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A Fuzzy Decision Support System for Traffic Control Centers*

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A Fuzzy Decision Support System for Traffic Control Centers

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ABSTRACT

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Abstract

We present a fuzzy decision support system that can be used in traffic control centers to provide a limited list of appropriate combinations of traffic control measures for a given traffic situation. The system we describe is part of a larger traffic decision support system that can assist the operators of traffic control centers when they have to reduce non-recurrent congestion using a network-wide approach. The kernel of our system is a fuzzy case base that is constructed using simulated scenarios. At a later stage this system will be complemented with an adaptive learning feature and with a set of fuzzy rules that incorporate heuristic knowledge of experienced traffic operators.

1 Introduction

Contemporary state-of-the-art traffic control centers use dynamic traffic management measures such as ramp metering, dynamic route information panels (with, for regular situations, queue length information, and otherwise indications of congestion, traffic jams and alternative routes), or variable message signs (with e.g. maximum speeds per lane or lane closures) to control the traffic flows on highways and urban ring roads. Recurrent congestion can usually be managed satisfactorily using local control measures. However, operators in traffic control centers often face a difficult task when non-recurrent, non-predictable congestion occurs (e.g. as a consequence of an incident or due to unexpected weather conditions). In such situations, local measures are usually insufficient and often an intervention at the network level is required to manage congestion and to return to a normal traffic situation. So the effects of congestion are attenuated by redirecting the traffic flows in a larger part of the network. The operator of the traffic control center then has to assess the severity of the situation, predict the most probable evolution of the state of the network, and select the most appropriate measures. This is a complex task, which requires specialist knowledge and a lot of experience, which usually can only be obtained after extensive training. As a result, the approaches used by human operators in traffic control centers are in general neither structured nor uniform.

Therefore, our aim is to provide a decision support tool to assist the operators of traffic control centers in their decisions when they have to take measures to deal with non-recurrent, non-predictable congestion. This decision support system should help the operators to react in a uniform and structured way to unusual situations. Since we want to create a decision support system that allows for an easy and smooth interaction with the human operators, with a decision process that is both intuitive and can be explained in linguistic terms, we have opted for a decision support system based on a fuzzy knowledge base.

In short, the system works as follows. Given the current state of the network and the optimization criterion (such as minimal total travel time, maximal throughput, or a weighted combination of several criteria), the fuzzy decision support system generates a ranked list of the best control measures and presents them to the human operator of the traffic control center. If necessary, the effect of these measures on the current traffic situation can be simulated by an external simulation unit. The resulting output of the system is a linguistic characterization of the actions that can be taken and their predicted effectiveness in the current situation. The system described in this paper operates in a multi-level control framework. At the lowest level we have semi-autonomous local traffic controllers for e.g. traffic lights or ramp metering. On a higher level the operation of several local traffic controllers is coordinated or synchronized by supervisory controllers. The role of our fuzzy decision support system in this set-up is to suggest whether a particular local traffic controller should be activated or not.

Several authors have described decision support systems for traffic management, such as FRED (Freeway Real-Time Expert System Demonstration) [7, 8, 11], or the

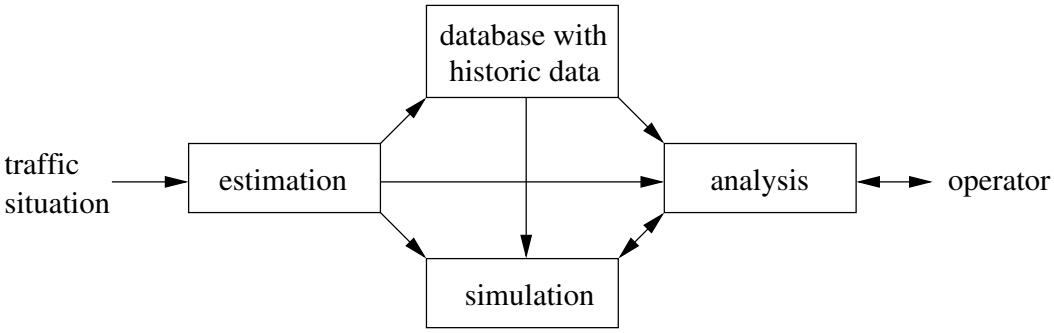

Figure 1: The overall traffic decision support system (TDSS).

Santa Monica Smart Corridor Demonstration Project [2, 9]. However, these architectures do not use fuzzy logic in their decision process. Since we also want a system with an intuitive operation process that is able to generate decisions in cases that are not explicitly covered by the knowledge base, we have opted for a fuzzy system. Other fuzzy decision support systems for traffic control have been developed in [1, 4, 6].

2 Overall framework

The decision support system we are developing is a part of a larger traffic decision support system (TDSS) [3] that is currently being developed by the Dutch Ministry of Transportation, Roadworks, and Water Management. The structure of this system is depicted in Figure 1. The inputs for the TDSS are the current traffic situation (traffic densities, average speeds, traffic demand, time of day, weather conditions, incidents, etc.). Furthermore, the traffic operator can provide or adjust additional parameters and specify which control objective should be used. Based on the measurements, historic data and traffic simulation, the system predicts the future traffic situation (more specifically, the TDSS uses the METANET macroscopic flow model [5] to make a forecast of the traffic situation). In that way we can also predict the performance of the traffic control measures (such as DRIP[1] messages, ramp metering, or lane closures) that will be applied. Since in general a large number of traffic control measures (and combinations of them) are possible, it is not tractable to evaluate all possible combinations of traffic control measures using macroscopic or microscopic traffic simulation. Therefore, in practice only a limited number of combinations can be simulated. The aim of the subsystem we are developing is to limit the number of possible combinations of control measures that should be simulated by using an intelligent decision support system to rank the possible combinations of control measures and to present the operator with a limited number of possibilities that deserve further examination. Afterwards, the operator can select the most appropriate control strategy. In this paper we present a small prototype system with two inputs (incident status and traffic demand) and three possible control measures (DRIP message, close 1 lane, close 2 lanes).

[1] DRIP: Dynamic Route Information Panel.

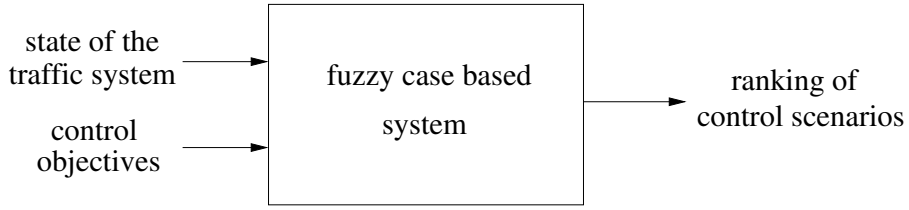

Figure 2: The fuzzy case-based decision support system.

3 The fuzzy decision support system

Our decision support system selects optimal combinations of traffic control measures for a given situation by using a weighted performance measure J defined as

$$J = \sum_{i=1}^{N} w_i J_{\mathsf{sub},i}$$

where the weights w_i are determined by the user and where the $J_{\mathsf{sub},i}$'s are partial performance measures such as predicted queue lengths, total travel times, waiting times, fuel consumption, etc. The weights w_i are not fixed, but can be changed on-line by the user (i.e. the operator in the traffic control center) depending on current traffic management policies and other considerations.

As a starting point for our fuzzy decision support system, we have constructed a case-based system (see Figure 2). The kernel of this system is a case base in which several scenarios (cases) are stored together with the corresponding performance measures. The scenarios are extracted from the simulation output files of METANET. Each scenario is characterized by

- the traffic situation (traffic densities, queue lengths, average speeds, traffic demand, incident status, etc.)
- the traffic control measures that are taken,
- the predicted result on the traffic conditions, i.e. the values of the partial performance measures $J_{\mathsf{sub},i}$.

Hence, given the weights w_i, we can compute the performance J for each scenario and consider it as a function of the traffic situation and the control measures that are applied.

Remark. An important difference between our approach and conventional case-based reasoning is that in case-based reasoning one usually has a fixed solution (for our application this would be a combination of traffic control measures) for each case in the case base. In the conventional case-based reasoning approach only the traffic situation would be used to characterize a case. However, since we consider an objective function J that is a weighted combination of the various performance indicators and

since the weights w_i are not fixed but variable, we cannot directly relate an optimal solution to each case (or traffic situation) and therefore we also have to include the control measures in the characterization of the cases.

When presented with a new traffic situation, we first select for each allowed set of control measures C the K cases (K is a user-defined integer parameter) for which the traffic situation corresponds best to the given traffic situation using a distance function d that describes the distance between two traffic situations. We could e.g. take the Euclidian distance function for d. We use a normalized distance function that is based on fuzzy membership functions. The distance between the current traffic situation, represented by a vector b_{current}, and the traffic situation of case i, represented by the vector b_i, is defined as

$$d(b_{\text{current}}, b_i) = 1 - f_{\text{membership},i}(b_{\text{current}})$$

where $f_{\text{membership},i}$ is the fuzzy membership function that corresponds to case i. The value of $f_{\text{membership},i}$ can be considered to express the degree of similarity between the current traffic situation and the traffic situation of case i: we have 1 for a perfect match and 0 for no similarity at all. This also implies that the distance function d is scaled between 0 and 1 and that its value is independent of the units for the different coordinates of the case vectors. The multidimensional membership function is described in Section 4.

Next we use fuzzy interpolation between these K closest cases to get an estimation of the performance for the combinations of the control measures that correspond to the K cases. Assume without loss of generality that the K closest cases correspond to the vectors b_1, b_2, ..., b_K. Let $J_{\text{case } i}(C)$ express the performance (i.e., the value of J) of the set of control measures C in case i. Then we determine the performance of C in the current traffic situation as

$$J_{\text{current}}(C) = \frac{\sum_{i=1}^{K} f_{\text{membership},i}(b_{\text{current}})\, J_{\text{case } i}(C)}{\sum_{i=1}^{K} f_{\text{membership},i}(b_{\text{current}})} \quad .$$

The best M combinations of control measures are then selected and presented to the operator (where M is again a user-defined integer parameter). By choosing M much smaller than the number of possible combinations of control measures we can significantly reduce the timed needed in the subsequent analysis process by removing from the decision process those combinations for which the performance will probably not be satisfactory.

4 Prototype of the FDSS

We have created a prototype of the decision support system in the mathematical software package Matlab (which includes a scripting language and the possibility to create

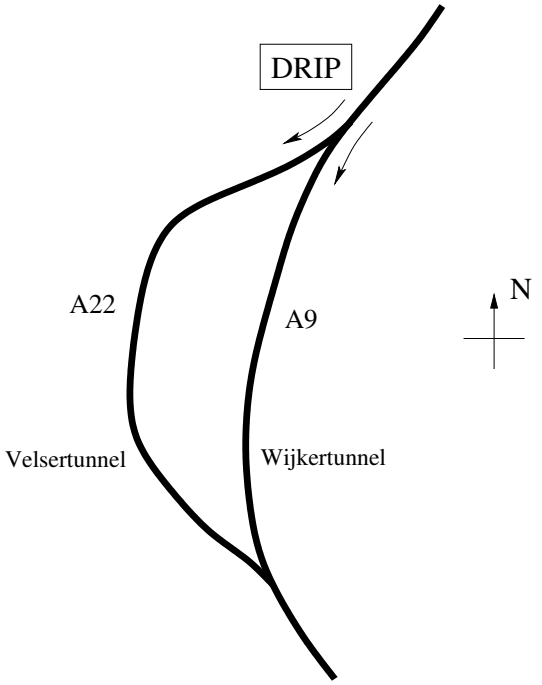

Figure 3: Set-up for the prototype system.

GUIs[2]) for a simple set-up consisting of a highway that at one point splits in two branches — a long one of 13 km (8.1 miles) and a shorter one of 11 km (6.8 miles)), — which join each other again at the end (see Figure 3). This network is part of the larger peri-urban network around the city of Amsterdam in the Netherlands. The long branch is the A22 highway that also includes the Velsertunnel; the shorter branch is part of the A9 highway and includes the Wijkertunnel. The A22 is mostly used for traffic having local origins or destinations whereas the A9 is mostly used for long distance traffic. We only consider traffic going from the north to the south. The two alternative routes that can be followed by the drivers are indicated by the arrows. Near the point where the highway splits there is DRIP that can display queue information. Furthermore, there are also variable direction signs.

There are two inputs for our decision support system (traffic demand and occurrence of incidents) and three possible control measures (c_1: closure of lane 1, c_2: closure of lane 2, and c_3: a Dynamic Route Information Panel (DRIP) message). The set allowed combinations of control measures equals $\{\emptyset, \{c_1\}, \{c_3\}, \{c_1, c_2\}, \{c_1, c_3\}\}$. Note that since our system has been programmed in modular way, the number of inputs and possible control measures can be extended very easily. Due to the small number of inputs we have selected the value $K = 2$ for the number of cases among which the fuzzy interpolation takes place.

The fuzzy membership functions are now defined as follows. We will consider each coordinate of the input space separately when defining the fuzzy membership functions.

[2]GUI: Graphical User Interface.

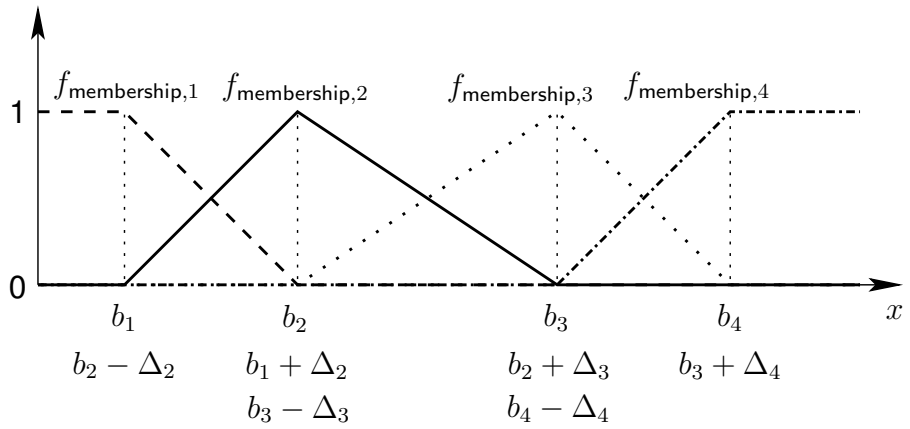

Figure 4: The fuzzy membership functions for real-valued coordinates are triangular functions; b_i is the center point of the ith membership function $f_{\text{membership},i}$ and $\Delta_i = b_i - b_{i-1}$ (for ease of notation the coordinate index j has been omitted in this figure).

The overall membership function $f_{\text{membership},i}$ for case i is then defined as the product of the membership functions $f_{\text{membership},i,j}$ for the separate coordinates:

$$f_{\text{membership},i}(x) = \prod_{j=1}^{m} f_{\text{membership},i,j}(x_j)$$

where m is the number of components of the case vectors.

For coordinates x_j that can only take on discrete values (such as e.g. the incident status, which can only be 0 (no incident) or 1 (incident)), we use singleton membership functions:

$$f_{\text{membership},i,j}(x_j) = \begin{cases} 1 & \text{if } x_j = (b_i)_j \\ 0 & \text{otherwise.} \end{cases}$$

For the real-valued coordinates x_j we use triangular membership functions (see Figure 4).

Figures 5 and 6 show some screenshots of the prototype system. The interface window that is presented to the operators has two modes: operator mode, and expert mode. In the operator mode (see Figure 5) the operator enters the parameters that describe the current traffic situation on the left; on the right she will then see a ranked list of the various possible combinations of control measures. The most promising combination(s) can then be examined in more detail (e.g. by microscopic or macroscopic traffic simulation). In the Weights subscreen of the expert mode view (see Figure 6), the user can specify the weights w_i for the various subcomponents $J_{\text{sub},i}$ of the objective function such as the total travel time (TTT), total waiting time (TWT), total waiting store-and-forward (TWSAF), total time in net (TTIN), total distance traveled (TDT), vehicles in net (VIN), vehicles driven in (VDI), vehicles driven out (VDO), and total fuel consumption (TFC). In the Prediction & Case-Base subscreen the values for each

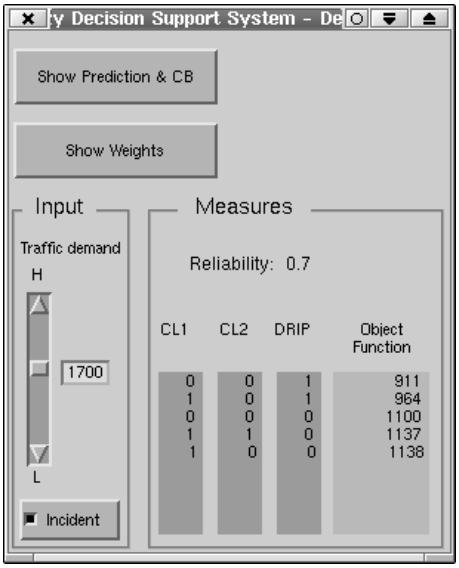

Figure 5: A screenshot of the demo of the decision support system in the operator view.

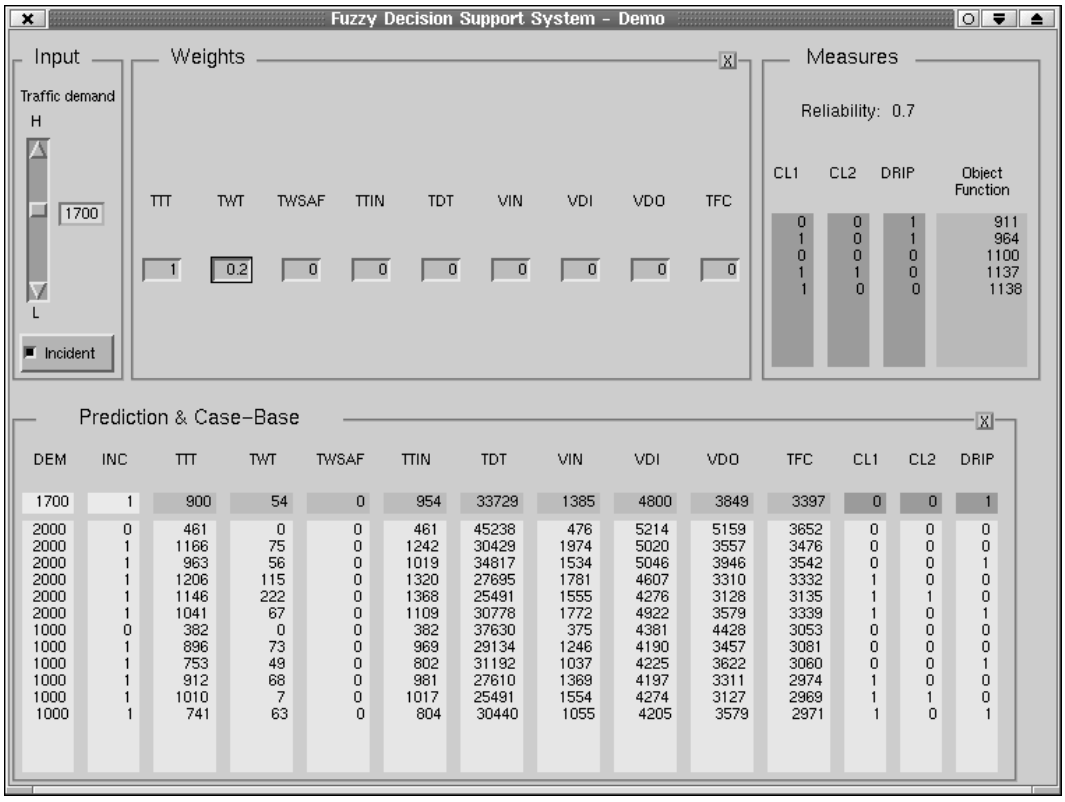

Figure 6: A screenshot of the demo of the decision support system in the expert view.

subcomponent of the objective function are then displayed for the current inputs and for each scenario in the case base. In that way the effects of the choice of the weights and the effects of the various control measures can be examined in more detail. However, this level of detail is usually not needed in daily operation. That is why we have chosen for a system with two modes (operator mode and expert mode).

5 Discussion

We have presented a fuzzy decision support system (FDSS) for traffic control centers. This system is part of a larger traffic decision support system that assists operators of traffic control centers when selecting the most appropriate traffic control measures to efficiently manage non-recurrent congestion. The subsystem we have developed uses a case base and fuzzy interpolation to generate a ranked listing of combinations of control measures and their estimated performance. Since the scenarios in the case base are generated by METANET, the quality of the ranking depends basically on the quality of the simulations. The predictions made by the case-based reasoning system can be made more precise by adding new cases. An important feature of our system is that the performance function is not fixed but consists of a weighted combination of several partial performance measures. In addition, the weights of this combination can be changed on-line depending on the current traffic management policy and on other considerations. Since the case base can be generated off-line, our subsystem reduces the time that is needed to determine the optimal traffic control for a given situation by limiting the number of combinations of control measures for which on-line traffic simulations should be performed in the traffic control center.

The current knowledge base of our FDSS is mainly based on simulations and measured situations. Once the system operates in a real traffic control center, we can include actual situations and the effects of control measures that have actually been applied to the traffic system in our case base. In that way we get an adaptive system that learns during operation. Such a system is described by [10].

Furthermore, the heuristic rules that are known by experienced traffic operators would be a useful addition to our system. Therefore, in the next stage of the project, we will include this knowledge into our system by adding a separate fuzzy knowledge module to our system. This could follow the same framework as the TRYS system presented by [1] and [6].

Another interesting question is how many inputs are needed in a larger traffic network to be able to make adequate decisions. In our network there was only one input link that characterized the traffic state, but in a larger network not only the demands on the input are important, but also the states (speed, density) on the internal links.

Moreover, we have not considered the dynamic aspects of the system. The time-of-day and day-of-week can carry important information about the expected traffic demands. This information could also be utilized to make better decisions.

Since the case-based system is a universal approximator (i.e., an be made arbitrarily precise by adding more cases) the validation of the system is not considered. The

quality of the system depends on the quality of the simulation that generated the cases. In this context the most important question is that — assuming that the quality of the simulation is good — how many cases do we need for a good performance.

References

[1] J. Cuena, J. Hernández, and M. Molina, "Knowledge-based models for adaptive traffic management systems," *Transportation Research Part C*, vol. 3, no. 5, pp. 311–337, Oct. 1995.

[2] A. Karimi and A. Gupta, "Incident management system for Santa Monica Smart Corridor," in *Proceedings of the 63rd Annual Meeting of the Institute of Transportation Engineers*, The Hague, The Netherlands, pp. 180–185, 1993.

[3] W.J.J. Knibbe, "Macroscopic traffic simulation for on-line forecasting," in *Proceedings of the 9th IFAC Symposium on Control in Transportation Systems 2000*, Braunschweig, Germany, pp. 34–39, June 2000.

[4] B. Krause and C. von Altrock, "A complete fuzzy logic control approach for existing traffic control systems," in *Mobility for Everyone, Proceedings of the 4th World Congress on Intelligent Transportation Systems*, Berlin, Germany, Oct. 1997. Paper no. 2045.

[5] A. Messmer and M. Papageorgiou, "METANET: A macroscopic simulation program for motorway networks," *Traffic Engineering and Control*, vol. 31, no. 8/9, pp. 466–470, Aug./Sept. 1990.

[6] M. Molina, J. Hernández, and J. Cuena, "A structure of problem-solving methods for real-time decision support in traffic control," *International Journal of Human-Computer Studies*, vol. 49, no. 4, pp. 577–600, Oct. 1998.

[7] S.G. Ritchie, "A knowledge-based decision support architecture for advanced traffic management," *Transportation Research Part A*, vol. 24, no. 1, pp. 27–37, Jan. 1990.

[8] S.G. Ritchie and N.A. Prosser, "Real-time expert system approach to freeway incident management," *Transportation Research Record*, no. 1320, pp. 7–16, 1991.

[9] D. Roseman and S.S. Tvedten, "Santa Monica Freeway Smart Corridor project operational multi-agency traffic management and expert system," in *Mobility for Everyone, Proceedings of the 4th World Congress on Intelligent Transport Systems*, Berlin, Germany, Oct. 1997. Paper no. 1032.

[10] A.W. Sadek, M.J. Demetsky, and B.L. Smith, "Case-based reasoning for real-time traffic flow management," *Computer-Aided Civil and Infrastructure Engineering*, vol. 14, no. 5, pp. 347–356, Sept. 1999.

[11] H. Zhang and S.G. Ritchie, "Real-time decision-support system for freeway management and control," *Journal of Computing in Civil Engineering*, vol. 8, no. 1, pp. 35–51, 1994.