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A Multi-Agent Case-Based Traffic Control Scenario Evaluation System

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***Abstract*—Traffic operators in traffic control centers have various measures at their disposition to control the traffic flows on motorways and on urban roads such as ramp metering, variable speed limits, dynamic route guidance, opening of shoulder lanes, etc. When having to determine which of these control measures have to be applied and where they have to be applied for a given traffic situation, the traffic operator should be able to predict the effect of a control scenario in order to be able to select the best scenario. As on-line, real-time simulation of a large number of possible scenarios is usually not tractable for even relatively small motorway networks, a fast method to predict the effects of control measures on-line is a key requirement for effectively applying traffic control. In this paper we develop a multi-agent case-based approach to assist traffic operators in evaluating or predicting the effects of control measures. The proposed approach is much faster than straightforward traffic simulation so that it can be used for on-line and real-time evaluation of a large number of different control scenarios. In addition, it is scalable so that it can also be used for large networks.**

***Index Terms*—Traffic flow control, case-based scenario evaluation, coordinated control, prediction, multi-agent control, fuzzy control.**

I. Introduction

Contemporary traffic control centers use dynamic traffic management measures such as ramp metering, DRIPs (dynamic route information panels) or VMSs (variable message signs) to control traffic flows on motorways and urban ring roads. The DRIPs can be used to display queue length information or indications of congestion, traffic jams and alternative routes. VMSs 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 over 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 expert knowledge and much experience, which can often only be obtained after extensive training. As a result, the approaches used by human traffic operators are in general neither structured nor uniform. Therefore, the aim is to provide a decision support tool to assist the operators 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. 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 decision support system presented in this paper 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 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 and visualized 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. As on-line simulation of a large number of different control scenarios via microscopic or macroscopic is usually not tractable, the system proposed in this paper uses a case-base that is constructed off-line. The current situation is then compared with the cases in the case base, and based on the similarity between the current traffic situation and the cases in the case base a prediction can be made about the effects of a given control scenario.

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. 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.

The number of cases in the case base should be sufficiently large to cover a wide range of operating conditions and control measures. The system presented in this paper is a major extension and improvement of the system we have developed in [1]. As the latter system did not scale well, it could only be used for small-sized networks and for a limited number of traffic situations and control scenarios. In order to obtain a scalable system we have now opted for a multi-agent approach where the total network is divided in (possible overlapping) subnetworks, each of which has its own case base and evaluation agent. In that way, we can effectively deal with the combinational explosion of the number of cases that is required to cover the state and control measure space as the size of the network grows.

Several authors have described decision support systems for traffic management, such as FRED (Freeway Real-Time Expert System Demonstration) [2], [3], [4], or the Santa Monica Smart Corridor Demonstration Project [5], [6]. 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 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 [7], [8], [9].

II. Overall framework

The system we are developing is a part of a larger traffic decision support system (TDSS) [10] 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 traffic flow model [11], [12] to make a forecast of the traffic situation). In that way we can also predict the performance of the traffic control measures (such as ramp metering, lane closures, shoulder lane openings, or rerouting via DRIP messages) 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

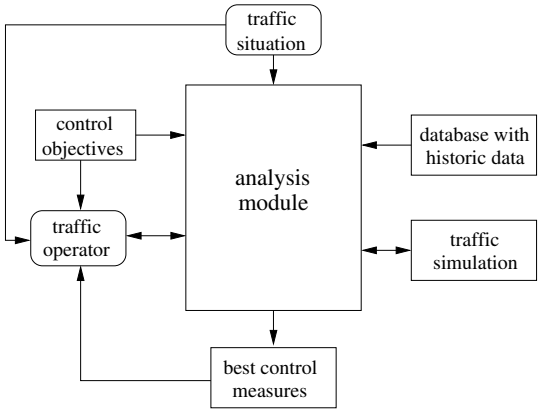

Fig. 1. The overall traffic decision support system (TDSS). The TCSES traffic control scenario evaluation system is a part of the analysis module.

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 (via a quick assessment based on the operator's experience or by a real-time traffic simulation program). Afterward, the operator can select the most appropriate control strategy.

III. The traffic control scenario evaluation system (TCSES)

A. Structure

Consider a traffic network consisting of several motorway stretches (also called links). Traffic enters the network via origin links (e.g., on-ramps or motorway links coming from outside the network), and leaves the network via destination links (e.g., off-ramps or motorway links going out of the network). The given traffic network will be divided into tractable subnetworks. Note that the subnetworks may overlap. In addition, each subnetwork will be divided into several subsubnetworks. Let $n_{\rm sub}$ be the number of subnetworks.

For each of the subnetworks a case base will be constructed with cases that describe the traffic situation in the subnetwork, the (predicted) boundary conditions (i.e., inflow demands and outflow restrictions), the control measures, the incident status. Let $T_{\rm pred}$ be the period over which the prediction will occur.

The structure of the cases in the case base is illustrated in Table I. Consider subnetwork j. The current state $x^{(j)}$ at time t of the subnetwork j is characterized by the average state (consisting of, e.g., densities, flows, speeds) in each subsubnetwork. The same holds for the "input" boundary conditions $d^{(j)}$ in the period $[t, t+T_{\rm pred}]$, where also the averages for each subsubnetwork are taken. The "input" boundary conditions are those conditions that determine the evolution

TABLE I
REPRESENTATION OF THE STRUCTURE OF THE CASE BASE FOR SUBNETWORK j.

Case number	Time	Initial state	Predicted boundary conditions (input)	Control scenario	Incident status	Predicted performance	Predicted boundary conditions (output)
1	$t^{(j)}_{\text{case } 1}$	$x^{(j)}_{\text{case } 1}$	$d^{(j)}_{\text{case } 1}$	$u^{(j)}_{\text{case } 1}$	$z^{(j)}_{\text{case } 1}$	$p^{(j)}_{\text{case } 1}$	$y^{(j)}_{\text{case } 1}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
n_j	$t^{(j)}_{\text{case } n_j}$	$x^{(j)}_{\text{case } n_j}$	$d^{(j)}_{\text{case } n_j}$	$u^{(j)}_{\text{case } n_j}$	$z^{(j)}_{\text{case } n_j}$	$p^{(j)}_{\text{case } n_j}$	$y^{(j)}_{\text{case } n_j}$

of the subnetwork in $[t, t+T_{\text{pred}}]$ such as the demands at the origin links that belong to subnetwork j, the inflows coming from the other subnetworks, and the output restrictions at the destination links that belong to subnetwork j and on the outflow links to other subnetworks. Traffic control measures are subdivided in globally operating measures (such as route guidance) that have an effect in the entire network, and local measures (such as ramp metering or variable speed limits) that mainly influence the traffic flows within the subnetwork. If in the period $[t, t+T_{\text{pred}}]$ global traffic measures are active somewhere in the network, then these measures are included in the corresponding cases for each subnetwork. Local measures are only included in the case for the subnetwork in which they are active. The components of the control scenario vector $u^{(j)}$ will vary between 0 (no control) and 1 (control active during the entire period $[t, t+T_{\text{pred}}]$ and in all controllable traffic links of the network (for global measures) or of the subnetwork (for local measures)). The incident status $z^{(j)}$ is also recorded in a similar way, i.e., we determine the severity (capacity reduction caused by the incident) and the duration of the incident. The performance vector $p^{(j)}$ over $[t, t+T_{\text{pred}}]$ contains the average values for quantities such as vehicle loss hours, total travel time, total travel distance, total time spent, average vehicle speed, total fuel consumption, etc. (see also the list of performance criteria in the screenshot of Figure 3). The "output" boundary conditions $y^{(j)}$ consist of the average flows to the other subnetworks in $[t, t+T_{\text{pred}}]$ and of the outflow restrictions for the other subnetworks in $[t, t+T_{\text{pred}}]$.

The cases can be generated in several ways, e.g., using macroscopic traffic simulation, microscopic traffic simulation, or by considering actual measurements of traffic situations during a given period. The initial case base will be generated off-line. Furthermore, once the system operates in a real traffic control center, we can extend it with an adaptive learning module. Then, if necessary, cases can be added on-line, e.g., if an encountered traffic situation is not sufficiently covered by the cases already present in the case base. For the newly added cases, we could either use simulation or actual traffic evolutions. This results in an adaptive system that learns during operation. Such a system is also described in [13].

Remark 3.1 An important difference between the approach proposed in this paper 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 use the case base to assign a performance indicator to a given traffic situation and control scenario, we also have to include the values of the performance indices in the characterization of the cases. Furthermore, since for the overall performance assessment we may consider an objective function J that is a weighted combination of various performance indicators (cf. Section III-C) and since the weights are not fixed but variable, we cannot directly relate an optimal solution to each case (or traffic situation). $\Diamond$

B. Operation

Once the case base is constructed it is used for scenario evaluation as follows. Suppose that the current time is $t = T$. First, the current state of the network is recorded. Next, the demand and the outflow restrictions for the period $[T, T+T_{\text{pred}}]$ are predicted (e.g., based on historic data, current weather conditions, and traffic measurements, etc.). If any incidents are present, their severity and predicted duration are also recorded. Finally, the control scenario to be evaluated is also selected. Based on this information, we can for each subnetwork j construct a vector $X^{(j)} = (x^{(j)}, d^{(j)}, u^{(j)}, z^{(j)})$ with the same structure as the vectors in the case base and with all components specified except for the inflows $d^{(j)}_{\text{in}}$ from the other subnetworks, and the outflow restrictions $d^{(j)}_{\text{out}}$ imposed by the other networks over the prediction period $[T, T+T_{\text{pred}}]$ as these are not yet known and as they depend on the interaction between the networks. These values are determined in an iterative way as will be discussed next.

As we have constructed a separate case base for each network, and as the predictions will be performed for each network separately, we have to take care that the predictions are consistent, i.e., that the inflows $y^{(j)}_{\text{in}}$ and outflows $y^{(j)}_{\text{out}}$ between subnetworks predicted by the agent for subnetwork j (i.e., the "output" boundary conditions) are consistent with the "input" boundary conditions $d^{(j')}_{\text{in}}$ and $d^{(j')}_{\text{out}}$ used by the other subnetworks $j' = 1, \ldots, n_{\text{sub}}$, $j' \neq j$ for their prediction. To this aim we use the following iterative algorithm:

- **Inputs**:
  - tolerance: $\varepsilon > 0$
  - relaxation parameter: $\lambda \in (0, 1)$
  - maximum number of iterations: $i_{\max}$
  - $X^{(j)} = (x^{(j)}, d^{(j)}, u^{(j)}, z^{(j)})$ for $j = 1, \ldots, n_{\text{sub}}$

- **Initialization**:
  - Set iteration index: $i = 0$
  - Set $y_{\text{in},0}^{(j)} = 0$ for all j
  - Set $y_{\text{out},0}^{(j)}$ to the maximal possible flow (i.e., capacity) of the corresponding links for all j
  - Set current error: $e = \infty$
- **Iteration**
  while $e > \varepsilon$ **and** $i \leq i_{\max}$ **do**
  - **for** each subnetwork $j = 1, \ldots, n_{\text{sub}}$ **do**
    - Extract the values of $d_{\text{in}}^{(j)}$ and $d_{\text{out}}^{(j)}$ from the vectors $y_{\text{in},i}^{(j')}$ and $y_{\text{out},i}^{(j')}$ for the other subnetworks $j' = 1, \ldots, n_{\text{sub}}$, $j' \neq j$
    - Use the case base to predict the new "output" boundary conditions $\hat{y}_{i+1}^{(j)} = (\hat{y}_{\text{in},i+1}^{(j)}, \hat{y}_{\text{out},i+1}^{(j)})$
    - Update the current "output" boundary conditions using relaxation:

$$y_{i+1}^{(j)} = \lambda \hat{y}_{i+1}^{(j)} + (1 - \lambda) y_i^{(j)}$$

  - Determine the error:

$$e = \left(\sum_{j=1}^{n_{\text{sub}}} \| y_{i+1}^{(j)} - y_i^{(j)} \|^2 \right)^{\frac{1}{2}}$$

  - Increment the iteration index: $i = i + 1$
- **Post-processing**
  - Set $y^{(j)} = y_i^{(j)}$ for $j = 1, \ldots, n_{\text{sub}}$
  - Determine the subnetwork performance $p^{(j)}$ and the similarity s_j between the current situation and the case base for $j = 1, \ldots, n_{\text{sub}}$
  - Compute the performance p of the total network and the total similarity s
- **Output**: p, s

In the experiments we have run for the case study of Section IV we have noticed that the algorithm converges rapidly, in about 4 to 8 iterations. In the next section we will discuss how the predictions for each subnetwork are done, and how the similarity between the current traffic situation and the cases in the case base is determined.

C. Prediction and performance determination

In order to predict the performance and the output ("output" boundary conditions) for a given vector $X^{(j)} = (x^{(j)}, d^{(j)}, u^{(j)}, z^{(j)})$, we first have to determine for which cases the traffic situation corresponds best to the traffic situation characterized by $X^{(j)}$. This is done by using a similarity function based on fuzzy membership functions that describe the degree of similarity between two traffic situations.

The similarity between the current traffic vector $X^{(j)}$ and the traffic situation $X_{\text{case } i}^{(j)}$ of case i of the case base for subnetwork j is characterized by $f_{\text{mbs},i}^{(j)}(X^{(j)})$ where $f_{\text{mbs},i}^{(j)}$ is the membership function that corresponds to case i. Note that the range of $f_{\text{mbs},i}^{(j)}$ is $[0, 1]$. So the similarity ranges from 0 for no similarity at all to 1 for a perfect match. The membership function $f_{\text{mbs},i}^{(j)}$ for case i of the case base of subnetwork j is defined as follows. We consider each coordinate of $X^{(j)}$ separately when defining the membership functions. The overall membership function $f_{\text{mbs},i}^{(j)}$ for case i is then defined as the mean[1] of the membership functions $f_{\text{mbs},i,\ell}^{(j)}$ for the separate coordinates:

$$f_{\text{mbs},i}^{(j)}(X) = \frac{1}{n_X^{(j)}} \sum_{\ell=1}^{n_X^{(j)}} f_{\text{mbs},i,\ell}^{(j)}(X_\ell)$$

where $n_X^{(j)}$ is the number of components of $X^{(j)}$. For the membership functions $f_{\text{mbs},i,\ell}^{(j)}$ we could take one of the standard trapezoidal or bell-shaped membership functions (see also Section IV).

Now the predicted output and the performance over the period $[T, T + T_{\text{pred}}]$ for subnetwork j are determined as

$$y^{(j)} = \frac{\sum_{i=1}^{n_j} f_{\text{mbs},i}^{(j)}(X^{(j)})\, y_{\text{case } i}^{(j)}}{\sum_{i=1}^{n_j} f_{\text{mbs},i}^{(j)}(X^{(j)})}$$

$$p^{(j)} = \frac{\sum_{i=1}^{n_j} f_{\text{mbs},i}^{(j)}(X^{(j)})\, p_{\text{case } i}^{(j)}}{\sum_{i=1}^{n_j} f_{\text{mbs},i}^{(j)}(X^{(j)})} \quad .$$

The total performance p is determined as

$$p = \frac{\sum_{j=1}^{n_{\text{sub}}} w_j p^{(j)}}{\sum_{j=1}^{n_{\text{sub}}} w_j} \quad ,$$

where the weight $w_j > 0$ expresses the relative contribution of subnetwork j to the total performance or the relative importance of subnetwork j. The similarity s_j for subnetwork j and the total similarity s are defined as

$$s_j = \max_{i=1,\ldots,n_j} f_{\text{mbs},i}^{(j)}(X^{(j)})$$

$$s = \frac{\sum_{j=1}^{n_{\text{sub}}} w_j s_j}{\sum_{j=1}^{n_{\text{sub}}} w_j} \quad .$$

D. Ranking

Now that the case base and the performance evaluation have been established, we move on to explain how the multi-agent case-based scenario evaluation system can be used to support the traffic operators when they have to decide which control measures will most effectively deal with the current traffic situation and the predicted demand and traffic evolution in $[T, T + T_{\text{pred}}]$.

First, the operator decides which control scenarios C_1, …, C_M should be considered. Furthermore, the operator can select to consider several performance criteria J_i (such as vehicle loss hours, average travel times, queue lengths, etc.) or a weighted sum $J = \sum_i \xi_i J_i$. The weights ξ_i are not necessarily

[1] In the fuzzy logic literature, several "aggregation" operators are defined such as $\min_\ell$, $\prod_\ell$, etc. depending on the specific application. However, for the TCSES application the mean operator seems to perform the best.

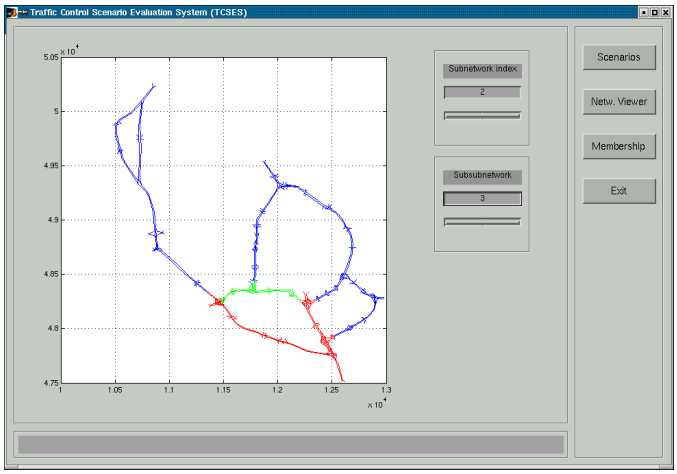

Fig. 2. The network considered in the prototype consists of the ring-road around Amsterdam, The Netherlands. The figure is a screenshot of the "Network Viewer" of the TCSES-GUI.

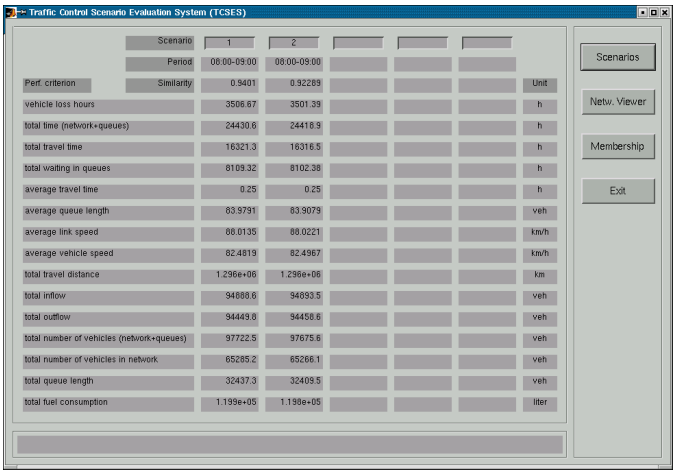

Fig. 3. Screenshot of the "Scenario Evaluation" tab of the TCSES-GUI.

fixed, but can be changed on-line by the traffic operator depending on the current traffic management policies and other considerations. Next, all data and control scenarios are fed to TCSES, and the predicted performance is evaluated. Note that the multi-agent case-based approach we use is sufficiently fast[2] so that a large number of control scenarios can be evaluated on-line. Finally, the scenarios are ranked according to their performance and presented to the operator. The operator can then select the P top-ranking scenarios and more closely assess their performance (based on experience or using traffic simulation). As P is much smaller than the total number of control scenarios M, we can significantly reduce the timed needed in the final analysis process by removing from the detailed decision process those combinations for which the performance will probably not be satisfactory.

IV. Prototype of the TCSES

In order to assess the technical feasibility of the approach proposed above, we have created a prototype TCSES for the ring-road around Amsterdam, The Netherlands and some connecting motorways (see Figure 2). The network was divided into $n_{\text{sub}} = 5$ subnetworks, each consisting of 3 to 4 subsubnetworks. The state of a subnetwork was characterized by the average link densities in each of its subsubnetworks. The prototype of the TCSES has been implemented in the mathematical software package Matlab (which includes a programming language and the possibility to create graphical user interfaces (GUIs)).

The cases have been constructed using METANET simulations for several incident and control scenarios. The incidents varied in duration from 30 to 60 min, and in severity from 25 % to 50% reduction in link capacity. The following control measures have been considered: ramp metering, variable speed limits, and shoulder lane openings. All these situation have been simulated in the macroscopic traffic flow simulation program METANET for the period from 6.00 am to 11.00 am (i.e., the morning peak hours). Note that the TCSES concept is generic enough to also allow other types of simulation or even the inclusion of real-life measured traffic evolutions. We have taken a prediction horizon $T_{\text{pred}} = 1$ hour. In total about 1500 simulations were performed (each resulting in 7 cases to be included in each subnetwork case base). Merging similar case resulted in a reduction of about 40 % of the resulting case bases. The final total size of the 5 subnetwork case bases saved in internal Matlab format is about 8 MB.

For the scenario evaluation the user has to provide input files (with a format similar to METANET) that describe the current traffic situation and the predicted demands and/or outflow restrictions. The scenarios can be evaluated in batch and/or by the "Scenario Evaluator" of the TCSES GUI (see Figure 3). Tests show that the prototype TCSES can evaluate a given scenario in under 1 s. Note that if we would implement the TCSES in C, this execution time can be reduced even further. The METANET program, which is already implemented in C, requires about 1 min for a scenario evaluation.

We have also included the option to change on-line the membership functions used for the scenario assessment (cf. Figure 4). Currently, we have implemented trapezoidal and bell-shaped membership functions, which are defined as

$$f^{(j)}_{\text{mbs,bell},i,\ell}(x) = \exp\left(-\frac{1}{2}\left(\frac{x - c_{i,\ell}}{\sigma_{\text{rel}}\,(x_{\max} - x_{\min})}\right)^2\right)$$

$$f^{(j)}_{\text{mbs,trap},i,\ell}(x) = \text{PWA}\Big(\big(c_{i,\ell} - \frac{1}{2}\nu_{\text{rel}}(x_{\max} - x_{\min}),\, 0\big),\; \big(c_{i,\ell},\, 1\big),\; \big(c_{i,\ell} + \frac{1}{2}\nu_{\text{rel}}(x_{\max} - x_{\min}),\, 0\big)\Big)$$

for the ℓth component of case i where the center $c_{i,\ell}$ of the membership function corresponds to the value of component ℓ of the vector $X^{(j)}_{\text{case }i} = (x^{(j)}_{\text{case }i}, d^{(j)}_{\text{case }i}, u^{(j)}_{\text{case }i}, z^{(j)}_{\text{case }i})$, and

[2]For the prototype we built the TCSES evaluates a scenario in less than 1 s, whereas METANET simulation takes about 1 min.

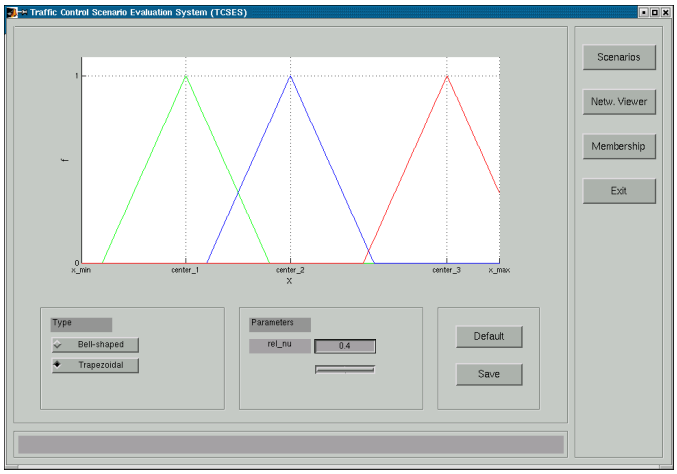

Fig. 4. Screenshot of the "Membership" tab of the TCSES-GUI.

where $\mathrm{PWA}((x_1, y_1), \ldots, (x_n, y_n))$ is the piecewise-affine function that interpolates in the points $(x_1, y_1), \ldots, (x_n, y_n)$. The parameters $\sigma_{\mathrm{rel}} > 0$ and $\nu_{\mathrm{rel}} > 0$ determine the relative size of the membership functions with respect to the range $[x_{\min}, x_{\max}]$ of the variable x. For $\nu_{\mathrm{rel}} = 1$ the base of the triangles of the membership functions equals $x_{\max} - x_{\min}$. For $\nu_{\mathrm{rel}} = 0$ and $\sigma_{\mathrm{rel}} \to 0$ the membership function is 0 everywhere except in its center point where the function value is 1 (note that this corresponds to crisp membership functions). So the choice $\nu_{\mathrm{rel}} = 0$ and $\sigma_{\mathrm{rel}} \to 0$ would result in a crisp case base (i.e., without fuzzy interpolation). The choice $\nu_{\mathrm{rel}} \to \infty$ or $\sigma_{\mathrm{rel}} \to \infty$ would correspond to membership functions that are identically 1 over the whole input range. We have selected $\nu_{\mathrm{rel}} = 0.7$ and $\sigma_{\mathrm{rel}} = 0.1$. Based on some preliminary experiments, the membership functions defined above appear to give the best results. Of course, other definitions and shapes of membership functions can easily be added to the TCSES prototype.

Finally, we have also compared the results of the TCSES system with full METANET simulation, and we found that TCSES indicates the same trend as METANET. Note however that the TCSES indicators provide much coarser information than the detailed METANET simulation results due to the aggregation of the network state into subnetwork states and due to taking the average of the period $[T, T + T_{\mathrm{pred}}]$. On the other hand, TCSES is much faster than METANET. Hence, we can effectively use TCSES to quickly and roughly rank several control scenarios according to their approximate performance, and then use METANET (or another traffic simulation program) to effectively assess the most promising ones.

V. Conclusions and Future Research

We have presented a multi-agent case-based traffic control scenario evaluation system (TCSES) for traffic control centers. The TCSES uses a case base and fuzzy interpolation to asses the approximate performance of several control scenarios. This results in a ranked list of control scenarios, of which the best-scoring scenarios can then be assessed in more detail via, e.g., microscopic or macroscopic traffic simulation. The main advantage of the TCSES is its speed. In addition, the multi-agent approach used in the TCSES, in which the network is split into several (possible overlapping) subnetwork each of which has its own case base, makes the system scalable so that it can also be used for large networks.

Currently, we have demonstrated the technical feasibility of the system. In the next stage of the project we will thoroughly examine the performance of the system (for more traffic situations and control scenarios than the ones 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.

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