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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 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.

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). 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 often can only be obtained after extensive training. As a result, the approaches used by human operators in traffic control centers are in general not 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 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. The inputs for the fuzzy decision support system are the current state of the network and the optimization criterion, such as minimal travel time, maximal throughput, or a weighted combination of several criteria. First, the inputs are fuzzified, i.e. translated into linguistic terms (e.g. a measured traffic density could be classified as uncongested, regular,
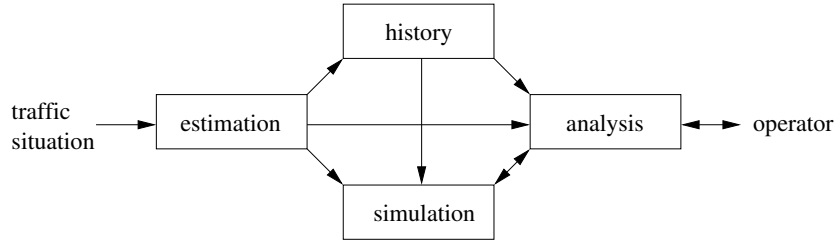
Figure 1: The overall traffic decision support system (TDSS).

dense or congested traffic, with a specific membership degree for each class). Next, we use a fuzzy knowledge base to determine the best policy for the given inputs. This fuzzy knowledge base is constructed using results of extensive traffic simulations for several traffic situations and combinations of traffic control measures, and complemented by rules and heuristics provided by experienced operators. 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.

Several authors have described decision support systems for traffic management (see e.g. Ritchie (1990) and Zhang, Ritchie (1994)). 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 by Cuena, Hernández, Molina (1995) and Krause, von Altrock (1997).

OVERALL FRAMEWORK

When non-recurrent congestion occurs on an urban ring road or a highway network, then often local control is not sufficient any more and measures on the network level are necessary to adequately deal with congestion. Selecting the appropriate measures is a difficult task for the operators in the traffic control centers. This entails estimating and predicting the effects of certain control measures on the traffic situation in the entire network. Moreover, the operator should have a good insight in the range of control measures that are available, and should be able to quickly perform an analysis of the current and future situation and then select the most appropriate measures. In general, the outcome of this process will depend heavily on the experience of the operator. Furthermore, the decision process is not structured and not uniform. Therefore, there is certainly a need for a system that can help the traffic operators in their difficult task. In order to increase the acceptance of the system by the traffic operators, the system should be designed as an advisory and analysis tool that assists the operators (instead of trying to replace them).

The system we are developing is a part of a larger traffic decision support system (TDSS) 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.). Based on the measurements, historic data and traffic simulation, the system predicts the future traffic situation. If necessary, the simulation can be repeated for several combinations of control measures. Afterwards, the operator can select the most appropriate control strategy. 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.

THE FUZZY DECISION SUPPORT SYSTEM

Our intelligent decision support system selects optimal combinations of traffic control measures for a given
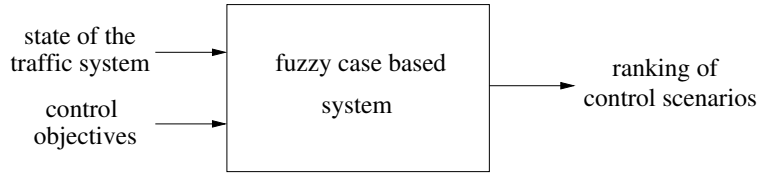
Figure 2: The fuzzy case-based decision support system.

situation using a weighted performance measure or objective function J, which is defined as

$$J = \sum_{i=1}^{N} w_i J_i$$

where the weights w_i are determined by the user and where the J_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 by the user (i.e. the operator in the traffic control center) depending on current traffic management policies and other considerations.

Let C be the set of possible traffic control measures, such as lane closures, ramp metering, dynamic route information message, 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 $\mathcal{C} \subset 2^C$ of allowed combinations of traffic control measures.

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 are stored together with the corresponding performance measures. Each scenario is characterized by

- the traffic situation (traffic densities, queue lengths, average speeds, traffic demand, etc.)

- the traffic control measures that are taken, i.e. an element of the set $\mathcal{C}$

- the predicted result on the traffic conditions, i.e. the values of the partial performance measures J_i.

So 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 that does not appear in the case base, we first select the K cases (K is a user-defined integer parameter) for which the input parameters correspond best to the given traffic situation using a distance function d that describes the distance between two cases (we could e.g. take a weighted Euclidian norm for d). Then we use a fuzzy interpolation[1] between these K cases to get an estimation of the performance for the combinations of the control measures that correspond to the K cases. The best M combinations are then selected and presented to the operator (where M is again a user-defined integer parameter). By choosing M much smaller that the number of combinations in $\mathcal{C}$ 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. A more detailed representation of the operation of our fuzzy decision support system is given in Figure 3.

We have created a prototype of the decision support system in Matlab for a simple set-up consisting of a highway that at one point splits in two branches (a long one and a shorter one) which join each other again after a while (see Figure 4). We only consider traffic going from the north to the south. There are

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[1]The weight for each case is equal to the value of the corresponding fuzzy membership function. The user can specify and change the fuzzy membership functions.
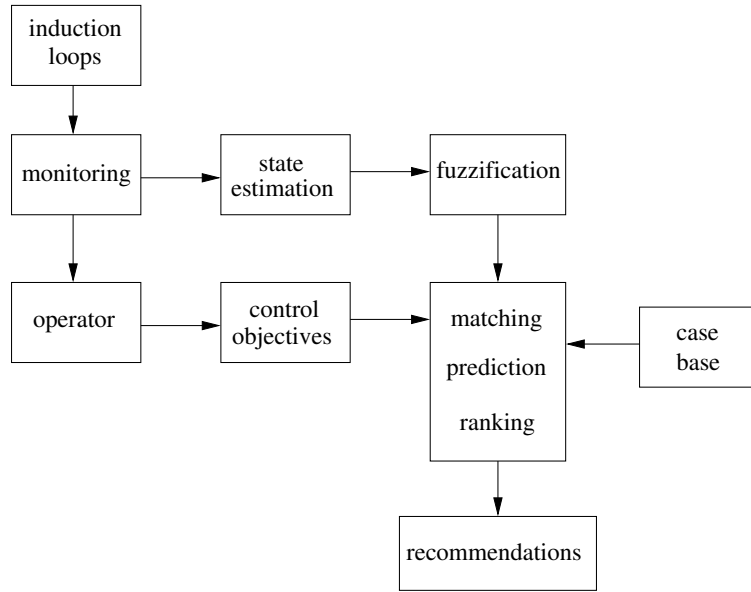
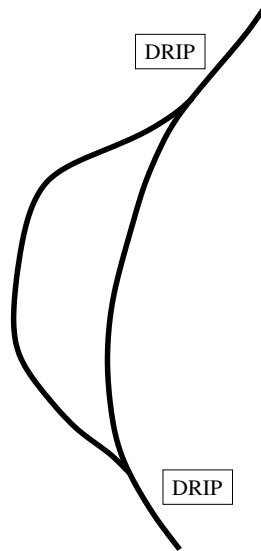Figure 3: A detailed view of the fuzzy case-based decision support system.

Figure 4: Set-up for the prototype system.

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 DRIP[2] message). The set $\mathcal{C}$ 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.

Figures 5 and 6 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 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 simulation). In the Weights subscreen of the full mode view (see Figure 6), the user can specify the weights w_i for the various subcomponents J_i of the objective function such as the total travel time, total waiting time, total waiting store-and-forward, total time in net,

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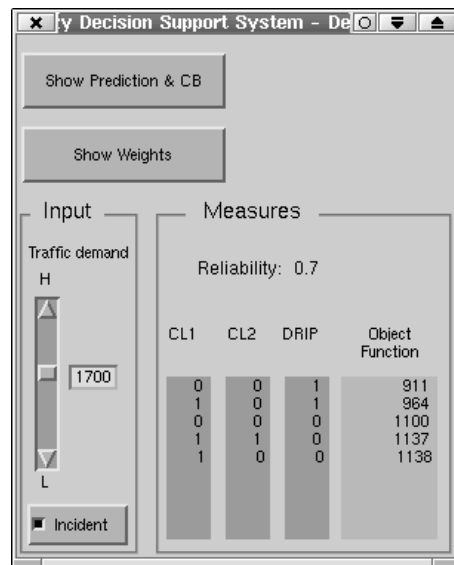
[2]DRIP: Dynamic Route Information Panel.

Figure 5: A screenshot of the demo 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).
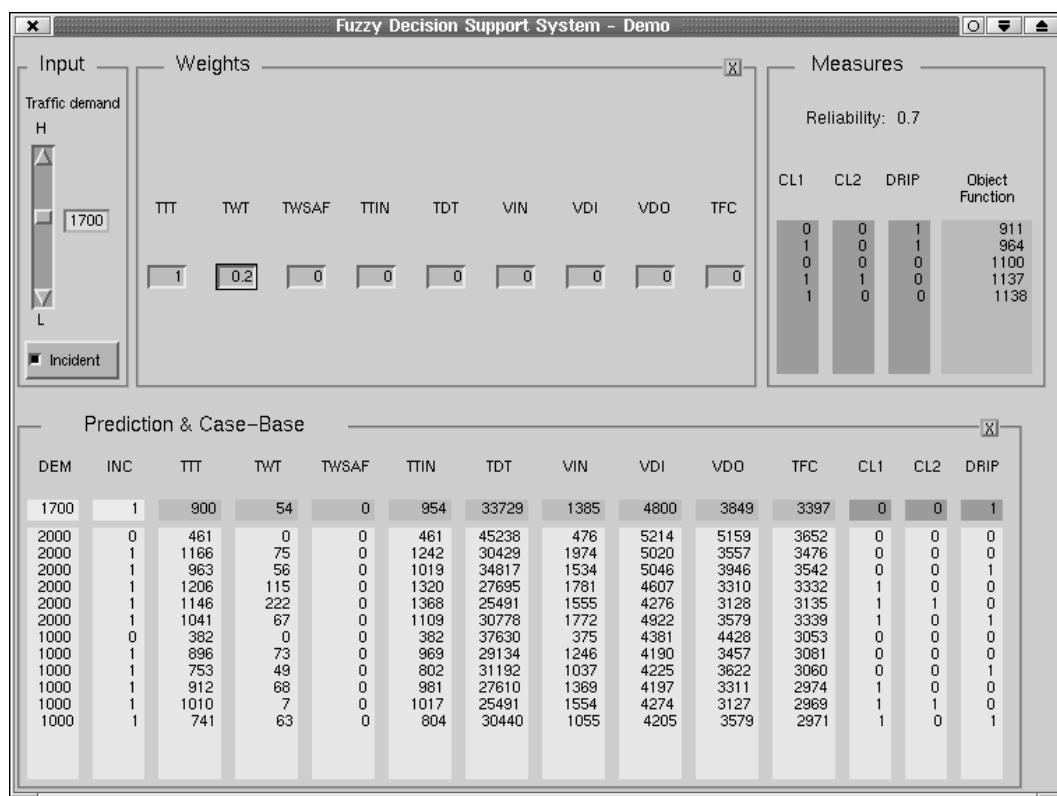

Figure 6: A screenshot of the demo of the decision support system in the full view (with DEM: traffic demand, INC: incident status, TTT: total travel time, TWT: total waiting time, TWSAF: total waiting store and forward, TTIN: total time in net, TDT: total distance traveled, VIN: vehicles in net, VDI: vehicles driven in, VDO: vehicles driven out, and TFC: total fuel consumption).

total distance traveled, vehicles in net, vehicles driven in, vehicles driven out, and total fuel consumption. In the Prediction & Case-Base subscreen the values for each 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).

EXTENSIONS

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 Sadek, Demetsky, Smith (1999). 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 could be determined using a (fuzzy) distance function).

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 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 Cuena, Hernández, Molina (1995) and Molina, Hernández, Cuena (1998).

CONCLUSIONS

In this paper we have presented the fuzzy decision support system that we are currently implementing. 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 logic to generate a ranked listing of combinations of control measures and their estimated performance. 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. In a later stage the system can be extended with a fuzzy module that incorporates expert knowledge and with an adaptive learning module.

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