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A Fuzzy Decision Support System for Traffic Control Centers

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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 is part of a larger traffic decision support system (TDSS) 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 the system is a fuzzy case base that is constructed using simulated scenarios. By using the case base and fuzzy interpolation the decision support system generates a ranked list of combinations of traffic control measures. The best combinations can then be examined in more detail by other modules of the TDSS that evaluate or predict their performance using macroscopic or microscopic traffic simulation. At a later stage the fuzzy decision system will be complemented with an adaptive learning feature and with a set of fuzzy rules that incorporate heuristic knowledge of experienced traffic operators.**

I. Introduction

Contemporary traffic control centers use dynamic traffic management measures such as ramp metering, DRIPs (dynamic route information panels) or VMS (variable message signs) to control traffic flows on highways and urban ring roads. The DRIPs can be used to display queue length information, or indications of congestion, traffic jams and alternative routes. VMS can be used to show dynamic speed limits per lane, advisory speeds, or lane closures. Recurrent congestion can usually be managed satisfactorily by 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 not sufficient and often an intervention at the network level is required to manage congestion and to return to a normal traffic situation.

The effects of non-recurrent congestion can be 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 control measures. This is a complex task, which requires expert knowledge and much experience, which can often be obtained after extensive training only. 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 human operators, and that uses 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. Furthermore, in order to increase the acceptance of the decision support system by the traffic operators, it is designed as an advisory and analysis tool that assists the operators (instead of trying to replace them).

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 overall system is a 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 signals or ramp metering. At a higher level the operation of several local traffic controllers is coordinated or synchronized by supervisory controllers. The role of the fuzzy decision support system in this set-up is to suggest whether a particular local traffic controller or control measure should be activated or not.

Several authors have described decision support systems for traffic management, such as FRED (Freeway Real-Time Expert System Demonstration) [1], [2], [3], or the Santa Monica Smart Corridor Demonstration Project [4], [5]. However, these architectures do not use fuzzy logic in their decision process. Since we want a system with an intuitive operation process that is able to generate decisions in cases that are

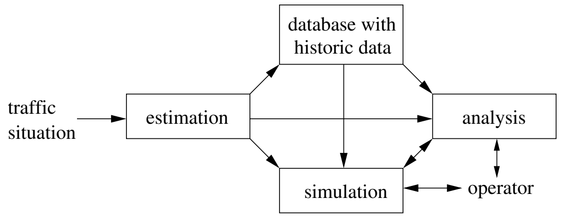

Fig. 1. The overall traffic decision support system (TDSS).

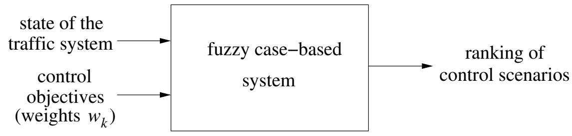

Fig. 2. The fuzzy case-based decision support system.

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 [6], [7], [8]. The TRYS system described in [6], [8] is an agent-based system for urban motorway control. The network is divided in possibly overlapping regions and to each region an agent is assigned. The agent has to detect and diagnose traffic problems in its region and subsequently suggest possible control measures to a higher level coordinator, that then decides which action will actually be taken. The decision process in the TRYS system is based on knowledge frames, and some of these frames use fuzzy logic. The paper [7] describes a fuzzy logic control architecture that can be applied in existing traffic control systems on a multi-lane highway with VMS. This system uses fuzzy logic to incorporate the experience of human traffic operators.

This paper is organized as follows. First, we describe the overall traffic decision support system of which the fuzzy decision support system is a subsystem. Next, we describe the set-up and operation of the fuzzy decision support system and a small prototype we have developed to assess the technical feasibility of the proposed approach. Finally, we propose possible extensions of the current system.

We assume that the reader is familiar with the basic concepts of fuzzy logic[1]. More information on fuzzy logic and fuzzy set theory can be found in [9], [10], [11] and the references therein.

II. Overall framework

The system we are developing is a part of a larger traffic decision support system (TDSS) [12] 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 indicators of the current traffic situation, such as 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 [13] 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 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.

[1]In fact the only concept from fuzzy logic used in this paper is that of *membership function*, which expresses the degree (between 0 and 1) to which an element belongs to a set or has a certain property.

III. The fuzzy decision support system

A. Structure

The fuzzy decision support system selects optimal combinations of traffic control measures for a given situation by using a weighted performance index J, defined as

$$J = \sum_{k=1}^{N} w_k J_{\mathrm{sub},k}$$

where the $J_{\mathrm{sub},k}$'s are partial performance indices such as predicted queue lengths, total travel times, waiting times, fuel consumption, etc. The weights w_k are not necessarily 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.

Let S_{cm} be the set of possible traffic control measures, such as lane closures, ramp metering, DRIP messages, etc. In general, we can combine several traffic control measures. However, not all combinations of control measures are possible or allowed. Therefore, we define a set $\mathcal{S}_{\mathrm{cm}} \subset 2^{S_{\mathrm{cm}}}$ of allowed combinations of traffic control measures.

As a starting point for the 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 are stored together with the corresponding partial performance index values. Each scenario or case is characterized by

- the traffic situation (traffic densities, queue lengths, average speeds, traffic demand, etc.), which we assume to be representable by a vector b_i belonging to a multi-dimensional space $\mathcal{B}$;
- the traffic control measures that are taken, i.e., an element C_i of the set $\mathcal{S}_{\mathrm{cm}}$;
- the predicted effect of C_i on the traffic conditions for traffic situation b_i, i.e., the values of the partial performance indices $J_{\mathrm{sub},k}(b_i, C_i)$.

So case i is represented in the case base by the tuple $(b_i, C_i, J_{\mathrm{sub},1}(b_i, C_i), \ldots, J_{\mathrm{sub},N}(b_i, C_i))$. Hence, given the

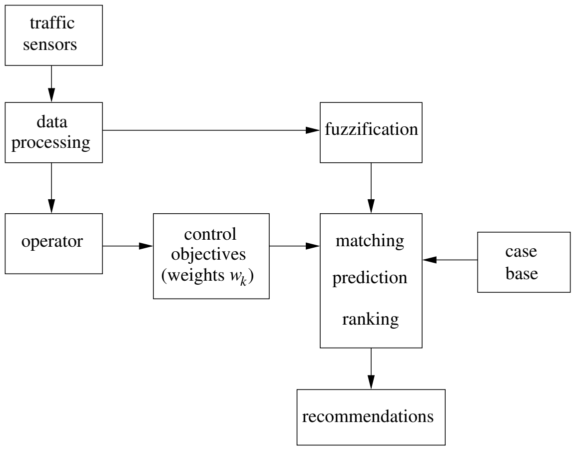

Fig. 3. A detailed view of the FDSS.

weights w_k, we can compute the total performance $J(b_i, C_i)$ of the set of control measures C_i in traffic situation b_i:

$$J(b_i, C_i) = \sum_{k=1}^{N} w_k J_{\mathrm{sub},k}(b_i, C_i) \ . \tag{1}$$

Remark. An important difference between our approach and conventional case-based reasoning is that in conventional 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. So 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 various performance indicators and since the weights w_k 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 and the values of the partial performance indices $J_{\mathrm{sub},i}$ in the characterization of the cases.

The core of the fuzzy decision process involves three steps: matching, prediction and ranking (see Figure 3).

B. Matching

When presented with a new traffic situation that does not appear in the case base, we have to select the cases for which the traffic situation corresponds best to the given traffic situation. This is done using a similarity function based on fuzzy membership functions that describes the degree of similarity between two traffic situations. The similarity between the current traffic situation, represented by the vector b_{current}, and the traffic situation of case i, represented by the vector b_i, is characterized by $f_{\mathrm{mbs},i}(b_{\mathrm{current}})$ where $f_{\mathrm{mbs},i}$ is the fuzzy membership function that corresponds to case i. Note that the range of $f_{\mathrm{mbs},i}$ is $[0, 1]$. So the similarity ranges from 0 for no similarity at all to 1 for a perfect match.

C. Prediction

Suppose that we want to predict the performance of the set of control measures C in the current traffic situation. First, we use the similarity measure introduced in previous subsection to select the K cases (K is a user-defined integer parameter) for which the traffic situation corresponds best to the current situation and in which the set of control measures $C_i = C$ is present. Assume without loss of generality that the K closest cases correspond to the vectors $b_1, b_2, \ldots, b_K \in \mathcal{B}$. Note that we have $C_1 = C_2 = \ldots = C_K = C$. Recall that $J(b_i, C)$ expresses the total performance J of the set of control measures C $(= C_i)$ in case i (cf. (1)). Then we estimate the performance of C in the current traffic situation as

$$\hat{J}(b_{\mathrm{current}}, C) = \frac{\sum_{i=1}^{K} f_{\mathrm{mbs},i}(b_{\mathrm{current}})\, J(b_i, C)}{\sum_{i=1}^{K} f_{\mathrm{mbs},i}(b_{\mathrm{current}})} \ .$$

D. Ranking

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 total number of combinations in $\mathcal{S}_{\mathrm{cm}}$ 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.

E. Membership functions

For each case i we define a membership function $f_{\mathrm{mbs},i}$. Recall that this membership function is used to express the degree of similarity between the current traffic situation and the traffic situation in case i. There are several possible membership functions such as trapezoidal, bell-shaped, and triangular. We have opted for the latter option.

We consider each coordinate of the space $\mathcal{B}$ separately when defining the membership functions. The overall membership function $f_{\mathrm{mbs},i}$ for case i is then defined as the product of the membership functions $f_{\mathrm{mbs},i,j}$ for the separate coordinates:

$$f_{\mathrm{mbs},i}(x) = \prod_{j=1}^{m_{\mathcal{B}}} f_{\mathrm{mbs},i,j}(x_j)$$

where $m_{\mathcal{B}}$ is the dimension of the space $\mathcal{B}$.

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

$$f_{\mathrm{mbs},i,j}(x_j) = \begin{cases} 1 & \text{if } x_j = b_{i,j} \\ 0 & \text{otherwise} \end{cases}$$

where $b_{i,j} = (b_i)_j$. Note that by using singleton membership functions for discrete-valued coordinates, the similarity between a situation with an incident and a case with no incident will always be 0, so that a case with no incident will never be used to determine the performance of control measures in an incident situation.

For the real-valued coordinates x_j we use triangular membership functions that can be parameterized using a width factor $\nu \in [0, \infty]$ (see Figure 4) and that are defined as follows.

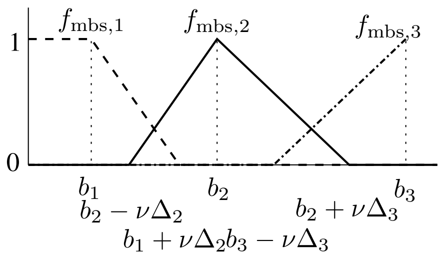

Fig. 4. The membership functions for real-valued coordinates used in the prototype are triangular functions parameterized using a width factor $\nu \in [0, \infty]$; b_i is the center point of the ith membership function $f_{\mathrm{mbs},i}$ and $\Delta_i = b_i - b_{i-1}$ (for ease of notation the coordinate index j has been omitted in these figures).

Assume that there are n cases b_1, b_2, …, b_n in the case base. Let $\Delta_{i,j} = b_{i,j} - b_{i-1,j}$. The membership function $f_{\mathrm{mbs},i,j}$ for the real-valued coordinate x_j has $b_{i,j}$ as its center point and is defined as

$$f_{\mathrm{mbs},i,j}(x_j) = \max\Bigg(0, \min\Big(\frac{1}{\nu\Delta_{i,j}}\big(x_j - (b_{i,j} - \nu\Delta_{i,j})\big), \\ -\frac{1}{\nu\Delta_{i+1,j}}\big(x_j - (b_{i,j} + \nu\Delta_{i+1,j})\big)\Big)\Bigg)$$

for $i = 2, \ldots, n-1$. So $f_{\mathrm{mbs},i,j}(x_j)$ is the piecewise affine curve that connects the points $(-\infty, 0)$, $(b_{i,j} - \nu\Delta_{i,j}, 0)$, $(b_{i,j}, 1)$, $(b_{i,j} + \nu\Delta_{i+1,j}, 0)$ and $(\infty, 0)$. The "border" membership functions $f_{\mathrm{mbs},1,j}$ and $f_{\mathrm{mbs},n,j}$ are defined as

$$f_{\mathrm{mbs},1,j}(x_j) = \max\Bigg(0, \min\Bigg(1, \\ -\frac{1}{\nu\Delta_{2,j}}\big(x_j - (b_{1,j} + \nu\Delta_{2,j})\big)\Bigg)\Bigg)$$

$$f_{\mathrm{mbs},n,j}(x_j) = \max\Bigg(0, \min\Bigg(1, \\ \frac{1}{\nu\Delta_{n,j}}\big(x_j - (b_{n,j} - \nu\Delta_{n,j})\big)\Bigg)\Bigg) \ .$$

So $f_{\mathrm{mbs},1,j}$ is 1 to the left of the first center point coordinate $b_{1,j}$ and $f_{\mathrm{mbs},n,j}$ is 1 to the right of the last center point coordinate $b_{n,j}$.

The parameter ν defines the width or degree of overlapping between the membership functions. The value $\nu = 0.5$ corresponds to non-overlapping membership functions that still cover the whole coordinate axis, so that in every point that is not a center point at least one membership function is nonzero. For $\nu = 0$ all non-border membership functions are 0 everywhere except in their center point where the function value is 1 (note that this corresponds to the singleton membership functions we have used for the discrete-valued coordinates). The choice $\nu = \infty$ would correspond to membership functions that are identically 1 over the whole input range. If $\nu = 1$ then in any point of the input space that is not a center point and that lies between the first and the last center point, exactly two membership functions are nonzero. The designer of the system can change the value of ν. Also note that due to the modular approach used in the prototype system we can easily replace the triangular membership functions by trapezoidal or bell-shaped membership functions.

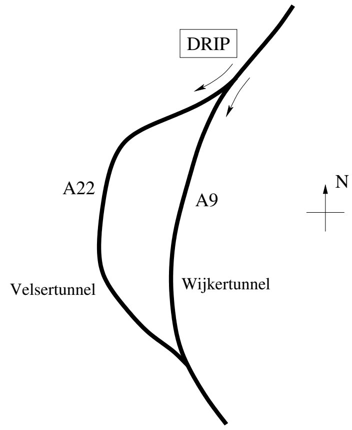

Fig. 5. Layout considered in the prototype system.

IV. Prototype of the FDSS

In order to *assess* the *technical feasibility* of the approach proposed above we have created a small prototype of the decision support system in the mathematical software package Matlab (which includes a programming language and the possibility to create graphical user interfaces (GUIs)) for a simple traffic system consisting of a highway that at one point splits in two branches — a longer one of 13 km and a shorter one of 11 km, — which join each other again at the end (see Figure 5). Both branches have two lanes for each direction. This network is part of the larger peri-urban network around the city of Amsterdam in the Netherlands. The longer 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 a DRIP that can display queue information.

Since at this stage of the project we only wanted to assess the technical feasibility of the system we have only considered a limited number of inputs, control measures and cases. Note, however, that since our system has been programmed in modular way, the number of inputs, possible control measures and cases can be extended very easily.

There are two inputs for the decision support system: traffic demand and occurrence of incidents on the A9; and three possible control measures:

- c_1: closure of lane 1 on the A9 (upstream of the incident),
- c_2: closure of lane 2 on the A9 (upstream of the incident),
- c_3: display a DRIP message.

The set $\mathcal{S}_{\mathrm{cm}}$ of allowed control measures equals $\{\emptyset, \{c_1\}, \{c_3\}, \{c_1, c_2\}, \{c_1, c_3\}\}$. The case base has been constructed using 10 METANET [13] simulations. Due to the small number of inputs and cases we have selected the value $K = 2$ for the number of cases among which the fuzzy interpolation takes place. For the width factor ν of the membership functions we have selected the default value $\nu = 1$.

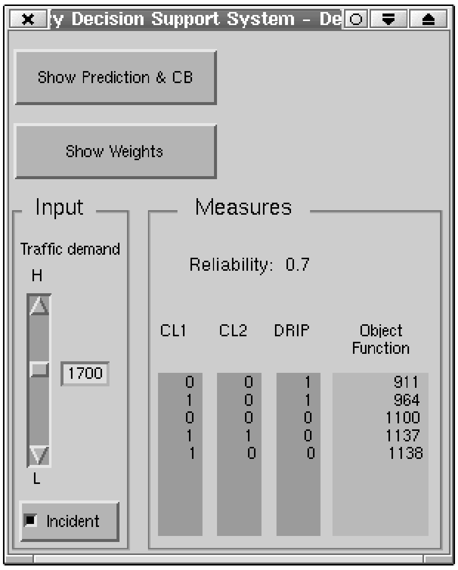

Fig. 6. A screenshot of the prototype of the decision support system in the operator view (with control measures CL1: close lane 1, CL2: close lane 2, and DRIP: display a DRIP message).

Figures 6 and 7 show some screenshots of the prototype system. The interface window that is presented to the operators has two modes: operator or basic mode, and expert or full mode. In the basic mode (see Figure 6) 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, and an indication of the reliability, i.e., the maximal degree of similarity between the current traffic situation and that of the cases in the fuzzy case base. The most promising combination(s) of control measures can then be examined in more detail (e.g., by microscopic or macroscopic traffic simulation). In the Weights subscreen of the full mode view (see Figure 7), the user can specify the weights w_k for the various subcomponents[2] $J_{\mathrm{sub},k}$ 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 subcomponent $J_{\mathrm{sub},k}$ 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 for daily operation. That is why we have chosen for a system with two modes (operator mode and expert mode).

V. Extensions

The current knowledge base of our FDSS is mainly based on simulations. 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 in [14]. We then get a process that consists of the cyclic application of the following steps:

1) Retrieve the most similar cases (in our case the similarity can be determined using the membership function as has been explained above).
2) Use these cases to solve the problem (in our case: to generate the ranking of the combinations of control measures using fuzzy interpolation).
3) Revise the proposed solution (in our case: see how the traffic system reacts to the proposed solution, i.e., determine or measure its performance).
4) Retain the parts of this experiences to be used for future application.

Furthermore, the heuristic rules that are known to experienced traffic operators would be a useful addition to our system. Therefore, at a later stage, 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 in [6], [8].

VI. Conclusions

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 FDSS 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 the 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, the FDSS 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. At a later stage the system can be extended with a fuzzy module that incorporates expert knowledge and with an adaptive learning module.

Currently we have demonstrated the technical feasibility of the system. In the next stage of the project we will examine the performance of the system (for a larger network than the one described in this paper), see how the parameters of the system have to tuned to improve the performance, and compare this performance with other traffic control strategies using both simulations and field experiments. The quality of the FDSS depends on the quality of the simulations that generated the

[2]The partial performance measures have been extracted from the METANET simulations that have been used to generate the cases for our simple prototype system. Due to the modular approach we have used, other partial performance measures can easily be included.

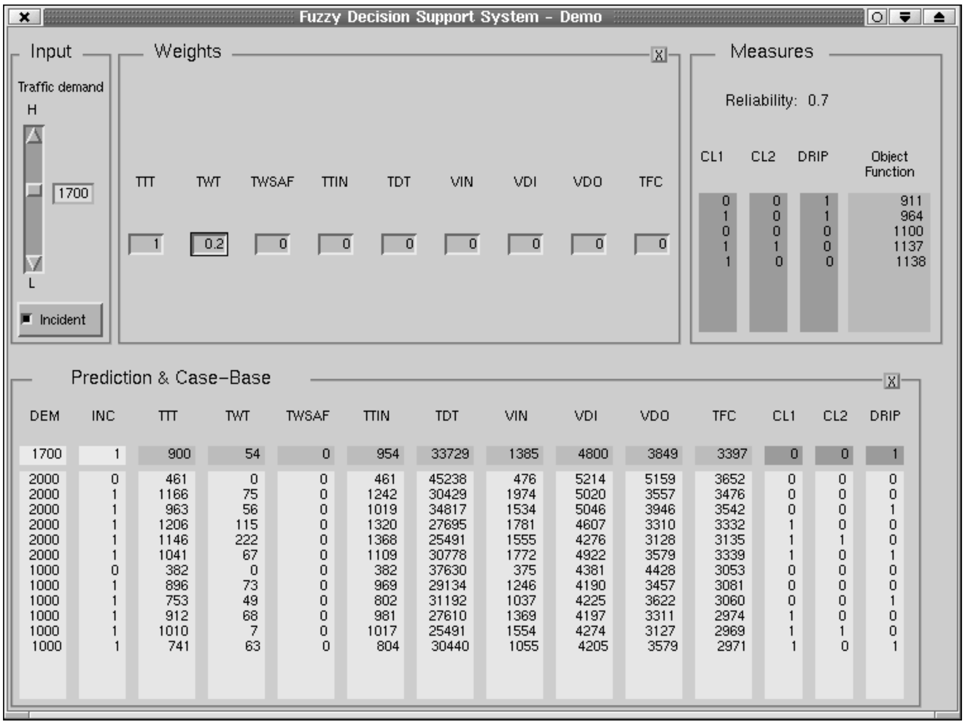

Fig. 7. A screenshot of the prototype of the decision support system in the expert view.

cases. In this context an important question is — assuming that the quality of the simulation is good — how many cases do we need for a good performance. Another interesting question is how many inputs are needed in a larger traffic network to be able to make adequate decisions. Moreover, the time-of-day and day-of-week can carry important information about the expected traffic demands. This information could also be used to make better decisions. If the number of inputs and control measures increases, the number of cases also has to increase, which might lead to tractability problems. These problems can be addressed by using a multi-level decision support architecture. The design of such an architecture will also be a topic for future research.

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