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Decision Support in Dynamic Traffic Management. Real-time Scenario Evaluation

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Abstract: To support operators in Regional Traffic Management Centers in their task to efficiently and safely manage traffic flows on the motorway and urban networks, a decision support system is being developed. An essential function of this system is its ability to predict the effects of a large number of candidate control scenarios, given the recurrent and non-recurrent conditions in the network.

This article proposes such a prediction system referred to as BSES (Boss Scenario Evaluation System), which can evaluate control scenarios in real time, predicting their effects in terms of various measures of effectiveness, such as total travel times, vehicle loss times, average speeds, fuel consumption, etc. The main characteristics of the system are 1) that it is case-based, i.e., it uses either synthetic or real-life examples of the effect of control scenarios under different circumstances; 2) that is determines the similarity of the current situation to different examples in the case base using fuzzy logic, and 3) that it is agent-based, meaning that it predicts the effects of the different measures for small subnetworks and combines these predictions afterwards.

In the article, synthetic data is used to set-up the case base. The test results described in the article illustrate the workings of the system, and shows that the system can provide the operator with real-time predictions. Furthermore, the predictions of the system are in comparable to the predictions from the simulation model used to fill the case base, showing that the method is applicable to generalize the — in this case synthetic — data it uses.

Keywords: Decision Support Systems, Dynamic Traffic Management, Fuzzy Logic

1 Introduction

Dynamic Traffic Management (DTM) is moving into a new era. Contemporary DTM focuses on the integrated (opposed to isolated) and coordinated (combination of different measures) deployment of measures, anticipating on future changes in traffic conditions. Controlling and guiding traffic flows by means using measures such as ramp-metering, variable speed limits, dynamic route guidance, opening shoulder lanes, providing route information, etc. are the core tasks of the Regional Traffic Management Centers (RTMC). In the RTMC, traffic operators decide when and which DTM measures are to be deployed in case of recurrent and non-recurrent conditions[1].

Until now, these decisions are based on the information from available measurement systems, which pertain solely to the current state of the network. It turns out that the operators require support in order

[1]Such a scheme is referred to as a control scenario in the remainder of the article.

to come up with optimal control decisions, mainly due to the fact that prediction the effect of deploying different combinations of control measures to different parts of the network is very important, but also a very difficult task, especially (but not only!) under non-recurrent conditions such as incidents and special events.

This is why the Traffic Research Center is developing a Decision Support System (DSS) called BOSS. In broad terms, the objective of BOSS is to provide the operators with conditional predictions on the future state of the traffic network under their supervision, given the current state of the network and conditional on the candidate control scenarios. Using these predictions, the operators can more efficiently intervene at the network level by deciding which control scenario is to be used. At the present time, two systems are being developed:

1. BOSS on-line, which is actually implemented in the RTMC, and used real-time traffic data to provide decision support to the network operator, and;

2. BOSS off-line, which is used by traffic engineers to prepare candidate control scenarios, which are in turn used by BOSS on-line.

BOSS uses traffic predictions of 1 hour ahead. The system will become operational at the end of 2003 in the RTMC De Wijde Blik.

Given the complexity of the networks to be controlled as well as the large number of control scenarios that may be used, using traffic flow models in the on-line simulation of these control scenarios will not be feasible due to limited computational resources. This is why on behalf of the Traffic Research Center, Delft University of Technology has developed an alternative method for the on-line evaluation of these control scenarios. This manuscript describes this approach.

The method that has been developed is referred to as Fuzzy Multi-Agent Case-Based Reasoning (FMA-CBR). The system is based on generalizing examples (so-called cases) that describe the effects of deploying control measures under specific recurrent or non-recurrent conditions. These cases may either be represented by real data or synthetic data (from simulation). The latter option was chosen in this article, due to the limited data availability at the time of writing. It is believed that the system will perform satisfactory with real data (or data from a more refined traffic simulation model) as well. The resulting prediction method is called BSES (BOSS Scenario Evaluation System).

This article is outlined as follows: the second section describes briefly the general problem of providing network operators with decision support; section 3 provides a rough overview of the different approaches to decision support, in particular focusing on operational systems. The remainder of the article focuses on explaining the developed approach and showing its workings. The final section discusses directions for future research.

2 Decision support for DTM

This article considers decision support for operational Dynamic Traffic Management, and will thus not consider the planning and installment of measures in order to solve recurrent local and network problems. In The Netherlands, these issues are resolved in the Architecture for Traffic Management, providing a framework prescribing different phases that eventually lead to deployment plans. The framework prescribes how policy related issues are translated into a so-called frame-of-reference, which described the desired traffic state (in terms of average speeds, queues, waiting times, etc.). The objective of operational traffic control is to control the state of the system towards this desired state. The frame-of-reference provides weighting factors indicating which parts of the network are to be prioritized, or if on certain parts of the network, congestion would be acceptable to the policy makers.

Before describing the approach to decision support considered in this article, an overview of the overall system architecture of which it is part is given briefly. An essential element is the traffic operator, who plays an essential role in regional Dynamic Traffic Management. An alternative approach would be the approach where the operator is out of the loop, i.e., where the operator only has a supervisory task.

2.1 Operator tasks

In general, traffic operators in Regional Traffic Management Centers (RTMCs) have a variety of task, amongst which are:

1. Monitoring the functioning of the relevant subsystems and measures (e.g., is the ramp-metering installation functioning properly?)
2. Monitoring the state of the network, recognizing irregularities and other problems, and diagnosing their causes (is there congestion in the network that is unacceptable given management policies? What are the causes of these problems?).
3. Setting up candidate solutions to solve the identified problems, choosing the optimal control scenario given current and future traffic conditions, and implementing the control scenario in practice (e.g., activating the ramp-metering installations in a particular part of the network).
4. Monitoring the developments in the system given the deployed control scenario: does the proposes solution solve the problems at hand?
5. Informing other actors (operators in other RTMCs, auxiliary services).

It is noted that the RTMC 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. This implies that if a local controller is active, it operates locally using only local traffic conditions. At a higher level the operation of several local traffic controllers is coordinated and synchronized by the supervisory operators in the RTMCs.

For the list of operator tasks, especially the state-monitoring (identification of traffic problems and problem diagnosis), prediction and control tasks are complicated. This is caused by among other things the following issues:

- Data interpretation problems cause by the large amount information received by the operator;
- Lack of insight into the network dynamics, in particular under non-recurrent circumstances;
- Diversity and complex interactions between the measures.

As a result of these complications, expert knowledge and experience are often not sufficient to adequately determine the cause of the problem at hand, or to determine the most efficient control scenario. This is why decision support is needed.

2.2 Tasks of a Decision Support System

The main tasks of a Decision Support System (DSS) are:

1. *Identification*. The identification task can be further divided into
   (a) *Monitoring*. Monitoring describes automatic collecting and summarizing data from the monitoring system. The DSS may invoke a dialog with the operator to collect additional information.
   (b) *Diagnosis*. Diagnosis pertains to identification of the cause of the problem, given the data collected during monitoring.
2. *Prediction*. Prediction or simulation pertains to the conditionally forecasting the traffic conditions in the network, given the prevailing traffic conditions, the predicted traffic demands, and the candidate control scenarios. The system described in this article in particular focuses on this task.
3. *Advise*. This task describes the fact that the DSS will present the operator with the control scenario that yields the optimal predicted traffic conditions, as determined by comparing the predicted situation with the frame of reference using weight factors. If only a limited number of control scenarios are available, this task will be limited to ordering the control scenarios given the relative important of the different network performance indicators.

The remainder of the article will be focused on a system that supports primary the prediction task and to a lesser extent advise tasks. First, however, a short overview of currently operational DSSs will be presented in the following section.

3 State-of-the-Art overview for decision support DTM

Several authors have described decision support systems for traffic management, such as FRED (Freeway Real-Time Expert System Demonstration) [8, 9, 11], or the Santa Monica Smart Corridor Demonstration Project [4, 10]. Fuzzy decision support systems for traffic control have been developed in [2, 6, 7].

The TRYS system described in [2, 7] is an agent-based system for urban motorway control. The network is divided in overlapping regions and to each region an agent is assigned. These agents have to detect and diagnose traffic problems in their regions and subsequently suggest possible control measures to a higher-level coordinator, taking care of negotiations, and deciding which action will be taken. The decision process in the TRYS system is based on knowledge frames, and some of these frames use fuzzy logic.

The paper [6] describes a fuzzy logic control architecture that can be applied in existing traffic control systems on a multi-lane motorway with VMSs. This system uses fuzzy logic to incorporate the experience of human traffic operators.

The main aim of the system presented in this article is to make the process of on-line, real-time evaluation and selection of the traffic management measures more efficient. To this end, fuzzy case-based interpolation was used to evaluate the effects of traffic control measures. In that way, a large set of possible traffic control measures for a given traffic situation can be rapidly evaluated, and the best control scenarios can then be simulated in more detail using microscopic or macroscopic traffic simulation.

3.1 Case-based reasoning

A common approach to decision support is so-called Case-Based Reasoning (CBR). Case-based reasoning is the process of solving new problems based on the solutions of similar past problems. The main characteristics of CBR distinguishing it from other AI methods are [1]:

- Actual knowledge describing what has happened in the past (domain knowledge) can be used directly, instead of using general knowledge of the considered system.
- After implementing the control scenario, the resulting situation can be added to the case base. That is, CBR provides the means for continuous step-wise learning.

It has been argued that case-based reasoning is not only a powerful method for computer reasoning, but also a pervasive behavior in everyday human problem solving. Case-based reasoning (CBR) has been formalized as a four-step process:

1. Retrieve (retrieve cases from memory that are relevant to solving it);
2. Reuse (map the solution from the previous case to the target problem, for instance using fuzzy reasoning);
3. Revise (test the new solution in the real world (or a simulation) and, if necessary, revise);
4. Retain (learning, i.e., store the resulting experience as a new case in memory).

In general, CBR starts with a set of cases or training examples; it forms generalizations of these examples, albeit implicit ones, by identifying commonalities between a retrieved case and the target problem.

3.2 Case base size and approach motivation

The advantages of using a case-based approach are clear. However, given the high-dimensionality of the prediction problem addressed in this paper, setting up a case base that has sufficient coverage is unfeasible. In illustration, the conditions in a network are typically described by the period of the day, densities of its links, traffic demands on the network boundaries, control measures that have been deployed, and the incident status.

Consider for instance a situation where 3 periods are considered (morning and evening peak hour, and off-peak period); the network is divided into 25 links, and 3 density levels are considered (low, medium, and high). This holds equally for the demand levels, describing traffic entering the network at 8 locations. We assume that in total 10 control scenarios are possible (including no control). Furthermore, we consider the case that one incident may occur on any of the 25 links (in practice, incidents may have different levels of severity). The size of the case base that will result from this specification (assuming that the case base includes all combinations of possible states) then equals $3^{25} \times 3^8 \times 10 \times 2^{25} = 1.86 \cdot 10^{24}$. Clearly, it is impossible to collect and story such a number of cases. Even if the number of cases can be reduced, by considering less links, or applying some other form of aggregations, the standard case-based approach will thus yield considerable problems with respect to the high number of cases (maintenance when network is changed, ability to upgrade to larger networks, etc.).

In this paper, we describe a novel approach which embodies the advantages of case base reasoning while at the same time ensuring that we can cope with realistically sized networks. As is presented in the ensuing, this is achieved in two steps: by using fuzzy case-based reasoning and by partitioning the network into smaller, interrelated subnetworks.

4 FMA-CBR approach to scenario evaluation

For the problem at hand, a case (either simulated or measured on a real network) contains the following information: description of the situation, including both the state in the network at the initial time (average densities on a set of network links referred to as subsubnetworks in the remainder), and the conditions at the boundary (inflows and outflow restrictions) of the network during the considered time period; the control scenario that was used during the period, and finally the result of applying the control scenario in terms of traffic conditions (average flows, densities, speeds, etc.) and performance criteria (travel times, fuel consumption).

Due to the characteristics of the control problem at hand, straightforward application of CBR to the decision support task sketched here is not feasible. The main reason for this is the exponential growth of the case base, given the requirement that it should be representative for most cases that can occur in practical situations. For medium-sized networks, the number of possible situations (and thus the number of cases) that can occur is extremely large.

To resolve the problem described in the previous section, two aspects are introduced into the CBR-framework to enable the generalization of the examples in the case base.

1. Fuzzy logic is used to combine different cases in the case base (F-CBR: Fuzzy Case-Based Reasoning). By doing so, a precise match between the current situation in the network and the example situations in the cases is not required. This approach has been successfully applied to small-scale networks [3]. For larger networks, the dimensionality of the vector describing the situation in the network still yields too many similar combinations that need to be stored in the case base.

2. The network to be controlled is divided in n partially independent subnetworks for which the aforementioned F-CBR approach can be applied. That is, for each subnetwork j, a case base is established. Except for the situation in the subnetworks itself (the state, described by prevailing and future densities), also the outflows to the other subnetworks are predicted using F-CBR.

The n subnetworks are of course interdependent. As a result, the traffic conditions in subnetwork j will to a certain extent be dependent on the outflows from subnetworks $j' \neq j$. In turn, the traffic conditions in subnetworks j' may be dependent on the outflows from subnetwork j. To attain consistency between the

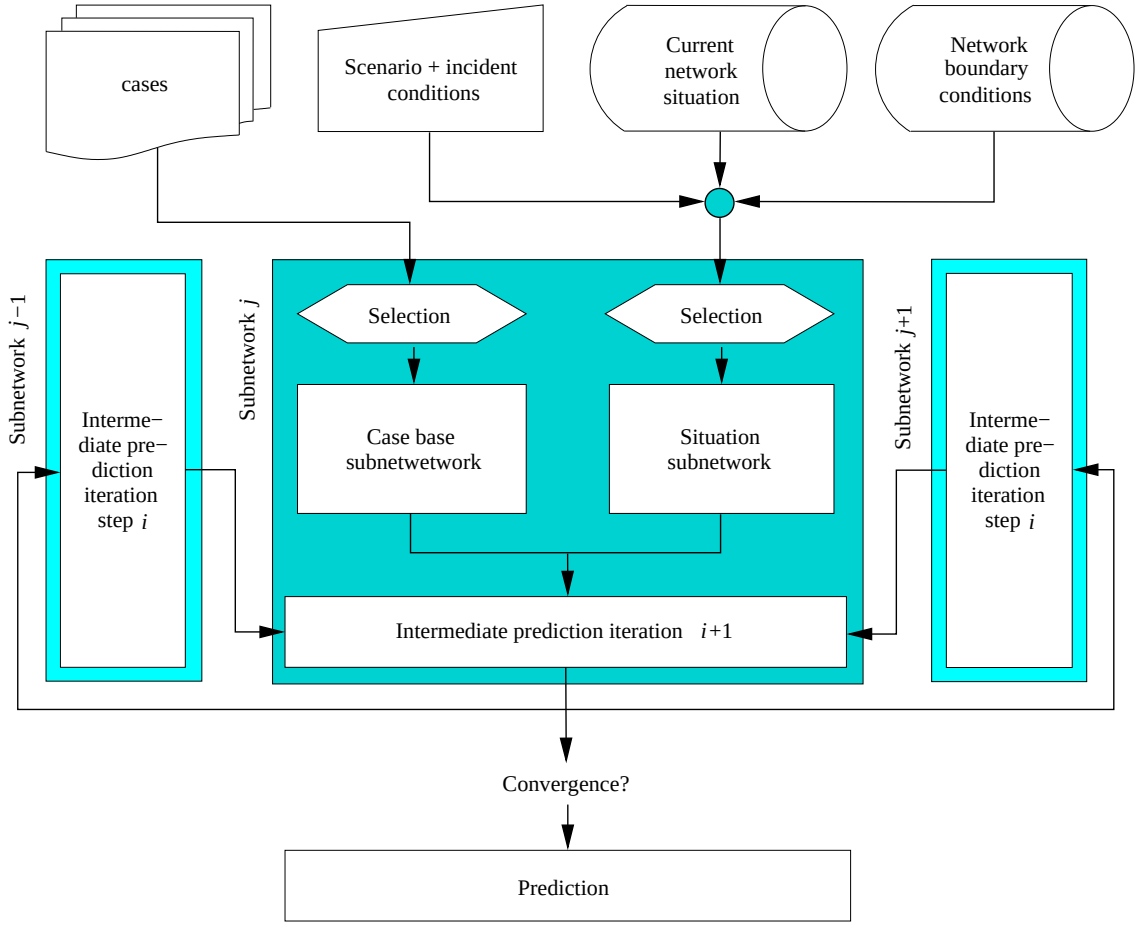

Figure 1: General iterative approach to FMA-CBR.

predicted traffic conditions and the subnetwork outflows, prediction of subnetwork conditions are iterated until a situation results in which all flows are consistent with each other.

Figure 1 depicts an overview of the approach, depicting its key elements: the case base, the input to the system (control scenario and incident conditions, current state, and boundary conditions), prediction for each subnetwork j, and iteration in order to get consistency of the flows.

In the remainder of this section, the key steps to the approach are discussed subsequently. First, we will describe the case base for a subnetwork j; next, the fuzzy case-based reasoning approach predicting the subnetworks' traffic conditions will be described, followed by the iterative approach applied to assure consistency between the inter-subnetwork flows. Finally, we will discuss the approach to determine the network performance.

4.1 Specification of cases for a subnetwork

It was mentioned that for each of the subnetworks $j = 1, \ldots, n$ case bases are determined. These case bases contain specific situations that have occurred in the subnetwork, and describe the relation between the input of the subnetwork and the output of the subnetwork for these situations. These "situations" are determined either from real-data or from simulations pertaining to the entire network.

Let T_{pred} denote the prediction horizon. A case for subnetwork j is described by the following input characteristics $\mathbf{x}$:

- period of the day (morning-peak, evening peak, off-peak),

- current state (i.e., average densities) on all subsubnetworks $K = 1, \ldots, K_j$ of subnetwork j at time t,
- average external traffic demands (traffic flowing into the network) and internal traffic demands (traffic flowing from the other subnetworks j' to the current subnetwork j) during period $[t, t + T_{\text{pred}})$,
- average external supply restrictions (for traffic flowing out of the network) and internal supply restrictions (for traffic flowing from the current subnetwork j to other subnetworks j') during period $[t, t + T_{\text{pred}})$,
- local measures deployed in the current subnetwork j (e.g., ramp-metering, speed-limit control) and global measurements deployed in other parts of the network (route information) during the period $[t, t + T_{\text{pred}})$,
- average incident conditions in the subnetwork (location, duration, severity) during period $[t, t + T_{\text{pred}})$,

and output characteristics $\mathbf{y}$:

- traffic conditions in the subnetwork and in particular on the boundaries (outflows, inflow restrictions) during the period $[t, t + T_{\text{pred}})$,
- average performance expressed via Measures-of-Effectiveness (e.g., queue lengths, travel times, delay times, etc.) during the period $[t, t + T_{\text{pred}})$.

The case base for subnetwork j thus consist of cases $i = 1, \ldots, m_j$ that link the input $\mathbf{x}^{(j)}$ for subnetwork j to the output $\mathbf{y}^{(j)}$ from subnetwork j. These cases can be written as rules R_i, which look like

> IF period = $\tilde{\mathbf{t}}_i$ AND currstate = $\tilde{\mathbf{r}}_i$ AND demand = $\tilde{\mathbf{d}}_i$ AND supplyrestr = $\tilde{\mathbf{s}}_i$ AND
> controlscenario = $\tilde{\mathbf{c}}_i$ AND incidentscenario = $\tilde{\mathbf{i}}_i$
> THEN outflowspred = $\mathbf{Q}_i$ AND inflowrestrpred = $\mathbf{S}_i$ AND performance = $\mathbf{P}_i$

for $i = 1, \ldots, m_j$. We have used the tilde-notation to show that the elements in the antecedent part of the rule are in fact fuzzy numbers, while the elements of the consequent part are crisp.

The fuzzy numbers (period, densities describing the current state, demands, etc.) are determined based on the (crisp) examples in the case base. These are fuzzified using either bell-shaped or triangular membership functions, the center of which lie at the crisp values that describe a case. In illustration, case (or rule) $i = 2$ may be represented by a time-averaged density of 30 veh/km/lane on subsubnetwork j_1 and of 20 veh/km/lane of subsubnetwork j_2, and the average external traffic demand of 3000 veh/h flowing into the subnetwork during a specific time period. These values will then represent the centers of the bell-shaped or triangular membership functions used to represent the current state and the demand.

The width of the membership functions is chosen relative to the domain of the respective variable, and can be specified by the end-user.

4.2 Fuzzy Case-Based Reasoning to determining predictions for a subnetwork

To determine which cases correspond best to the current situation, and to combine different cases in order to provide a prediction of the traffic conditions and performance indicators for subnetwork j, fuzzy inference is used to describe the similarity between the current state (period, state, demand, supply restrictions) and the fuzzy antecedent part of case i, which can be reflected by rules as was shown in the previous section.

For each subnetwork j, this entails the following two steps:

1. Determining similarity $\mu_i(\mathbf{x})$ of the current situation $\mathbf{x} = (x_1, \ldots, x_{N_j}) = (\mathbf{t}, \mathbf{r}, \mathbf{d}, \mathbf{s}, \mathbf{c}, \mathbf{i})$ with each of the cases i in the case base, and
2. Combining the consequences of the cases using these similarities $\mu_i(\mathbf{x})$ to determine the total prediction.

For each case i, the similarity $\mu_i(\mathbf{x})$ (or degree of membership) with the current situation (current period, state, demand, etc.) in subnetwork j is determined by considering the mean membership of the elements of the antecedent part of the rule, i.e.,

$$\mu_i(\mathbf{x}) = \frac{1}{N_j} \sum_{l=1}^{N_j} \mu_{i,l}(x_l) \quad , \tag{1}$$

where N_j denotes the number of elements in the antecedent part of rule i for subnetwork j. In other words, the mean fuzzy membership was used to quantify the fuzzy "AND" operator used in the rule representation shown in the previous section.

When $\mu_i(\mathbf{x})$ has been determined for all rules c.q. cases i, the prediction $\mathbf{y} = (\mathbf{Q}, \mathbf{S}, \mathbf{P})$ for the conditions in subnetwork j is determined by taking the weighted sum of the consequent part of all rules i, using $\mu_i(\mathbf{x})$ as the weights, i.e.,

$$\mathbf{y} = \frac{\sum_{i=1}^{m_j} \mu_i(\mathbf{x}) \mathbf{y}_i}{\sum_{i=1}^{m_j} \mu_i(\mathbf{x})} \quad , \tag{2}$$

where $\mathbf{y}_i = (\mathbf{Q}_i, \mathbf{S}_i, \mathbf{P}_i)$ denotes the crisp consequent part of rule i (i.e., the output flows, inflow restrictions, and the performance); m_j denotes the number of cases in the case base of subnetwork j. In turn, this operator describes the fuzzy "OR" operator, used to aggregate consequences of the specific prediction rules.

The approach will yield a conditional prediction of the output (outflow and performance) of subnetwork j. The prediction is conditional, since part of the state $\mathbf{x}$ (and thus also the prediction) depends on the endogenous demands from other subnetworks j' as well as the supply restrictions limiting the flows to these subnetworks j'. The next section discusses the approach used to determine consistency of the conditional flows between the subnetworks.

There are a variety of approaches to determine the cases in the case base of subnetwork j. For instance, real life measurements can be used where traffic demands and traffic conditions are monitored using for instance inductive loops. The case base used in the prototype application have been determined using a simulation software. Using this software, network traffic conditions for the entire network (so not just the subnetwork) where determined using various prespecified input and control settings. For each subnetwork j, the traffic state was determined from the simulation results.

4.3 Iterative approach for finding consistent solution

For each subnetwork, the approach discussed in the previous section computes among other things the conditional outflow and inflow restrictions. These predictions are condition on the internal traffic demands and supply restrictions for the other subnetworks. In turn, these may depend on the outflow and inflow restrictions of the current network. In the end, the solution is sought in which the internal traffic demands and the supply restrictions are consistent.

To solve this fixed-point problem, an iterative scheme was developed. Figure 2 shows an overview of the iterative approach to prediction the conditions in the network. Without formally deriving scheme stability criteria, it turns out that in practice the scheme converges within only a few iterations (less than 10).

4.4 Predicting network performance

The previous sections have described how the BSES determines predictions of the traffic conditions and the performance indicators for the different subnetworks j, as well as an iterative approach, which will is applied to ensure that the predictions for the different subnetworks are determined such that they are consistent with respect to each other.

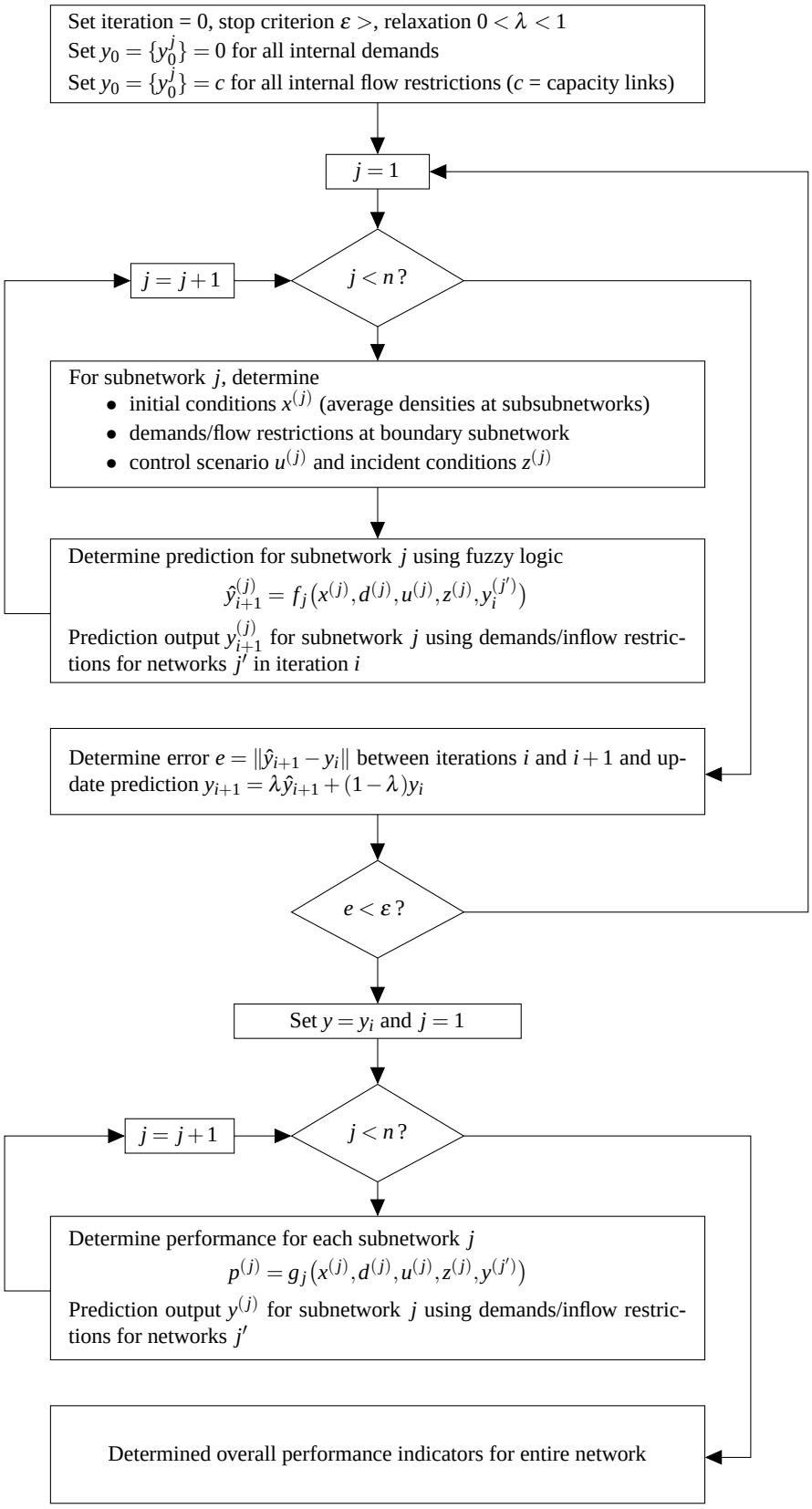

Figure 2: Iterative approach to prediction network state and performance indicators.

Predicting the performance of the entire network is then a very easy task: the different indicator values determined for the subnetworks j are simply added or averaged in an appropriate manner. To do so correctly, the overlap between the different subnetworks is taken into account explicitly. With respect to the output, the system will provide both results pertaining to the different subnetworks and the entire network.

4.5 Example BSES applications

To test the concept of the system described in this article, an off-line prototype BSES was implemented. The system was implemented for verification and demonstration purposes, and not for actual application in a RTMC. The prototype consists of the prediction model developed in line with the method described in this article, and a simple Graphical User-Interface (GUI).

The user of the system must first prepare a number of "scenarios" or situations, which he or she aims to evaluate. A scenario is defined by the following

1. The current state in the network, generally determined by the monitoring system (e.g., inductive loops), consisting of the densities on the subsubnetworks of the network considered;

2. The predicted network inflows (demands) and network outflow restrictions (i.e., the external boundary conditions), in general determined from historic traffic data;

3. The control scenario (i.e., the settings of the different control / ITS measures available in the network, such as ramp-metering, speed homogenizing control, shoulder lanes opening, lane closures, etc.);

4. The incident conditions (duration of the incident, severity of the incident, location).

The GUI allows the user to study the evaluation results, to change the membership functions, and to show the network and subnetwork definition. Furthermore, the GUI warns the user when the predictions become unreliable because the examples in the case base are not representative for the scenario the user wants to evaluate. If this occurs, the user is advised to extend the case base with additional cases.

In the remainder of this section, the development of the prototype system, in turns of setting up the case base as well as the first results of verification, are discussed. Note that the verification is *not* intended to show the expected effects of incidents or of deploying DTM measures, but aims to show how the system is able to predict network conditions in line with the cases in the case base (in this case stemming from METANET simulations); the predictions are at best as accurate as the off-line predictions in the case base (which can be very accurate when historic data is used!).

4.6 Verification results

To test the BSES, a case base was set-up using simulation results of the macroscopic simulation model METANET. METANET is a macroscopic traffic flow simulation package, primarily aimed at the simulation of large motorway networks (cf. [5]). The initial case base consists of 1464 cases describing different situations (e.g., control scenarios, incident conditions, etc.) in the motorway network around the Dutch city of Amsterdam (see Figure 3). The network is divided into 5 subnetworks, which are in turn split up into 3 or 4 subsubnetworks. The definition of subnetworks and subsubnetworks was done manually by identifying which links belong to which (sub)subnetwork. The subsubnetworks were defined such that they contained at most one major link or a major node. A major link may contain several on-ramps, off-ramps, lane-drops, etc. A major node connects two or more major links. It is clear that the way in which the network is divided into sub- and subsubnetworks has an influence on the accuracy and reliability of the prediction results. Fine-grained divisions lead to more accurate results, at the expense of larger case bases and computation time.

METANET computes a number of performance indicators, examples of which are shown in Table 1. It is emphasized that the use of a different simulation model would naturally lead to a different set of and values for the performance indicators.

To make interpretation of the results possible, let us briefly discuss the definition of the indicators shown in Table 1. The *total travel time* (3) for subnetwork j is defined as the cumulative instantaneous travel times for all links in the subnetwork during the entire simulation period. The *total queuing time* (4)

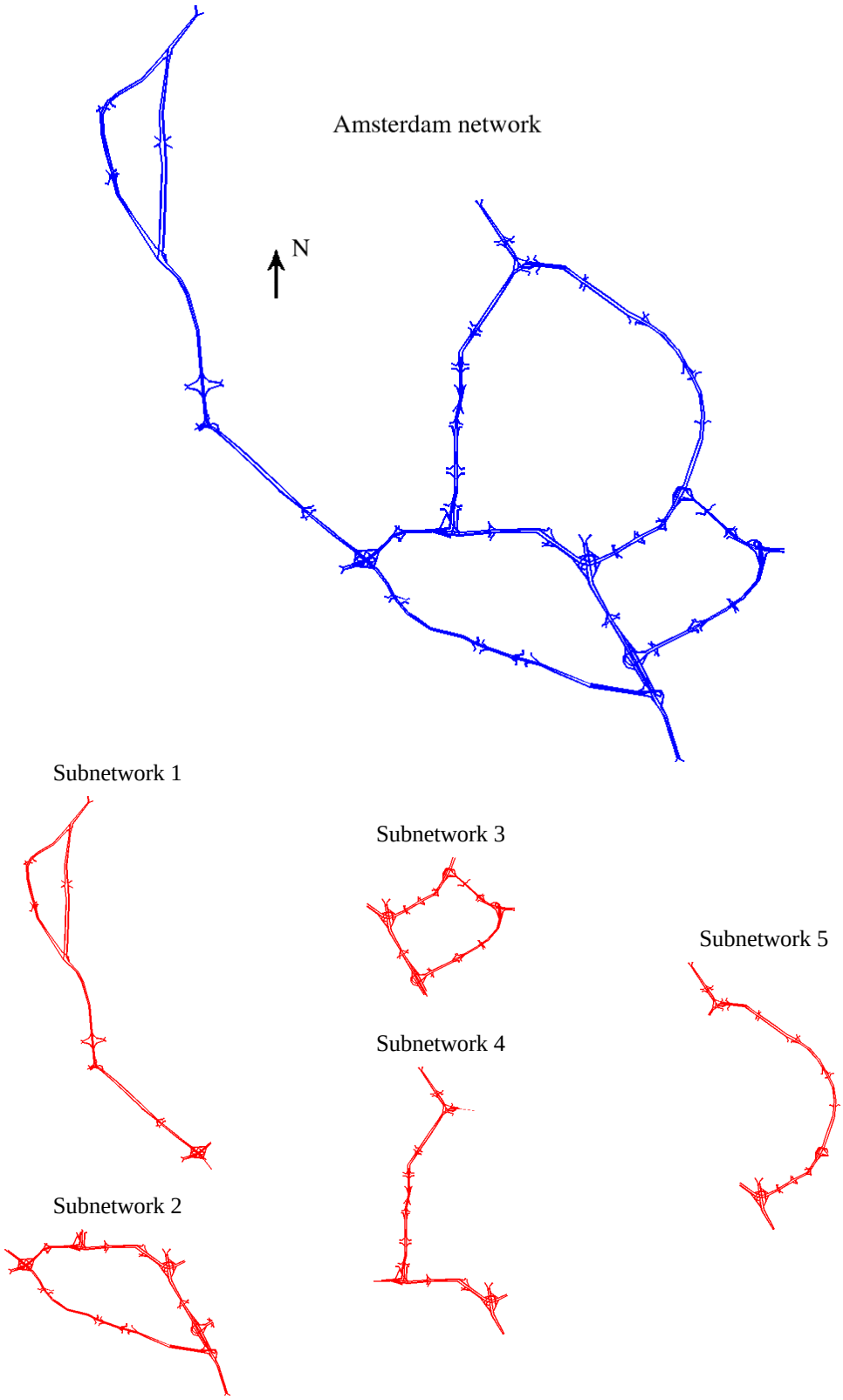

Figure 3: Amsterdam network and division in subnetworks 1 to 5.

Table 1: BSES prediction results for subnetworks 1–5 and entire network (reference).

Results scenario 1		**subnetwork**				**total**	
	Unit	**1**	2	**3**	**4**	**5**	*****
Weight	–	*0.16*	*0.32*	*0.16*	*0.12*	*0.24*	*1.00*
1. Vehicle loss time	h	894	301	127	679	634	2108
2. Total time spent	h	3278	5215	2911	8811	8286	22847
3. Total travel time	h	2960	4983	2750	3492	3029	14837
4. Total queuing time	h	318	232	161	5319	5258	8011
5. Mean queue length	veh	19.55	9.78	6.78	202.62	221.38	81.06
6. Mean link speed	km/h	90.95	88.89	92.70	85.11	90.47	89.80
7. Mean vehicle speed	km/h	78.26	93.39	94.86	80.06	78.77	86.80
8. Total distance traveled ($\times 10^3$)	km	231.2	465.2	260.7	279.5	238.5	1475.2
9. Total inflow	veh	22250	30411	19221	22809	17676	95552
10. Total outflow	veh	20897	35642	19546	24624	14165	98768
11. Total number of vehicles	veh	13111	20861	11643	35242	14165	98768
12. Number of vehicles in network	veh	11840	19931	10999	13967	12114	59346
13. Number of vehicles in queues	veh	1271	930	644	21275	21031	32042
14. Total fuel consumption	liter	20853	36302	20689	32394	29307	117858

equals the total time vehicles wait at the origins (on-ramps) to enter the network The *total time spent* (2) is the sum of the total travel time and the total waiting time. The *vehicle loss time* (1) is defined by the total time spent minus the total time spent in case all vehicles drive according to the prevailing speed limits.

The average travel time is defined by the total time spent divided by the total number of vehicles that experience this travel time. For the average travel time, the *average vehicle speed* (7) is determined. The *mean link speed* (6) is the arithmetic mean speed for all links m in the network during the entire simulation period. The *mean queue length* (5) is defined according to the time-average length of the queues at the network origins, i.e., at the on-ramps of the network. The *total distance traveled* (8) is the sum of the instantaneous traveled distances for all time-sliced in the simulation.

The *total inflow* (9) and *total outflow* (10) of the network are defined by the sum of all inflows and outflows respectively during the simulation. The *number of vehicles in the network* (12) is defined by the time-average number of vehicles present during the simulation period. This is determined by multiplying the average density k_m on a link m by the length of the link for each time slice. The *number of vehicles in queues* (13) is defined by the time-average number of vehicles at the queues at the origins during the simulation. The *total number of vehicles* (11) is simply the sum of both. Finally, METANET also computes the *total fuel consumption* (14).

Table 1 shows the prediction results for regular circumstances, i.e., no incidents and no control measures. The table shows the predicted performance indicators for the different subnetworks 1–5, as well as for the total Amsterdam network. The table also shows the weights that are assigned to the different subnetworks. For instance, it shows how subnetwork 2 is assigned a larger weight than the other subnetworks, indicating the (hypothesized) high importance of that part of the network. Subnetwork 4 has a lesser importance, which is reflected by the smaller weight. In practical applications, the weights will stem from the frame of reference discussed in the introduction.

Another example is Table 2, which shows the BSES prototype prediction results of applying ramp-metering on part of the Amsterdam network. In this particular case, the scenarios 11–14 represent *different ramp-metering settings*, i.e., which ramp-meters are operational in different parts of the network. In scenarios 11 and 12, all on-ramps to the main arterial of subnetwork 4 (see Figure 3) in respectively the North-bound direction and the South-bound direction are metered; scenario 13 describes the case where all on-ramps of subnetwork 4 are metered. Scenario 14 describes the case where only 1 on-ramp in the Northbound direction is metered. The results shown in Table 2 pertain to the entire network.

The table shows predictions of total loss-time, total travel time, average vehicle speed, average waiting times, etc. As mentioned earlier, the system also indicates the reliability of the predictions: when the

Table 2: Overview of BSES predictions describing the effects of ramp-metering.

Result scenarios	**Scenario index**					
Performance criteria	**1**	**11**	**12**	**13**	**14**	
Period	**8:00–9:00**	**8:00–9:00**	**8:00–9:00**	**8:00–9:00**	**8:00–9:00**	
Reliability	**0.847**	**0.826**	**0.790**	**0.768**	**0.794**	**unit**
Vehicle loss time	-1805	-1806	-1686	-1687	-1799	h
Total time spent	18443	18463	18320	18340	18437	h
Total travel time	11308	11316	11196	11204	11303	h
Total queuing time	7134	7146	7123	7135	7133	h
Time stamp	0.25	0.25	0.25	0.25	0.25	h
Mean queue length	87.6	87.8	87.4	87.6	87.6	veh
Mean link speed	89.8	89.8	90.1	96.1	89.8	km/h
Mean vehicle speed	85.5	85.5	86.5	86.5	85.5	km/h
Total distance traveled	966464	967171	967312	968018	966486	km
Total inflow	74691	74768	74722	74799	74692	veh
Total outflow	76208	73194	76216	76202	76208	veh
Total number of vehicles	73772	73852	73281	73361	73749	veh
Number of vehicles in network	45234	45266	44787	44819	45214	veh
Number of vehicles in queues	28537	28585	28493	28541	28535	veh
Total fuel consumption	93109	91389	91400	91479	91312	liter

situation to be predicted is too dissimilar from the cases in the case base, the system will warn the user and advise to add cases to the case base that better reflect the current situation. From Table 2, it can be observed that in general, deployment of ramp-metering has a beneficial effect on traffic conditions on the main-roads. Given the expected effects and the effects predicted by BSES, we conclude that the predictions are plausible.

As a final example, Table 3 shows the difference between the reference situation (see Table 1) and a situation in which an incident occurred on one of the links on subnetwork 3. Clearly, the traffic conditions in subnetwork 3 worsen as a result of the incident as is shown by the different performance indicators. The incident also has a small effect on the other parts of the network, in particular on subnetwork 2, but also on subnetworks 4 and 5.

It is finally mentioned that the different tests show that the system converges within only a few iterations (less than 10). As a result, it is able to compute a prediction within less than one second on a P-III (1 GHz).

4.7 Comparative analysis

The predictions determined by the BSES system have been compared to the results of a METANET simulation. It turns out that the predictions made by BSES are in line with the predictions of METANET. However, the time BSES needs to compute a prediction is much less than the time needed to do a METANET simulation (factor between 30 and 3000, depending on the mode of simulation of METANET), showing the potential for the system to be applied in an on-line system setting.

It is clear that the accuracy of the BSES predictions is directly determined by the accuracy of the underlying METANET model simulation, and that in fact verification only proves that the system is able to reproduce the predictions of the METANET model. However, the results obtained so far indicate that the system work equally satisfactory if the case base is filled with either real-life data or with results of more accurate simulation models.

Table 3: Difference between scenario 1 (reference) and scenario 6 (incident situation) for subnetworks 1–5 and entire network (only values unequal to zero are shown)

Differences scenarios 1 and 6				**subnetwork**			**total**
	unit	**1**	**2**	**3**	**4**	**5**	*****
Vehicle loss time	h			-556	1	1	-455
Total time spent	h		-4	-781	4	38	-276
Total travel time	h		8	-470	2	6	-179
Total queuing time	h		-12	-311	1	32	
Time stamp	h		-0.5	-13.1	.0.05	1.35	-1.84
Mean queue length	veh		-0.02	4.01	-0.01	0.02	0.61
Mean link speed	km/h		0.01	16.39	-0.02	-0.01	2.02
Mean vehicle speed	km/h			94.86	80.06	78.77	86.80
Total distance traveled	km	3	833	8329	101	485	9751
Total inflow	veh		38	-31	-6	-4	22
Total outflow	veh		169	385	23	52	508
Total number of vehicles	veh		-15	-3123	14	152	-1818
Number of vehicles in network	veh		33	-1878	9	25	-1103
Number of vehicles in queues	veh		-48	-1245	5	128	-715
Total fuel consumption	liter		28	-278	7	90	-51

5 Conclusions and future research

This paper describes a new approach to the on-line prediction of the effect of control scenarios under a variety of circumstances in the network. The paper describes the developed approach, which is based on combining fuzzy logic, case-based reasoning, and multi-agent approaches. The main advantages of the approach are the speed of computation (compared to using traffic flow models), the ability to use actual knowledge directly (rather than general knowledge or simulated data), and the ability to learn from previous experiences (*continuous step-wise learning*). The former is of paramount important to large-scale applications in Regional Traffic Management Centers.

It turns out that the system is able to very quickly produce predictions on the impact of different control scenarios to the traffic operations in the network, and can thus support operators in their decision tasks in a real-time decision environment. These predictions appear to be in line with the expectations regarding the effects of traffic management measures as well as with the control simulations used to test the system. It can therefore be concluded that the system indeed functions properly and provides useful information to the anticipated users, i.e., the operators in the RTMCs.

Future research will be aimed at more rigorous testing of the system and its reliability. When this test phase is finished, the system will be implemented in the decision support environment BOSS within due time. From that point onwards, experience will be gain with real-life decision support to operators in RTMCs.

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