general less than 10% with the exception of one case for each method.

The clustering-RBFNN model appears to have the attractive characteristics of training stability (the training results are not sensitive to the initial selections of the weights), accuracy, and quick convergence. In the next section, the clustering-RBFNN model is used to perform a parametric study of the main factors affecting the work zone capacity.

PARAMETRIC STUDIES OF WORK ZONE CAPACITY

This study is done for an actual freeway work zone scenario with measured data provided in Dixon et al. (1997). The work zone site is a two-lane rural freeway on I-95 in North Carolina with one lane closure (Figure 5a). Dixon et al. (1997) provide values for only nine out of seventeen input variables used in the computational models created in this research, as summarized in Table 4. Data are not provided for pavement grade, lane width, work zone length, work zone speed limit, proximity to a ramp, weather and pavement conditions, and driver composition. Parametric studies presented in this paper, however, are for eleven factors influencing the work zone work intensity: percentage of trucks, work zone configuration, layout, weather conditions, pavement conditions, work zone lane width, pavement grade, presence of ramps, work day, and work time. The impact of other factors is not investigated because insufficient data existed in the neural network training data set available to the authors.

Work Intensity

Work intensity in the parlor of the freeway work zone is a qualitative and subjective concept without any standard classification scheme. In this research, the work intensity is divided into six categories from the lightest to the heaviest, represented numerically by one to six, respectively, as summarized in Table 5. Keeping all other variables in the given work zone constant, the work zone capacities for six different work intensities are estimated using clustering-RBFNN model. The results are summarized in Table 4 and displayed in Figure 5b, which shows the work zone capacity reduces with an increase in the intensity of the work, as expected.

Percentage of Trucks

Keeping all other variables in the given work zone constant, the work zone capacities for nine different percentages of truck, ranging from 8% to 30%, are estimated. The results are summarized in Table 4 and displayed in Figure 5b, which shows the work zone capacity reduces with an increase in the percentage of trucks, as expected. The measured value provided by Dixon et al. (1997) for the truck percentage of 26.2 is 1284 vphpl. The clustering-RBFNN model provides the estimate of 1265, with a small error of less than 2%.

Work Zone Configuration, Layout, and Weather/Pavement Conditions

Parametric studies of work zone configurations include the total number of lanes (2, 3 or 4), number of lane closures (1, 2 or 3), and work zone layout (i.e., merging, shifting, and crossover). Further, the influence of weather conditions (i.e., rainy or snowy) and pavement conditions (i.e., wet or icy) on the work zone capacity are also investigated. The work zone configurations are shown in Figure 6 and their results are summarized in Table 6 and graphically shown in Figure 7.

Three different work zone scenarios are studied. Scenario 1 is for a two-lane freeway with one-lane closure, Scenario 2 is for a three-lane freeway with two-lane closure, and Scenario 3 is for a four-lane freeway with three-lane closure (Figure 6). In all scenarios only one lane is open. The results are summarized in the Table 6. For a single open lane, the work zone capacity reduces as the total number of lanes increases. Compared with a two-lane freeway, this reduction is only 1% for a three-lane freeway, but 9% for a four-lane freeway. This suggests that for a four-lane freeway a cost-benefit analysis should be performed for the option of keeping two lanes open versus maintaining just one lane open. The results of parametric studies indicate that the work zone capacity varies significantly with the number of freeway lanes as well as number of lane closures which is consistent with the study on freeway work zones in Texas by Krammes and Lopez (1994).

The per lane work zone capacity for the merging layout is about 14% more than that for the crossover layout and about 8% more than that for the shifting layout. The work zone capacity for the sunny weather (dry pavement) condition is about 6% more than that for the rainy weather (wet pavement) and about 10% more than that for the snowy weather condition.

Work Zone Lane Width and Pavement Grade

Keeping all other variables in the given work zone constant, the work zone capacities for seven different lane widths, ranging from 2.7 m (9 ft) to 3.6 m (12 ft) in increments of 0.15 m (0.5 ft) are estimated for two cases, in the presence and absence of the pavement grade. The results are shown in Table 7 and graphically in Figure 8. In the presence of the pavement grade, the estimated work zone capacity ranges from 1054 vphpl (for the smallest lane width of 2.7 m) to 1342 vphpl (for the largest lane width of 3.6 m). In the absence of the pavement grade, the estimated work zone capacity ranges from 1262 vphpl (for the smallest lane width of 2.7 m) to 1862 vphpl (for the largest lane width of 3.6 m). The following observations are made. The work zone lane widths in the range of 3.3 m (11 ft) to 3.6 m (12 ft) (the U.S. standard lane width) do not affect the work zone capacity by any significant measure. As the work zone lane width reduces the work zone capacity decreases significantly. The presence of the work zone pavement grade exacerbates the traffic flow constriction (e.g., speed) and affect drivers' behaviors, resulting in a significant reduction in the work zone capacity in the range of 20% for a work zone lane width of 2.7 m (9 ft) to 39% for a width of 3.6 m (12 ft).

Presence of Ramp

The neural network models take into account the effect of presence of ramps on the work zone capacity. The presence of ramps is treated as a qualitative variable instead of a quantitative one. An example of ramp proximity to the work zone is illustrated in Figure 9a. The work zone capacities estimated for a two-lane rural freeway on I-95 in North Carolina with one lane closure in the presence and absence of a ramp are summarized in Table 8 and shown in Figure 9b. The presence of ramp reduces the capacity by 12.6%.

Work Day and Work Time

Work zone capacities for four combinations of work day (weekday or weekend) and work time (daytime or night) are summarized in Table 8 and presented in Figure 9b. Since in all likelihood commuters and regular travelers during the weekdays are more familiar with the configuration of the work zone and the traffic control plans in the affected areas (e.g. route diversion) than non-commuters (e.g. tourists) traveling during the weekends, the work zone capacity is somewhat larger during the weekday than during the weekend. The parametric study performed in this research can quantify this observation. The estimated capacities for the weekend are about 37% smaller that those for the weekday during both daytime and night.

The driver behavior and traffic characteristics differ during daytime and nigh time. Night construction can decrease the work zone capacity because of the reduced travelers' attention and inferior visibility during nighttime (Al-Kaisy and Hall 2001). Again, the results performed in this research can quantify this observation. The estimated work zone capacities for construction at night are 10-11% smaller that those for the construction at daytime.

FINAL COMMENTS

The results of validation indicate that the work zone capacity can be estimated by clustering-neural network model in general with an error of less than 10%, even with limited data available to train the models. With additional data and training of the models the accuracy can be improved substantially. The computational models presented in the paper are general. The parametric studies, however, are based on the adaptation of the work zone in a two-lane rural freeway on I-95 in North Carolina with one lane closure. There is no intention to offer generalized conclusions for every other work zone situation. However, the computational models provide a powerful tool to perform parametric studies for other work zone situations.

The results of a parametric study of the factors impacting the work zone capacity can assist work zone engineers and highway agencies to create effective TMPs for work zones quantitatively and objectively. To the authors' best knowledge this quantitative parametric study is the first of its kind. A number of observations are made based on the limited data available for training the models. There is a definite need to collect additional data for various work zone conditions. Such data will have two significant applications. First, they can be used to further train the clustering-neural network models in order to improve the accuracy of work zone capacity estimation. Second, they can be used for more detailed sensitivity analysis.

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Appendix I. References

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Table 1 Training, checking, and validation data set

State	Index	52 data sets		
		Training	Checking	Validation
Indiana	1	9	1	2
Maryland	2	9	1	2
North Carolina	3	7	1	1
Texas	4	7	1	2
Toronto	5	7	1	1
Total		39	5	8

Table 2 Input values for 8 work zone scenarios used to validate three work zone capacity estimation models

Var.	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}
Data set	Truck (%)	Grade (%)	No. of lanes	No. of Lane closures	Lane Width	Layout	Work Intensity	Length of closure (km)	Speed (km/h)	Ramp	Location	Work dur.	Work time	Work day	Weather Cond.	Pave. Cond.	Driver comp.	State
1	32	-	2	1	-	M	6	11.7	-	-	Rural	Long	Day	Weekday	-	-	-	Indiana
2	10	-	2	1	-	C	2	11.7	-	-	Rural	Long	Day	Weekday	-	-	-	Indiana
3	8	5	4	1	-	-	1	0.18	48	Yes	Urban	Short	Day	Weekday	Sunny	-	0	Maryland
4	8.5	0	4	2	-	-	6	2.2	34	Yes	Urban	Short	Night	Weekday	Sunny	-	0	Maryland
5	26.2	-	2	1	-	-	6	-	-	-	Rural	Long	Day	Weekday	-	-	-	N. Carolina
6	-	-	4	1	-	-	1	-	-	-	-	Short	-	-	-	-	-	Texas
7	-	-	5	3	-	-	3	-	-	-	-	Short	-	-	-	-	-	Texas
8	-	3	3	1	-	-	-	-	-	-	Urban	Short	Day	-	Sunny	Dry	1	Toronto

M = Merging, C = Crossover, - Unavailable data

Table 3 Comparisons of the work zone capacity estimates by neuro-fuzzy logic, clustering-BPNN, and clustering-RBFNN models

State	Data set number	Open lanes	Closed lanes	Measured value (C_i) (vph)	Neuro-fuzzy logic ($\hat{C}_i$) (vph) (Adeli&Jiang, 2003)		Clustering-BPNN ($\hat{C}_i$) (vph)		Clustering-RBFNN ($\hat{C}_i$) (vph)	
					Values (vph)	Error (%)	Values (vph)	Error (%)	Values (vph)	Error (%)
Indiana	1	1	1	1308	1320	0.9	1326	1.4	1287	1.6
	2	1	1	1595	2138	34.1	1265	20.7	1540	3.4
Maryland	3	3	1	5205	5343	2.6	4982	4.3	5211	0.1
	4	2	2	2456	2652	8.0	2624	6.8	2588	5.4
North Carolina	5	1	1	1284	1290	0.5	1287	0.2	1264	1.6
Texas	6	3	1	4590	4649	1.3	4200	8.5	4563	0.6
	7	2	3	2680	2900	8.2	2779	3.7	2914	8.7
Toronto	8	2	1	3904	3779	3.2	4039	3.5	3793	2.8
Root mean square error = $\sqrt{\frac{\sum_{i=1}^{8}(\hat{C}_i - C_i)^2}{8}}$					229		215		114	

Table 4 Work zone capacity variations with work intensity and percentage of trucks

State: North Carolina	Location: Rural	Work duration: Long-term
Number of lanes: 2	Number of lane closures: 1	Truck percentage: 26.2
Work intensity: 6	Work time: day	Workday: weekday

Measured work zone capacity: 1284 vphpl

Work intensity	1	2	3	4	5	6
Capacity (vphpl)	1522	1515	1505	1342	1276	1265

Percentage of trucks (%)	8	12	16	20	24	26.2	30
Capacity (vphpl)	1548	1513	1409	1314	1268	1265	1264

Work intensity: 1=Lightest, 2=Light, 3=Moderate, 4=Heavy, 5=Very heavy, 6= Heaviest

Table 5 Classification of work zone intensity

Intensity level	Qualitative description	Work type examples
1	Lightest	Median barrier Installation or repair
2	Light	Pavement repair
3	Moderate	Resurfacing
4	Heavy	Stripping
5	Very heavy	Pavement marking
6	Heaviest	Bridge repair

Table 6 Variation of work zone capacities with influencing factors

Factors	Scenarios	No. of lanes	No. of lane closures	Estimated capacity (vphpl)
Work zone configuration	1 (8a)	2	1	1287
	2 (8d)	3	2	1274
	3 (8e)	4	3	1171
	Scenarios	Layout	Estimated capacity (vphpl)	
Work zone layout	1 (8a)	Merging	1287	
	2 (8b)	Shifting	1193	
	3 (8c)	Crossover	1112	
	Scenarios	Weather condition	Pavement condition	Estimated capacity (vphpl)
Weather/ Pavement	1	Sunny	Dry	1287
	2	Rainy	Wet	1213
	3	Snowy	Snowy/Icy	1159

Table 7 Work zone capacities with lane width and pavement grade

Lane width (m)	Estimated work zone capacity (vphpl)	
	With pavement grade	Without pavement grade
2.70	1054	1262
2.85	1132	1422
3.00	1225	1615
3.15	1294	1761
3.30	1327	1830
3.45	1339	1856
3.60	1342	1862

Table 8 Work zone capacities with influencing factors

Group	Scenarios	Location	Ramp	Estimated capacity (vphpl)
Work zone Location/ramp	3	Rural	No	1287
	4	Rural	Yes	1143
Group	**Scenarios**	**Work time**	**Workday**	**Estimated capacity (vphpl)**
Work day/time	1	Daytime	Weekday	1287
	2	Night	Weekday	1164
	3	Daytime	Weekend	934
	4	Night	Weekend	847

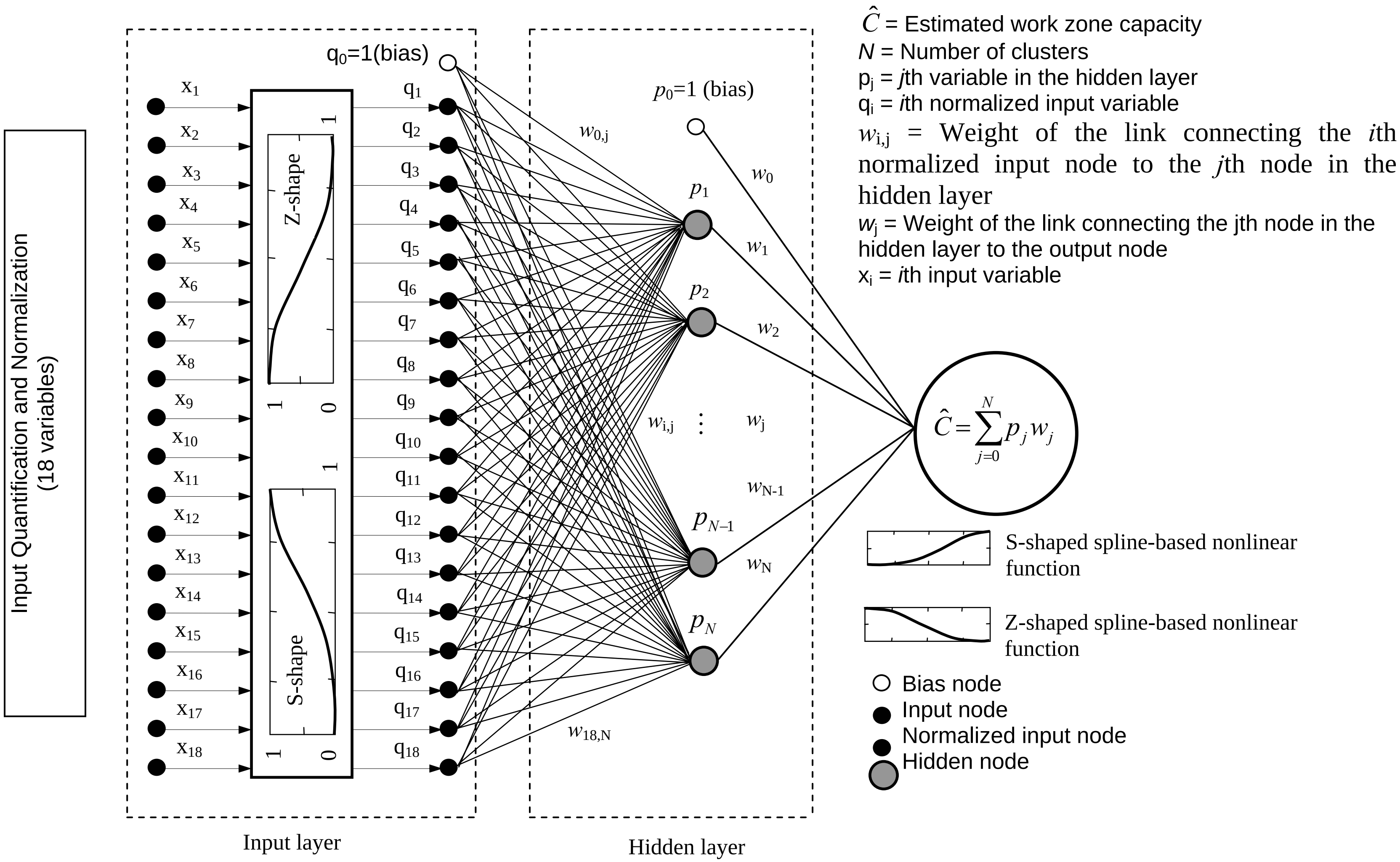
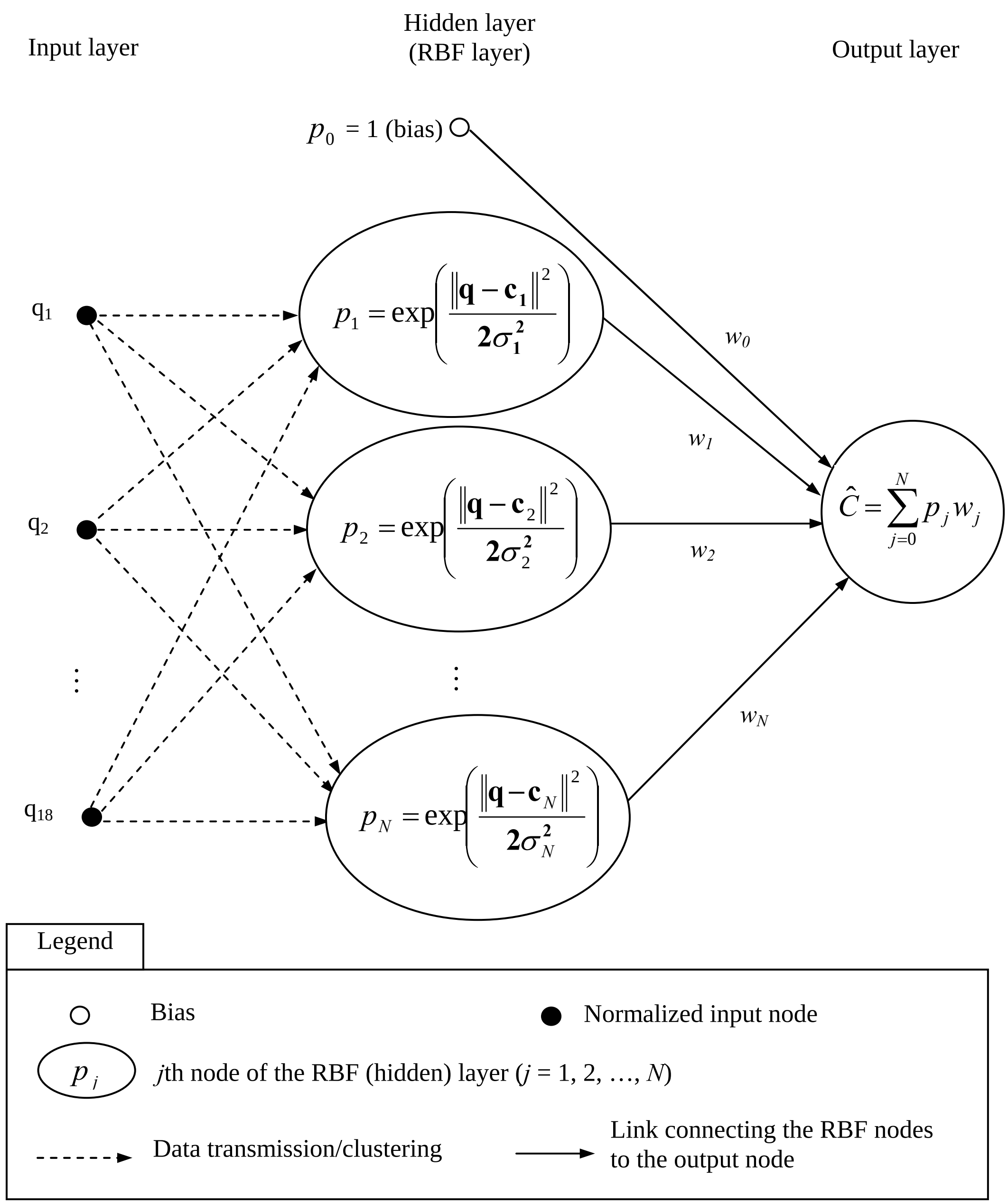


Figure 1 Topology of the neural network models for estimating the work zone capacity



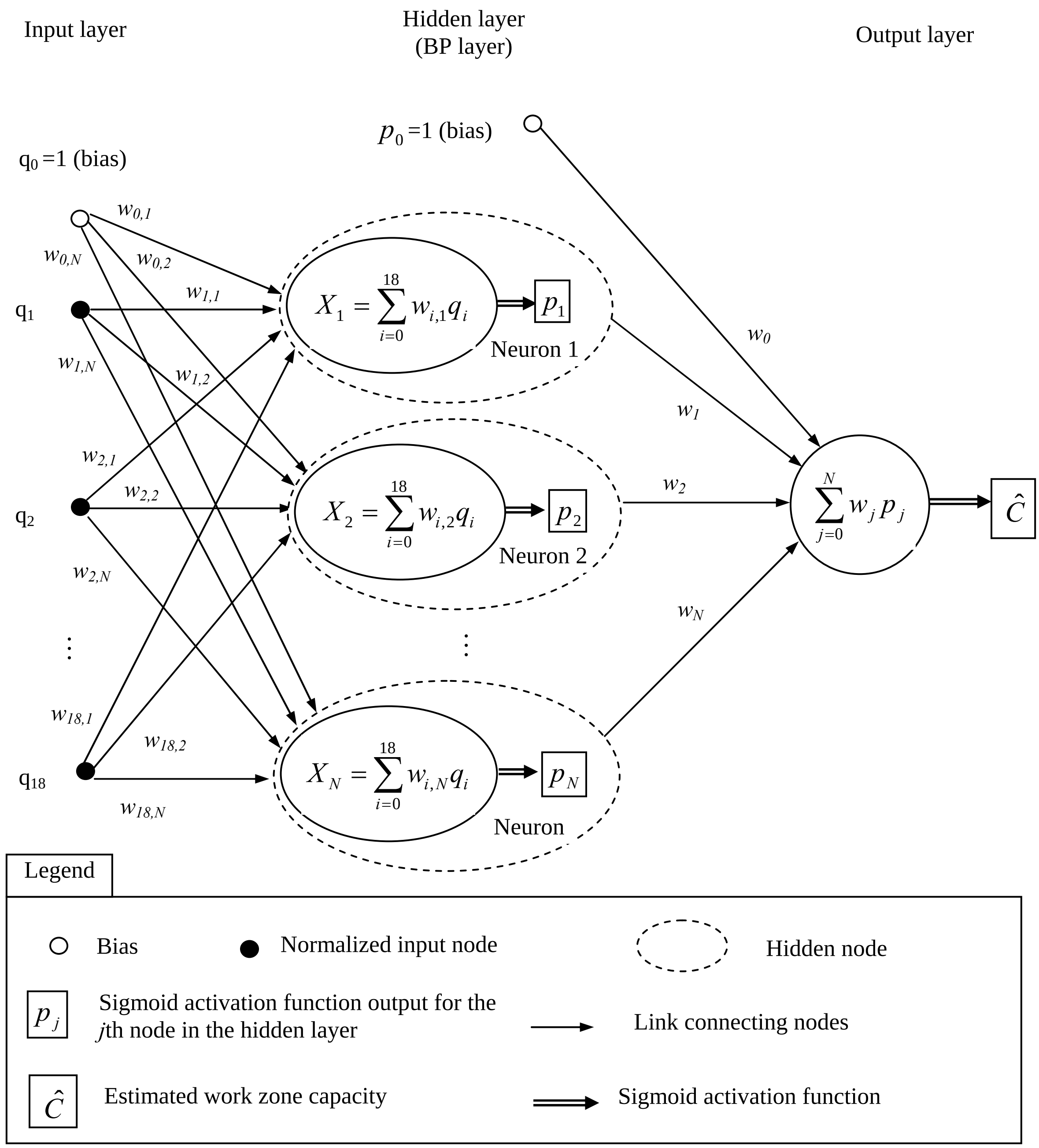
$\mathbf{c}_j$ = Vector of the jth clustering center

$\hat{C}$ = Estimated work zone capacity

σ_j = Influencing range of the Gaussian function

N = Number of clusters

Figure 2 Architecture of the clustering-RBFNN model for estimating the work zone capacity

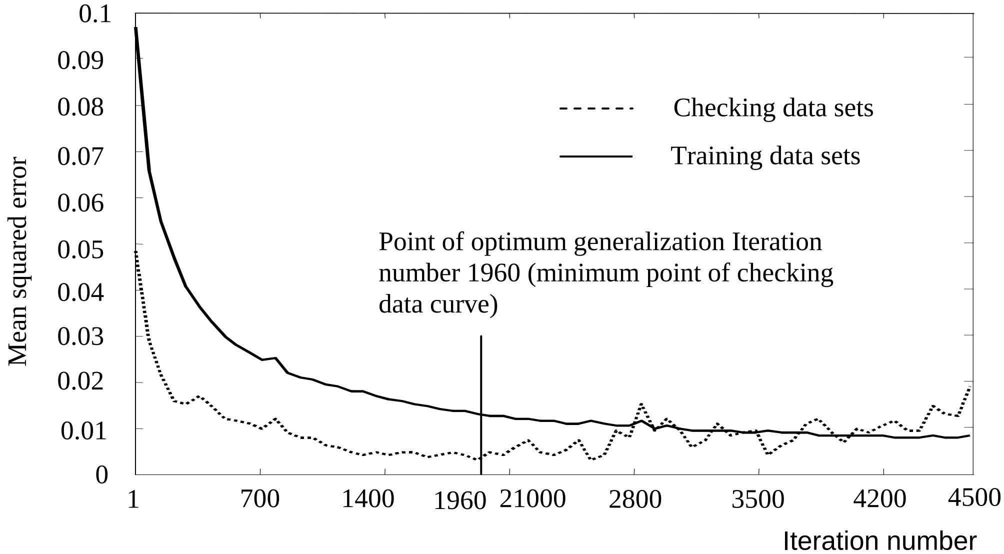


$\hat{C}$ = Work zone capacity value in the output layer

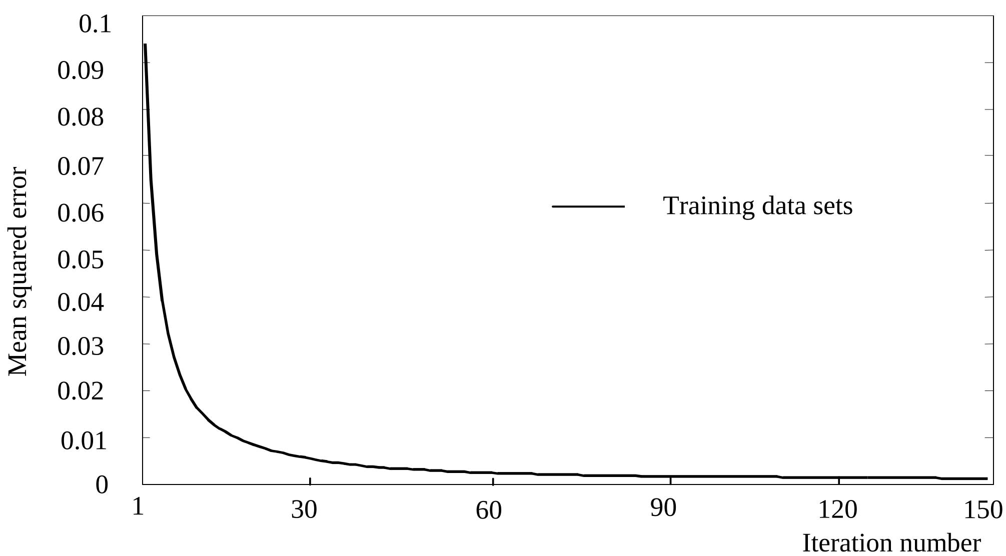
N = Number of clusters

p_j = jth sigmoid function (j = 1, 2, …, N)

Figure 3 Architecture of the clustering-BPNN model for estimating the work zone capacity

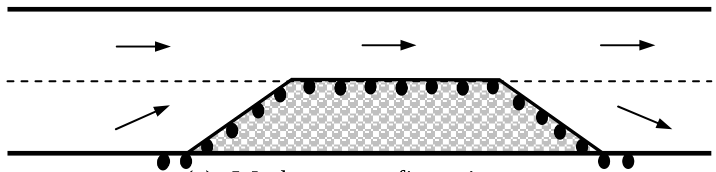


a) Clustering-BPNN

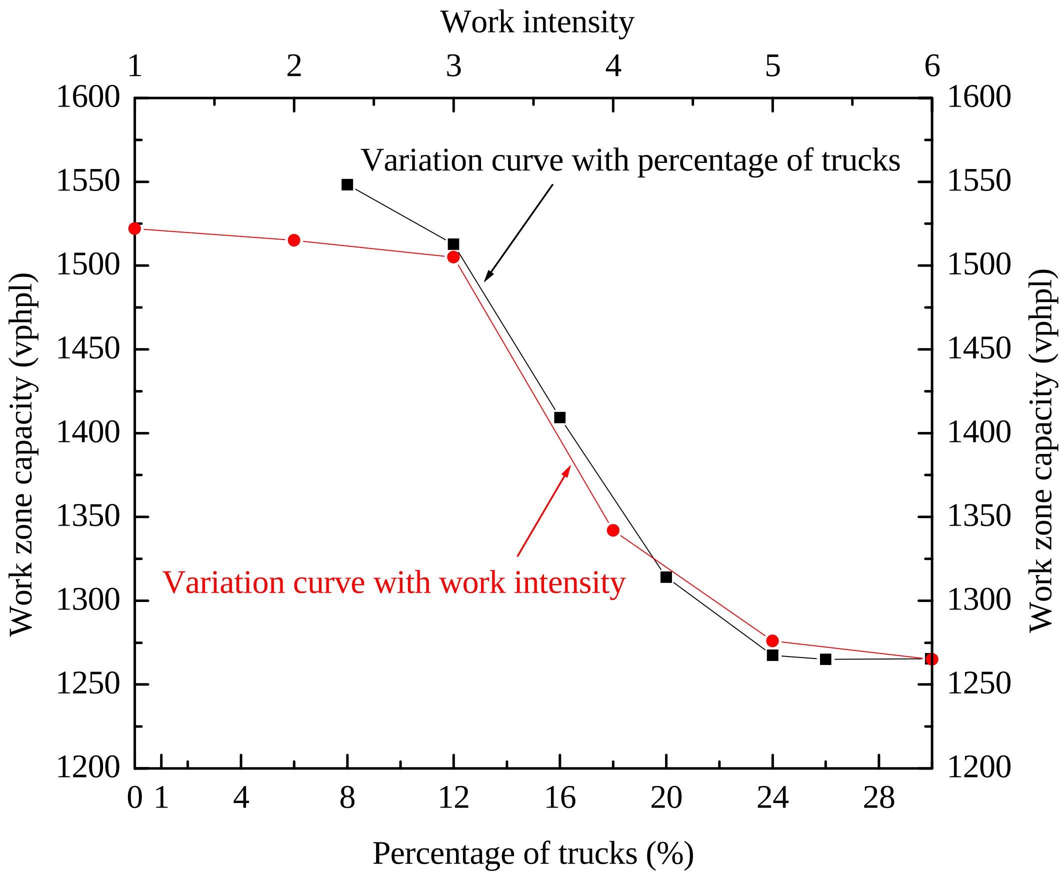


b) Clustering-RBFNN

Figure 4 Convergence curves for training the clustering-neural network models

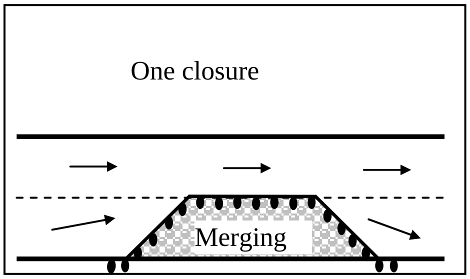


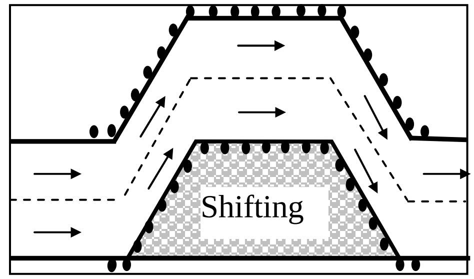
(a) Work zone configuration



(b) Variation curves

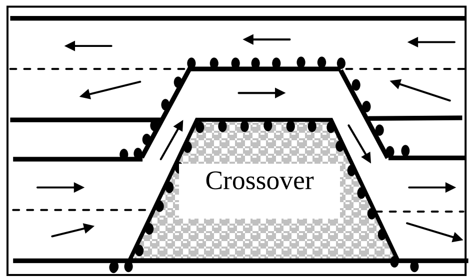
Figure 5 Variation of work zone capacity with work intensity and percentage of trucks (The top horizontal axis represents work intensity and the bottom horizontal axis represents percentage of trucks)



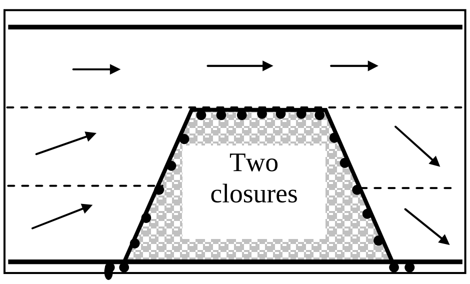


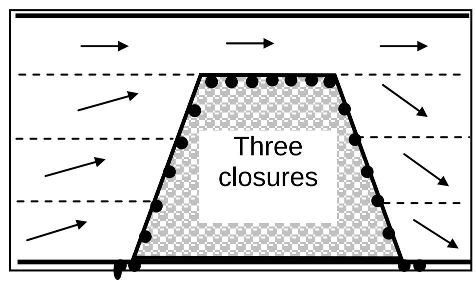
(a) Merging with one lane closure in two lane freeway

(b) Shifting in two lane freeway



(c) Crossover





(d) Two closures in three-lane freeway

(e) Three closures in four-lane freeway

Figure 6 Work zone configuration and layout

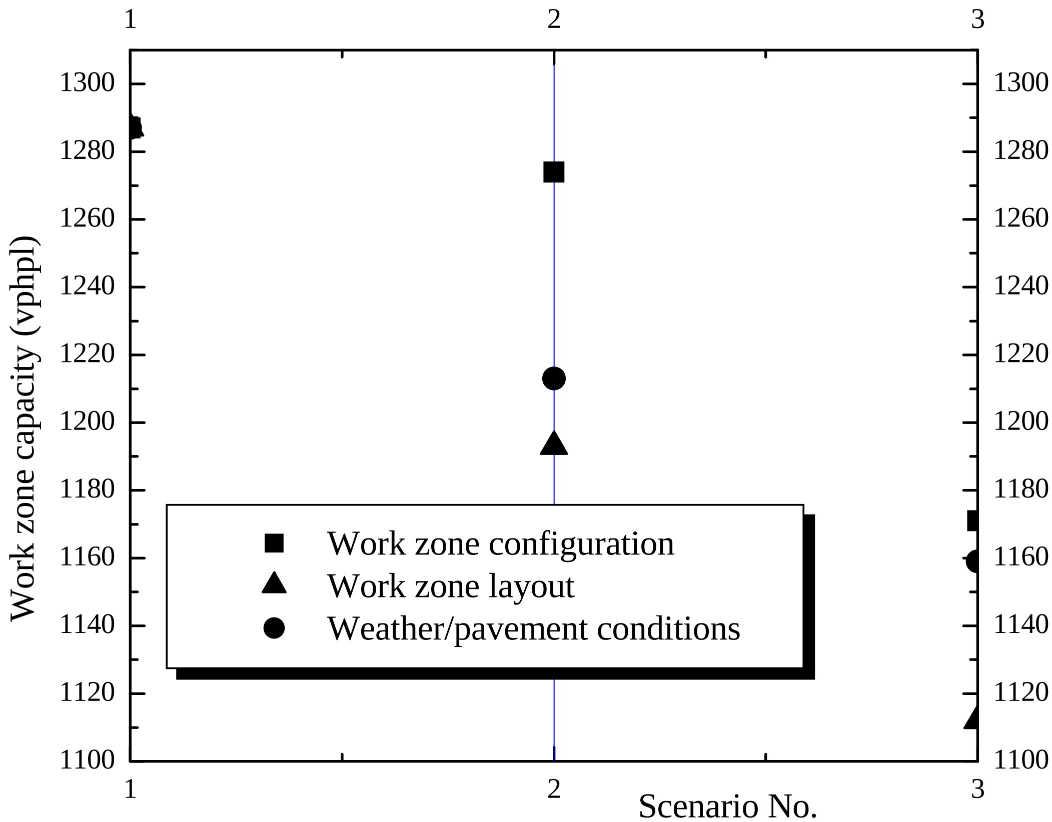
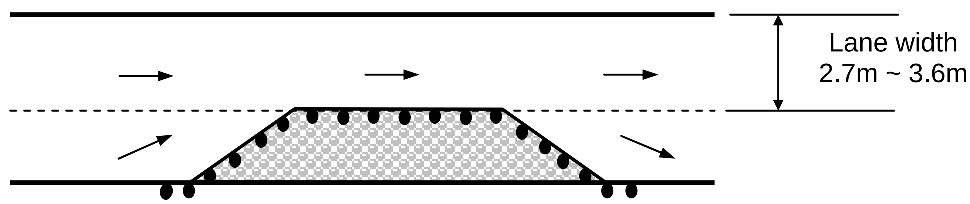
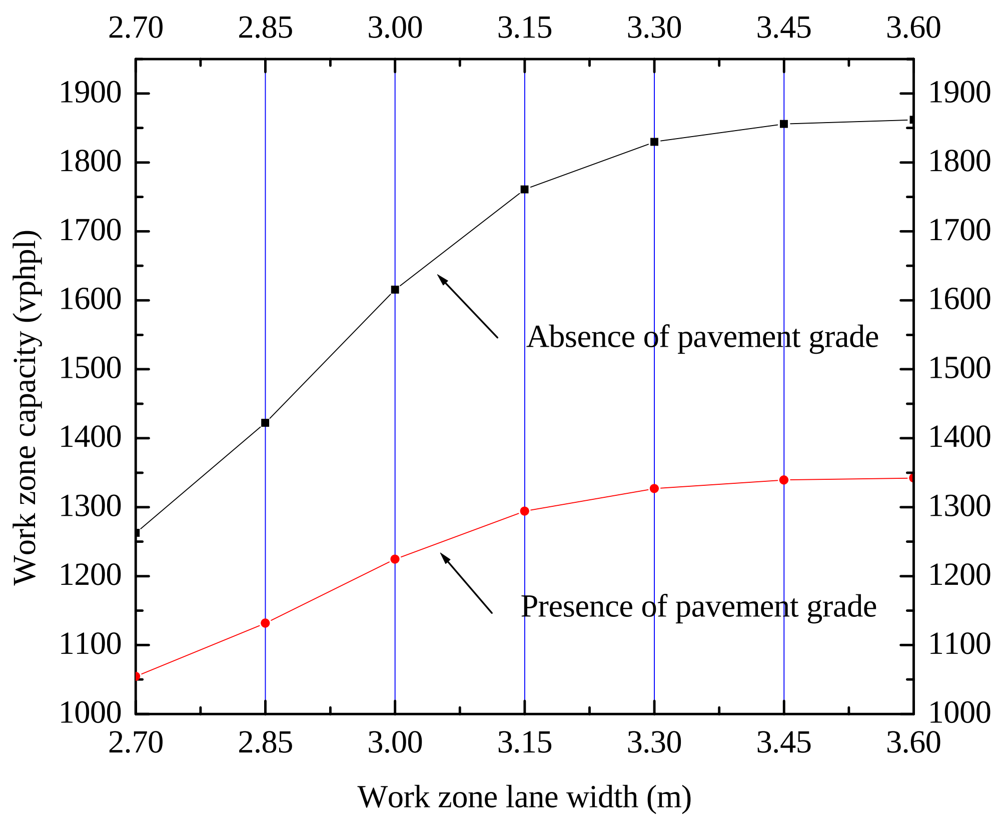


Figure 7 Variation of work zone capacities with work zone configuration, work zone layout, and weather/pavement conditions

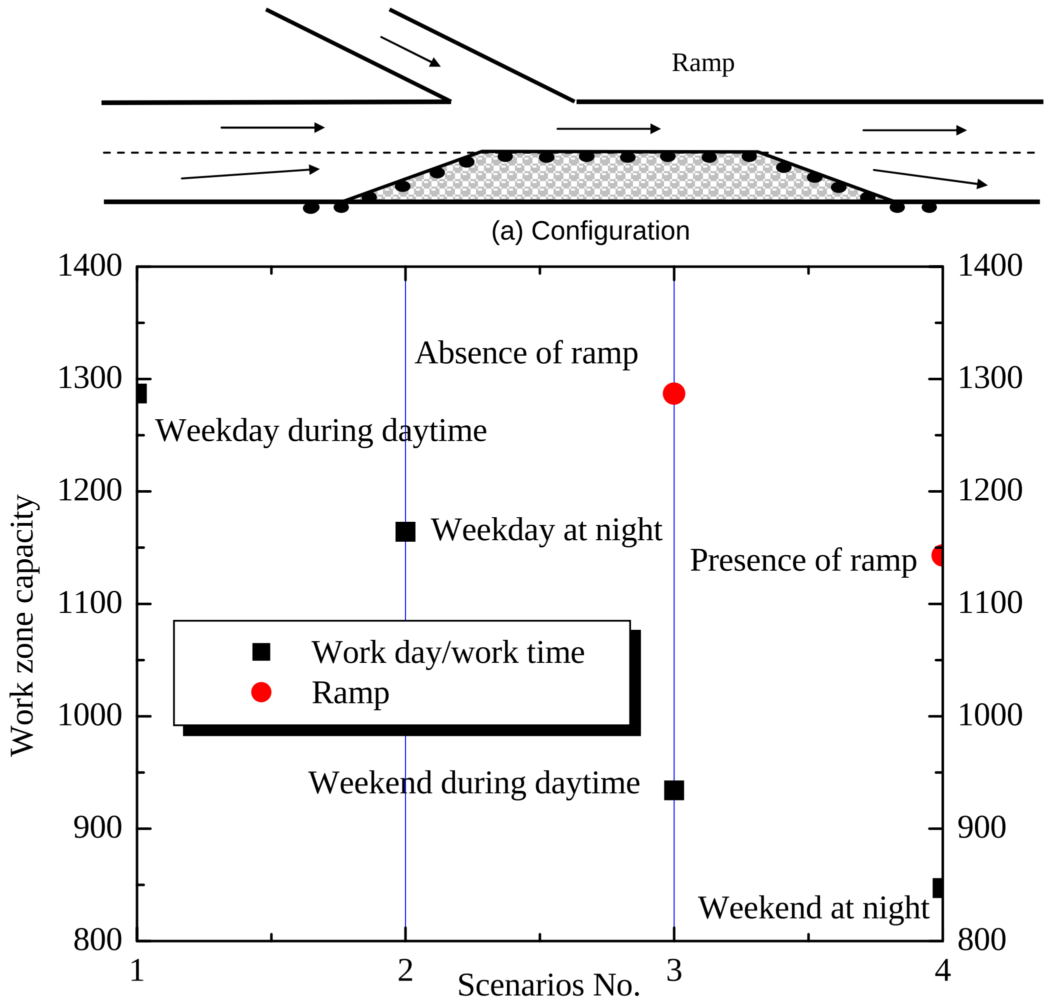


(a) Configuration



(b) Variation curves

Figure 8 Variation of work zone capacities with lane width and pavement grade



(b) Variation curves

Figure 9 Variation of work zone capacities with workday and work time as well as work zone location and ram