A Large-Scale Urban Traffic Decision Support System with Dynamic Traffic Assignment

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Abstract

A large-scale Decision Support System (DSS) has been developed and will be applied for Beijing city in China. The main purpose is to be able to propose best suitable measures for a given (either recurrent or non-recurrent) traffic situation, and to apply it to a real-life traffic management, with focus on the application around the Olympics Area. A major issue for operational management is to be able fast to recognize primary problems and to be quick to recommend/retrieve corresponding solutions. This paper proposes a novel self-learning approach using conjointly expert knowledge-based choice and case-based reasoning. Key aspects to support such process include: (a) problem identification that is based on a mesoscopic large-scale network dynamic simulation with dynamic traffic assignment; (b) measures that have been successfully implemented in a priori cases would serve as new initial scenarios to the new situations, and (c) measure evaluation that can be performed according to performance indictors. Effective scenarios (measure to problem) are stored into KBEST (knowledge-based expert system) and made available for offline and online calls. System building and a calibration process are being followed, and an implementation of such system to an incident management and route guidance is foreseen and being designed.

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Keywords: Decision Support System, knowledge-based system, self-learning system, incident management, and dynamic traffic management

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1 Introduction

The success of ITS deployment depends on the availability of advanced traffic analysis tools to predict network conditions and to analyse network performance in the planning and operational stages. Many ITS sub-systems, especially, Advanced Traffic Management Systems (ATMS), Advanced Traveller Information Systems (ATIS), and Emergency Management Systems (EMS), depend on the availability of timely and accurate wide-area estimates of prevailing and emerging traffic conditions. Thus, there is a strong need for a Traffic Estimation and Prediction System to meet the information requirements of these sub-systems and to aid in the evaluation of ITS traffic management and information strategies.

However, it is still a complicated task for a traffic control centre operator and traffic management practitioners to interpret monitoring data and to pose the diagnosis to an observed problem, due to the complex interactions between measurements, and a lack of insight into network dynamics, in particular when facing non-recurrent situations. It is beneficial for traffic management to provide a decision support tool to these personnel in order for them to be able to select an effective measure to a given problem.

Various approaches have been tried and tested, which include rule-based and case-based reasoning, using either artificial intelligence (AI) or expert-based system (Ritchie, 1990). It is still not possible to handle large and complex networks in an urban area. Major difficulty resides in the fact that a specific and real problem at a given location in a large network is hardly easy to be represented and prompted to a readily available solution.

This paper suggests a self-learning approach, which recognises that a solution may not be available to a specific problem but a most likely one may be recommended when experienced successful cases are registered into a relational database. The more the successful cases have been collected, the more efficient the system performs. But it is the restriction also that a case should remain sufficiently robust, so that both generic characteristics of cases and efficient operation of the system can be achieved in balance.

The paper will address further issues in problem recognition, solution matching as well as knowledge database expansion. Note that the paper addresses mainly the technical solutions to support traffic management tasks, and does not deal with the potentially important institutional and usability issues such as the authority and responsibility of the operator and the measure to which this system supports the task execution (van Zuylen 1990).

Ongoing development in a large metropolitan city, Beijing, China, will also be presented (Chen et al., 2000-2006).

2 Methodology

The ambition is to be able to propose a best suitable solution to a given (either recurrent or non-recurrent) traffic problem, and to apply it to real-life traffic management. This problem-driving approach requires a fast diagnosis of problems and a quick generation/retrieval of corresponding solutions.

Decision support systems for traffic management can be distinguished in:

[1] Rule based systems, where knowledge stored in structured databases, decision rules (if … then …) and procedures, is augmented with real-time monitoring data. The system can reason about the meaning and consequences of the monitoring data and draw conclusions about the cause of a traffic problem (diagnosis) and the best measures (remedy). These rule-based systems may be made probabilistic (conclusions are drawn with a certain probability) or fuzzy (a diagnosis or remedy are given as membership to certain sharply defined states).

[2] Case-based systems, where an a-priori database is made of situations with traffic conditions and control measures (scenarios). These scenarios are evaluated with respect to certain objective functions. After the occurrence of a traffic situation, a match is made between the real situation and the cases in the database. The case that has the best match with the real situation and gives the best performance with respect to a chosen objective is selected and the measures of the scenario are recommended (Hegyi et al. 2000, 2001, Hoogendoorn and De Schutter 2003).

[3] Real-time simulation, where a simulation runs parallel to the real traffic. Monitoring data are used to adapt the simulation to the real situation. The simulation program can run faster than real time and the operator can investigate what will happen in the future if he takes a measure (Mahmassani 2004).

In this paper a mixture of these approaches is followed. Three major steps are being followed in the proposed DSS:

- a matching rule enables to recognize a problem and to propose a robust solution – i.e. an approach like the rule-based DSS;

- further search continues to identify a most likely scenario that has been successfully executed before – the case based approach; and
- successful scenarios for traffic situations that have not been analyzed before, can be prepared offline and stored to a relational database after being tested.

The problem of the first approach is that it is very difficult to acquire a sufficiently complete set of rules to be able to react on most traffic situations. Expertise on network management is needed and in practice only knowledge about the most generic situations can be specified in a rule-based system. The second approach has the limitation that only a limited number of scenarios can be prepared and stored in a database. In a real network, even one of a moderate size, billions of possible scenarios can be relevant and defining and assessing them all is unfeasible. The third approach is necessary to collect the most relevant scenarios and derive rules from them. This makes the system (self) learning.

These three steps are closely linked to each other and are complementary in its function. In the case that no suitable scenarios are found, a further analysis is needed. The monitoring data are stored for further off-line search for a suitable new control scenario.

2.1 Establishing a learning-based mechanism

This consists of the following major steps:

- A rule-based robust choice approach,
- A case-based reasoning for most likely scenario,
- The development of new scenarios if necessary.

This combination would be able to combine both existing experts' knowledge of best practices, simulation-based scenarios and new knowledge.

A rule-based robust choice approach

A rule-based approach is similar to the current approach in a traffic control centre, where an operator follows a manual and selects procedures/measures to implement.

However this is not a replication of an operator's manual. It is a robust entrance to a more detailed case-based reasoning, which will be discussed next. This is to help structure the complex process, and avoid considering all kinds of technical and physical possibilities. Basically the rule base contains especially the meta-knowledge of the case base, i.e. the knowledge about the use of the case-base.

Again this step focuses on the desired traffic situation and proposed method to achieve it. The question of exactly what to use to achieve the targeted level will be answered by case-based measures.

On structured control of motorway and urban ring roads where the configuration of control devices is known, rules can be pre-set to actuate the control when events/incidence occur. Various scenarios can be possible for a same situation and performance indicators can be calculated to assess the measure of effectiveness for each of the scenarios. The best scenario can then be chosen. Further a performance indicator to a specific measure can be saved for further use.

A Case-based reasoning for most likely scenarios

On irregular or unstructured roads where control devices are not configured structurally, a rule-based approach may not be suitable to deliver the best control. But a rule-based approach can suggest a robust solution that is based on combination of various effective measures on known situations. As presented previously, a rule-based approach stores a typical measure to a typical situation, which allows coming up with a probable combination of measures. The robust solution needs to become a concrete measure to implement and to be operational.

There would not be a specific measure to a given problem that could happen at anywhere in the network at any moment. There is however a most likely one, based on the following:

- Knowledge-based expert system database (KBEST);
- Most likely pattern matching based on likelihood maximization.

The KBEST is filled in by historical and simulated cases, which will be the topic for the next paragraph.

The pattern matching is based on the likelihood that a case from the case base is identical with the observed situation. A short description is given below, following (Hegyi et al. 2000, 2001). The likelihood concept is represented by fuzzy sets, where the likelihood is converted into the membership of a situation to the class of a particular case.

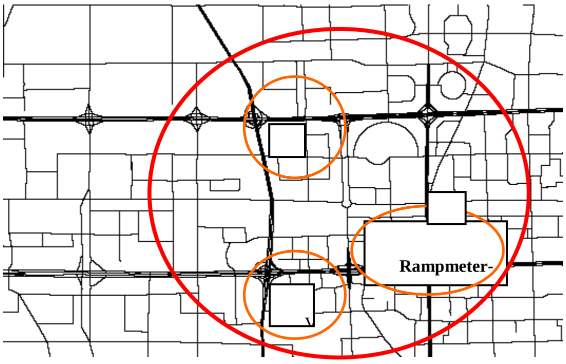

Figure 1: Example of individual area-measure membership functions

The fuzzy set approach is based on a set of 'fuzzy' cases characterized by parameters, where each fuzzy case has a certain domain of parameter values. Observed states observed having parameters within the range of a fuzzy case, are considered as a member of this fuzzy case, where the membership is determined as follows. Let the input vector $X = X^{(j)}$ summarize all the relevant parameters of the case for an area j. For all parameters, the membership (or similarity) relative to case c can be defined by a function $\mu_{i,c}(X_i)$ which expresses how much the parameter value Xi can be considered to belong to case c.. Considering all elements of the input vector X, the similarity of case c can be determined e.g. by taking the mean over the similarities of parameters i:

$$\lambda_c(X) = mean_i\{\mu_{i,c}(X_i)\} \qquad (1.1)$$

The predictions of the output $Y^{(j)}$ can be determined easily by considering the output or antecedent part $Y_c^{(j)}$ of the cases c:

$$Y^{(j)} = \frac{\sum_{c=1}^{n} \lambda_c(X^{(j)}) * Y_c^{(j)}}{\sum_{c=1}^{n} \lambda_c(X^{(j)})} \qquad (1.2)$$

where $Y_c^{(j)}$ denotes the predicted conditions in sub-network j as indicated in case c.

The example is based on measures (devices). It works also with other traffic attributes, such as a set of links.

A simulation approach for assessing the performance of a scenario

Computation effort may become excluded to find a best measure to a problem when a large network with many control measures is present, in the case-based reasoning as discussed above. To bypass this difficulty, a dynamic simulation approach is used.

The principle is as follows:

- code a traffic network, suitable for dynamic modelling
- obtain a dynamic (time-sliced) OD matrix
- load the OD into the network, with DTA (Dynamic Traffic Assignment) technique
- introduce also traffic control and measures into the DTA loading process

This would allow experts to choose only possible combination of measures to be evaluated in simulation, reducing potentially a large number of combinations with the case-based reasoning. Of course, it may happen that some relevant combinations are skipped or missed.

The real time generation of measures and its assessment by simulation looks as an interesting option, but has a limitation in the case of Beijing. The standard procedure for traffic management measures is that they should be approved before implementation. This means that the operator can develop a control strategy and assess it by simulation, but he should get approval before implementation. Therefore, a simulation approach needs to be followed by a (slow) process of verification and approval, after which it can be inserted in the case base. This shows that a new decision support tool has to be combined with a task analysis and task reconstruction in order to be effective and usable (van Zuylen and Gerritsen 1990)

A learning mechanism

At a traffic control centre, an experienced operator should know the performance of a specific measure or scenario (combination of various measures). This can also be established with a dynamic simulation where measures can be evaluated.

Performance of a measure or a scenario can be stored together in a relational database. A best performing one would replace or update the existing one in the database, or saved in the database if none is available yet.

With this possibility, any scenario/measure, whether existing or new, can be simulated and evaluated. A best solution can emerge in practice.

2.2 Building a relational database of scenarios

A learning-based mechanism requires that following actions be taken:

- Rule-based approach to provide a robust first suggestion to service a problem,
- Case-based reasoning to approximate more specific measures under the category service,
- Dynamic simulation to evaluate the performance of a specific scenario/measure.

The rule-based approach provides a robust and overall first level suggestion. This is based mainly on operators and practitioner's experiences. It stores effective scenarios as well as individual measure to problem, together with performing indicators, into a relational database (KBEST, in following section), where historical and simulation-based evaluation need to be performed to filled in the data. A dynamic traffic measure (Chen et al., 2004) is an action that produces signals to control traffic behaviour by informing, recommending, warning, facilitating, or enforcing.

The case-based approach provides more specific measures and needs most efforts to prepare. Again similar info such as in the rule-based cases is stored into the database.

The database contains these info: (1) event description (type, location and time, etc.), (2) traffic response (area, devices and time, etc.), and (3) measure of effectiveness (area, indicator, etc.). It is meant for both storage and retrieval.

Further the measure will have also a location and time indication, so that implementation can take place. Together with performance indicators provided by a dynamic simulation, this information will be stored into the KBEST for further retrieval.

3 Scenario analysis, generation and evaluation

To store effective scenarios (measure to problem) into KBEST and made them offline and online available, two sources are used: historical and simulated cases.

Key aspects to support such process include: (a) a problem identification based on a fuzzy matching procedure; and (b) a measure evaluation that can be performed according to performance indictors evaluated by a mesoscopic large-scale network dynamic simulation.

A mesoscopic dynamic traffic simulation model is used to incorporate major traffic elements together and simulates their interactions. These elements include the traffic network, traffic demand (vehicles), traffic control, and network-wide traffic control strategy. The flows in the dynamic simulation are based on Dynamic Traffic Assignment (DTA) method.

DTA has in this DSS the following characteristics:

- Dynamic simulation: time-step to a few seconds (OD-time slices may be further to minutes),
- Individual vehicles are simulated,
- Traffic control: coordinated control/split, offset,
- VMS, Ramp-metering,
- Road work, incidents,
- Guidance: travellers information such as speed signs and VMS, etc.,
- Network size: major roads within and including Beijing 5th ring,
- Number of vehicles: 1.5 million.

The simulation program evaluates a measure to a given problem with respect to certain objectives and determines whether it is the good scenario in a given circumstance. This is a built-in function of the DTMS (Dynamic Traffic Management System) (Figure 2). This can be performed specifically for all recommended measures to all identified problems. More interesting is that it can be done offline to prepare the KBEST and using the expert experiences for matching measure to problem.

A successful evaluation gives us a good case to store effective scenarios into KBEST. They can be called later on by real-case operations. The case-based reasoning is applied in the following way:

- Check further whether there are cases available in KBEST; this includes checking the availability of a specific measure in the given area;
- If available, select or update the case, based on the maximum likelihood of cases. This is where KBEST is filled in and updated.

The selection and retrieval of scenarios is done by assessing the membership of scenarios. The match is based on traffic patterns parameterized by flow, speed, travel time at given locations/areas or between defined OD pairs.

How quick a scenario can be recommended to an online operation depends largely on the size of the case base KBEST and how fast the matching procedure runs.

The Scenario Analysis, Generation and Evaluation System (SAGES) allows users to customize with the DSS system and to learn how to identify major traffic problems and what impact a traffic management measure or control scheme has on the network traffic.

Effective scenarios are then sent to real operations (TCSS – Traffic Control and Surveillance System) for the traffic operators to execute the actions.

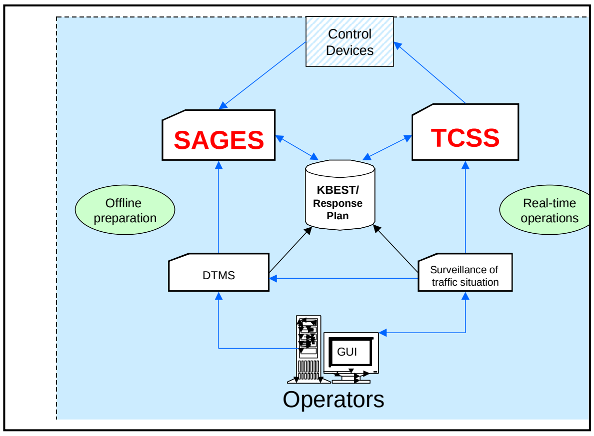

Figure 2: DSS Operations

3.1 Network-wide mesoscopic simulation

To access the impact of a given measure to a problem, two possibilities exist. One is to use a dynamic simulation to access the scenario offline, and the other is to evaluate it in site by real operations observation. See Figure 2. Both methods are adopted, by testing first offline with a dynamic simulation and then implement and test online. At this moment with ongoing development, only the simulation method is presented in this paper.

3.2 Network and data model

The whole Beijing network in the simulation model includes the major arterials and the 5th ring road (circular distance of 66 km) and the inside area. The city centre is within the 2nd ring, and the Olympic area between 3rd and 4th ring of the north part of the city. The network contains more than 610 zones, with 24 matrices sliced at 10 minutes each.

Each link is coded with a type, number of lanes (or turn-bay), as well as a traffic flow model to apply. Variable message signs (VMS), incident, work zone and ramp metering are also added to each link. Each node (junction) has a type, controlled or not, with turning movements.

3.3 Dynamic OD estimation

In order to represent the dynamic situation of traffic flow in Beijing, around 700 traffic counts are located in the whole network, providing flows and speeds observation intervals of 2 minutes. An a-priori matrix of 610 zones is available. The major challenge now is to estimate the dynamic matrices of 10 minutes interval, by these available data. The calibration of the OD matrices follows the approach as proposed by Chen (1992). This is similar to that by Zhou, Qin and Mahmassani (TRB, 2002). However Chen’s method tries to keep the original OD structure and minimizes a weighted sum of squared differences between the a-priori OD matrix and the estimated one, and the observed and estimated flows:

$$\min Z = \left\{ (1-w)\sum_{l,h}[\sum_{t,i,j} p_{(l,h),(t,i,j)} \cdot d_{(t,i,j)} / c_{(l,h)} - 1.0]^2 + w\sum_{i,j}[\sum_{t} d_{(t,i,j)} / g_{(i,j)} - 1.0]^2 \right\} \tag{1.3}$$

where

w = a positive weight between 0 and 1

p = link flow proportion, for departure time t, origin i and destination j, at link l and observation interval h

d = estimated traffic demand

c = measured traffic flows

g = historical static demand

Dynamic matrices have been estimated. Numerical results are reported elsewhere.

3.4 Calibration of a simulation model

Dynasmart-P (Mahmassani 2004) has been chosen for such an application. It uses a modified Greenshields model for the traffic propagation, which takes into account relationship between speed and density.

On major sections, Greenshields traffic flow models are estimated, using time-sliced traffic counts. This has been done in a few chosen areas and for different types of roads, ring roads, arterials, etc.

An overall flow display per 2 minutes, combining counts, CCTV (camera) monitoring, road work and congestion report are also used to calibrate the running Dynasmart model.

4 Application case

Actually the complete DSS is being implemented for a large urban area (5th ring road and inside) of Beijing. As a concrete application, the DSS recommends also scenarios for incident management, which is foreseen and being designed for north part of the city.

Among others, the complexity of the DSS includes also the large network, mixed traffic and large number of vehicles, as well as control plans, road layout and route guidance, which makes a pattern-match of a scenario to a problem a huge challenge.

5 Concluding remarks

A large and unprecedented urban DSS is being implemented in Beijing for a large urban network with huge amount of mixed traffic. A self-learning mechanism is being implemented in the three level decision support process, which is based on best practice and case-based reasoning. Key is to select and prepare effective scenarios by historical and simulated cases, and then to store and retrieve these scenarios into KBEST for further use. Dynamic simulation has been used for offline assessment and the evaluation of relevant scenarios and the KBEST provides background for case-based selection. At the moment of writing, development of systems is still ongoing and no further numerical results are available at moment. More findings will be reported in a later stage.

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