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# Managed information gathering and fusion for transient transport problems

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# Managed information gathering and fusion for transient transport problems

**Abstract: This paper deals with vehicular traffic management by communication technologies from Traffic Control Center point of view in road networks. The global goal is to manage the urban traffic by road traffic operations, controlling and interventional possibilities in order to minimize the traffic delays and stops and to improve traffic safety on the roads. This paper focuses on transient transport, when the controlling management is crucial. The aim was to detect the beginning time of the transient traffic on the roads, to gather the most appropriate data and to get reliable information for interventional suggestions. More reliable information can be created by information fusion, several fusion techniques are expounded in this paper. A half-automatic solution with Decision Support System has been developed to help with engineers in suggestions of interventions based on real time traffic data. The information fusion has benefits for Decision Support System: the complementary sensors may fill the gaps of one another, the system is able to detect the changing of the percentage of different vehicle types in traffic. An example of detection and interventional suggestion about transient traffic on transport networks of a little town is presented at the end of the paper. The novelty of this paper is the gathering of information – triggered by the state changing from stationer to transient – from ad hoc channels and combining them with information from developed regular channels.**

**JEL codes: R40**
**Keywords: information gathering, information fusion, Kalman filter, transient traffic, Decision Support System**

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## 1. Introduction: traffic management at Traffic Control Center

This paper deals with vehicular traffic management by wired and wireless communication technologies from Traffic Control Center (TCC) point of view in road networks. The traffic operators, engineers, experts at TCC should manage the traffic by urban road traffic operations, controlling and interventional possibilities in order to minimize the traffic delays and stops for the particular pattern of traffic flows and to improve traffic safety on the roads [28].

At stationer traffic, where the features of the traffic are almost permanent (i.e. fluctuation is small), the traffic engineers are monitoring the traffic, and they usually take only little and/or usual interventions. The reason of the lack of necessity of large interventions is the preliminary planning based on the historical statistical data: the traffic management has been planned considering the features of the traffic, like flow of the traffic, average speed on the road, average queue length before the traffic lamp. At stationer traffic the values of these traffic indicators are almost constants, therefore the planning can be taken relatively well, and the human interventions into the traffic is small and rare.

Traffic management at transient traffic – between stationer traffic states – is a more complex problem, where the control is crucial; because it can not be exactly planned for transient phenomena (transient behaviour of traffic flow can easily cause local congestions). One possibility to solve the traffic management at transient traffic is the totally automatic control systems without human interventions, but this has not realized in the immediate future. The other possibility is a half-automatic solution, where decision support system (DSS) helps with traffic engineers, operators (as can be see in Fig. 1.) in suggestions of interventions based on real time traffic data. This paper focuses on preparation for decisions by information gathering and fusion, which is the base of the feedback.

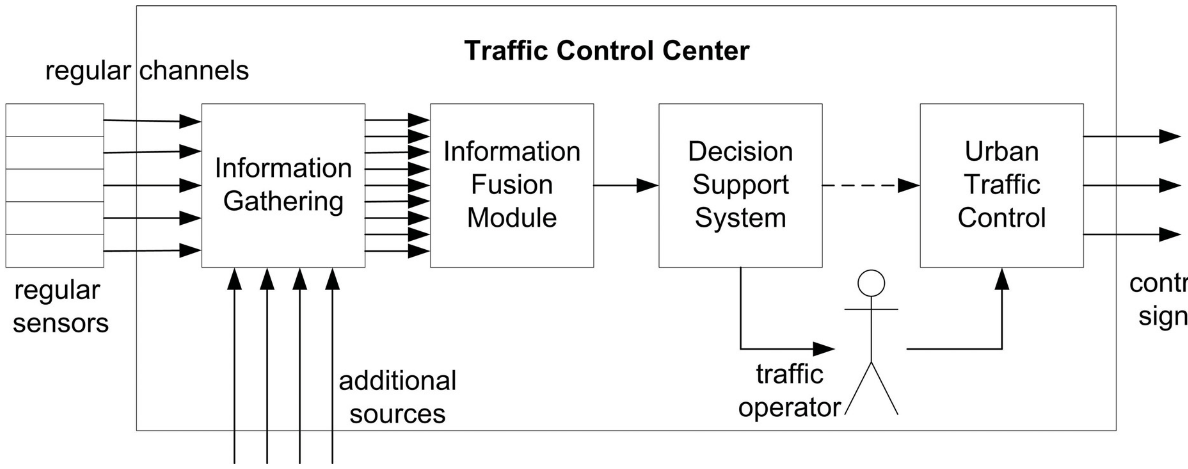

Figure 1. Parts of the Traffic Control Center

Modern TCC systems contain not only input and output possibilities for control, but some important parts as well as can be seen in Fig. 1. The Information Gathering part selects the regular sensors and channels for collecting information about traffic and circumstances of the traffic and gathers the information from them. In this part the communication between the sensors and TCC should be solved. The Information Fusion Module (IFM) aggregates the information coming from different sources. The goal of the information fusion is to get more reliable information in order to support the decisions. The next module of the flow of TCC is Decision Support System (DSS), which helps with traffic operators by suggestions (or prediction [1] at advanced DSS). Some decisions of DSS may control the Urban Traffic

Control (UTC) module directly, these are the automatic ones. Generally the UTC is half-automatic, it is controlled manually by traffic operators, engineers as well. UTC is a traffic responsive module based on a central computer and communications to individual traffic controllers by control signs [17]. It has continuous communication between each controller and the central computer, data pass to each controller in every second. The central computer performs an adaptive control on the traffic lights, and local controllers do not perform any regulating action, but can act independently if required.

## 2. Information gathering

### 2.1. Sensors

Detecting real-time traffic conditions is a key element to advanced traffic management and traveller information systems. Until the last decade, inductive loop detectors were the conventional method for collecting permanent on-sites traffic data. In recent years, technological innovations have given rise to many new and different types of advanced traffic detectors using magnetic, ultrasonic, microwave, infrared, and video sensors (video detection system). They provide direct measurement for counting, occupancy measurement, presence detection, queue detection, speed estimation and vehicle classification.

There are number of sensing technologies including fixed on-the-ground, mobile on-the-ground, remote sensing and on-board vehicle sensors. In an Intelligent Transportation System (ITS) these sensors can be the following: laser-based scanners, inductive loops, smart video cameras, high-resolution CMOS cameras, radar sensors, weather station, or innovative sensors [4][13], like ice detector. In the next some sensors of them are described in more details.

There are two different types of laser-based scanners: laser scanner perpendicular to the road and laser scanner multifunction. In the first case the system is based on two perpendicular laser beams focus to the road that are interrupted successively by the crossing of vehicles. The distance between these two laser beams is known and the vehicle speed can be obtained by this configuration.

Vehicles-behaviour analysis using video systems are usually based on CCTV cameras with a set-up optimised for normal traffic surveillance. Abnormal flow behaviour is recognised and after it the sensor provides an indication of the occurrence of an incident. Software connected to CCTV camera provides accurate presence and queue detection in addition to vehicles counts. Moreover, video has real potential to be used in detecting pedestrians and cyclists.

Several methods have been applied toward the general category of road surface condition sensing. The presently used technology for ice detection consists of a thermometer: it is clear that the information coming from the air temperature measurement only is very partial and can be considered just as a generic warning. The state-of-the-art solution is based on an innovative idea to detect the road surface conditions by new method. The new approach consists of the IR (Infrared Range) spectral analysis of the road surface [9]. The result of the measurement is very important information for the drivers in the vehicles. Furthermore this information may be important for TCC as well with the purpose of alerting the other drivers. In order to gather this information into TCC the ad hoc communication channel should be established.

## 2.2. Communication channels

The automatic exchange of information between the infrastructure and vehicles is important. Vehicles, as mobile elements, are used to collect data about weather and traffic conditions, this information are combined with other information. This aggregated information (e.g. an event in a time, in a given place measured by rear, front, lateral distance, etc.) is used to control traffic signals, inform drivers and give advice about the optimal route.

At case of stationer traffic the traffic operators at TCC make decisions based on information gathered from channels evolved for this purpose (the gathered information are generally sufficient for thorough decisions). The developed regular channels are mostly wired, but some wireless communication ones can be found as well. At case of transient phenomena the traffic experts use the same information sources, the same channels, but further information would be useful for thorough decisions in controlling. The further information can be gathered from ad hoc channels, which are typically wireless communication technologies. The novelty of this paper is the gathering of information – triggered by the state changing from stationer to transient – from ad hoc channels and combining them with information from developed regular channels.

In the investigation of possible communication technologies for ad hoc channels the GSM, GPRS [6], Zigbee and WIFI 802.11 p - WAVE [14] communication standards have been considered. The last one, WIFI - WAVE (Wireless Access for the Vehicle Environment) defines enhancements to 802.11 required to support Intelligent Transportation Systems (ITS) applications. This includes data exchange among high-speed vehicles and between a vehicle and the roadside infrastructure in the licensed ITS band of 5.9 GHz. It expands on conventional 802.11 wireless networking to allow for provisions that are specifically useful to automobiles.

A good possible communication technology for further information gathering is Mobile Ad-hoc NETwork (MANET – a collection of mobile devices which cooperate as a dynamic network without using fixed infrastructure) [21][19]. Other possibility is Vehicular Ad-Hoc Network (VANET) [22], which turns every participating car into a wireless router or node, allowing cars approximately 100 to 300 metres of each other to connect and, in turn, create a network with a wide range. As cars fall out of the signal range and drop out of the network, other cars can join in, connecting vehicles to one another so that a mobile Internet is created. MANET and VANET are similar to each other, but the details differ. Rather than moving at random, vehicles tend to move in an organized fashion. The interactions with roadside equipment can likewise be characterized fairly accurately. And finally, most vehicles are restricted in their range of motion, for example by being constrained to follow a paved highway. The third possibility is Intelligent Vehicular Ad-Hoc Networking (InVANET) [5], which defines an intelligent way of using Vehicular Networking. InVANET integrates on multiple ad-hoc networking technologies such as WiFi IEEE 802.11p, WAVE IEEE 1609, WiMAX IEEE 802.16, Bluetooth, IRA, ZigBee for easy, accurate, effective and simple communication between vehicles on dynamic mobility. Effective measures such as media communication among vehicles can be enabled as well methods to track the automotive vehicles are also preferred. InVANET helps in defining safety measures in vehicles, streaming communication between vehicles, infotainment, but this is not foreseen to replace current mobile (cellular phone) communication standards .

The author has participated in a common international work, where Smart Dust MANET solution has been used in the communication. The vehicles have been equipped with off-theshelf Smart Dust mote [2] from Crossbow Technologies called MPR2400 MICAz. MICAz motes are equipped with a Zigbee radio [3] chip, allowing them to communicate with other MICAz motes within range (approximately 70m). The motes broadcast information that will be picked up by other motes or a base station (a mote connected to a PC) within range. The Smart Dust MANET can be used to pass information from one point (sensor) to another when there is no fixed-network coverage. The motes can also hold compatible sensors, allowing various measurements such as light and temperature readings, speed and magnetic field. The most important information, like speed should be sent to TCC through the base station.

The concept of information gathering with Smart Dust MANET communication technologies and usage them for traffic management [18] described above has been implemented at TCC in Valencia as an experiment in a common work.

## 3. Information Fusion

The usage of additional information is not trivial; this could fill in the gaps of regular information, but could be opposite to regular one. Information fusion [7] should be executed to aggregate all information into coherent one. Information fusion techniques such as Bayesian inference [26], Dempster-Shafer inference, Kalman filter [24], Fuzzy Logic [20], and Artificial Neural Networks [20] can be used in Intelligent Transportation Systems for road traffic analysis and prediction. The author has used Dempster-Shafer inference in previous work [27] of routing on transport networks – Dempster-Shafer theory of evidence [23][10] represents confidence levels by belief functions – thus Bayesian inference, Fuzzy Logic, and Kalman filter are described here, as the most recent information fusion techniques in international transportation projects.

### 3.1. Bayesian inference

Bayesian inference is one of the oldest decision making technique that combines observations to infer the probability of a hypothesis; it is mainly used for classification applications. The degree of confidence in a hypothesis is represented by a subjective probability that is a numerical estimation that can be used like a classical probability. Bayesian inference enables these estimations to be updated when some observations become available. The Bayesian theorem combines the prior estimations of the degree of confidence with the observations.

Let $\Omega = \{H_1, \ldots, H_n\}$ be the set of all possible states of the system; in a classification system for instance, $\Omega$ would be the set of classes. These states are mutually exclusive and complete (exhaustive), which means that the system is in one and only one of these states. The probability $P(H_1)$ is an expression of the belief or confidence that the system is in state $H_1$ in absence of any other knowledge. Once we get more knowledge in form of an observed evidence E then the appropriate expression to be associated with the proposition $H_1$ is the posterior probability $P(H_1 \mid E)$. The Bayes theorem gives:

$$P(H_1 \mid E) = \frac{P(E \mid H_1) P(H_1)}{P(E)}$$

If we have several sources of observations $E_1 \ldots E_M$ and if we assume statistical independence between them, we can combine observations to infer the state of the system with the Bayes theorem:

$$P(H_i \mid E_1..E_M) = \frac{\prod_j P(E_j \mid H_i) P(H_i)}{P(E_1..E_M)}$$

The most used decision rule selects the hypothesis that maximises this posterior probability. This Bayesian based fusion techniques have some drawbacks. This method needs the knowledge of the prior probability distributions, which are not always easy to calculate. The source independence is seldom satisfied in practical applications. In the Bayesian framework there is no way to represent and handle ignorance. In addition, no information is provided about the quality of the fused probability, in terms of our trust in our evidence or the existence of conflicting evidence.

### 3.2. Fuzzy Logic based information fusion

Other representations of confidence degrees have been investigated more recently that do not use probabilities. The measures of possibility have been introduced by Dubois and Prade [11][12], the degree of confidence assigned to a hypothesis is represented with fuzzy membership functions formerly introduced by Zadeh [30].

Let us assume that $\Omega = \{H_1, \ldots, H_n\}$ is the set of possible decisions concerning for instance the value of a parameter $\theta$; each decision $H_i$ could be represented by a fuzzy membership function. A source X is given a possibility distribution $\pi_X(x)$ with values in [0,1] that represents the degree of possibility that $\theta$ is equal to x. Fig. 2 gives an example of a classical shape for possibility distribution.

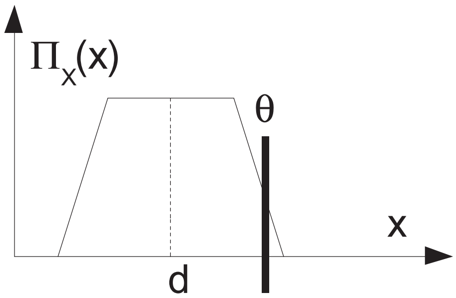


Figure 2. An example for possibility distribution

Possibility distributions enable us to define possibility measures $\Pi$ on the powerset $2^{\Omega}$, which is the set of all possible sub-sets of $\Omega$:

$$\Pi : \quad 2^{\Omega} \rightarrow [0;1]$$

$$A \rightarrow \Pi(A) = \sup_{u \in A} \pi(u)$$

with $\Pi(\phi) = 0$ and $\Pi(\Omega) = 1$

There is an important equation based on the previous ones:

$$\max\left(\Pi(A), \Pi(\overline{A})\right) = 1$$

The quantity (1 - $\Pi(A)$ ) is the dual necessity measure of A. Different aggregate operators are available to combine possibility distributions given by two (or more) sources:

- Conjunctive operators (i.e. fuzzy set intersection) are well suited when sources are both reliable:

$$\pi_{1,2}(u) = \min(\pi_1(u), \pi_2(u))$$

- Disjunctive operators (i.e. fuzzy set union) should be preferred when at least one source is not reliable:

$$\pi_{1,2}(u) = \max(\pi_1(u), \pi_2(u))$$

The last category concerns adaptive operators that take conflict between sources into account to combine distributions. Dubois and Prade [11] propose a measure of the source conflict (see Fig. 3):

$$h'(\pi_1, \pi_2) = 1 - h(\pi_1, \pi_2) = 1 - \max(\min(\pi_1(u), \pi_2(u)))$$

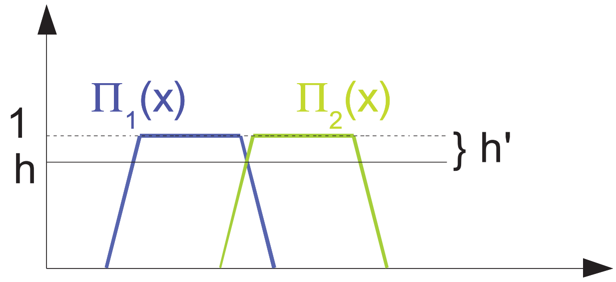


Figure 3. Dubois and Prade's measure h' of source conflict

They define an adaptive fusion operator with:

$$\pi_{1,2}(u) = \max\left(\frac{\min(\pi_1(u), \pi_2(u))}{h}, \min(\max(\pi_1(u), \pi_2(u)), h')\right)$$

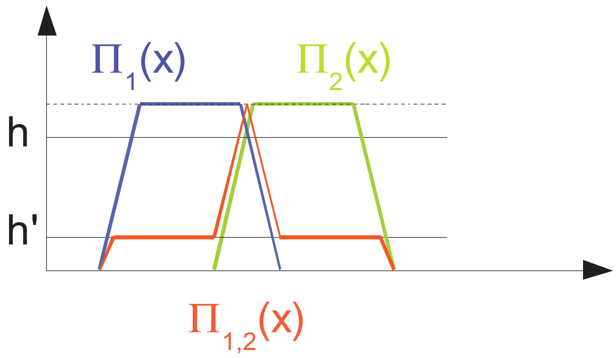


Figure 4. Dubois and Prade's adaptive operator

The more important the conflict is, the more uncertain the resulting distribution (can be seen in Fig. 4.). The decision is generally driven by the maximum of probability measures (optimistic decision). This formalism is especially well suited to represent imprecision (the reliability of a source can be expressed), and it gives tools to detect conflict and take it into account. A large part of sensor fusion applications are based on fuzzy sets and possibility measures.

### 3.3. Kalman filter

The Kalman filter [15] is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimises the mean of the squared error. The filter is very powerful in several aspects: (i) estimations of past, present, and even future states are supported, (ii) estimations can be achieved even when the precise nature of the modelled system is unknown.

A Kalman filter is simply an optimal recursive data processing algorithm. There are many ways of defining optimal dependability upon the criteria chosen to evaluate performance. One aspect of this optimality is that the Kalman filter incorporates all information that can be provided to it. It processes all available measurements, regardless of their precision to estimate the current value of the variables of interest with use of:

- knowledge of the system and measurement device dynamics,
- the statistical description of the system noises, measurement errors and uncertainty in the dynamics model,
- any available information about initial conditions of the variables of interest.

The Kalman filter does not require all previous data to be kept in storage and reprocessed every time a new measurement is taken. The filter is actually a data processing algorithm (computer program). It inherently incorporates discrete-time measurement samples rather than continuous time inputs.

The Kalman filter addresses the general problem of trying to estimate the state $x \in \Re^n$ of a discrete-time controlled process that is governed by the linear stochastic difference equation:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$

with a measurement $z \in \Re^m$ that is

$$z_k = Hx_k + v_k$$

The random variables $w_k$ and $v_k$ represent the process and measurement noise, respectively. They are assumed to be independent (of each other), white noise, and with normal probability distributions

$$p(w) \sim N(0, Q)$$
$$p(v) \sim N(0, R)$$

In practice, the *process noise covariance* $Q$ and *measurement noise covariance* $R$ matrices might change with each time step or measurement, however here we assume they are constant.

The $n \times n$ matrix $A$ in the first difference equation described relates the state at the previous time step $k-1$ to the state at the current step $k$, in the absence of either a driving function or process noise. Note that in practice $A$ might change with each time step, but here we assume it is constant. The $n \times l$ matrix $B$ relates the optional control input $u \in \Re^l$ to the state $x$. The $m \times n$ matrix $H$ in the measurement equation (the second one stated) relates the state to the measurement $z_k$. In practice $H$ might change with each time step or measurement, but here we assume it is constant.

The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the Kalman filter fall into two groups: *time update* equations (predict) and *measurement update* equations (correct) The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step.

The measurement update equations are responsible for the feedback, i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate. The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm resembles that of a predictor-corrector algorithm for solving numerical problems. The specific equations of Discrete Kalman filter for the time updates are presented in the following:

Project the state ahead:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1}$$

Project the error covariance ahead:

$$P_k^- = AP_{k-1}A^T + Q$$

The specific equations of Discrete Kalman filter for the measurement updates are presented in the following:

Compute the Kalman gain:

$$K_k = P_k^- H^T \left(HP_k^- H^T + R\right)^{-1}$$

Update estimate with measurement $z_k$:

$$\hat{x}_k = \hat{x}_k^- + K_k\left(z_k - H\hat{x}_k^-\right)$$

Update the error covariance:

$$P_k = \left(I - K_k H\right)P_k^-$$

The first task during the measurement update is to compute the Kalman gain, $K_k$. The next step is to actually measure the process to obtain $z_k$, and then to generate an a posteriori state estimate by incorporating the measurement as in the second equation in the discrete Kalman filter measurement update equations table. The final step is to obtain an a posteriori error covariance estimate via the last equation from this same table. After each time and measurement update pair, the process is repeated with the previous a posteriori estimates used to project or predict the new a priori estimates. This recursive nature is one of the very appealing features of the Kalman filter, only initial estimates for $\hat{x}_{k-1}$ and $P_{k-1}$ are required.

## 4. Decision Support System

The Information Gathering (IG) module monitors the status of the sensors in real time and the DSS make decisions according to information from IG (via IFM). In Fig. 5 Decision Support System can be seen for transient traffic management. A preprocessing phase is executed before the most important module, the Transient Detection. If transient traffic is recognized then Transient Detection module gives alert and suggestions according to the type of transient (in priority order) for traffic operators; otherwise stationary part of DSS controls the traffic. At output of preprocessing module some statistics are available, which are used for long term decision making. This long term DSS is very useful for traffic experts and planners in traffic planning.

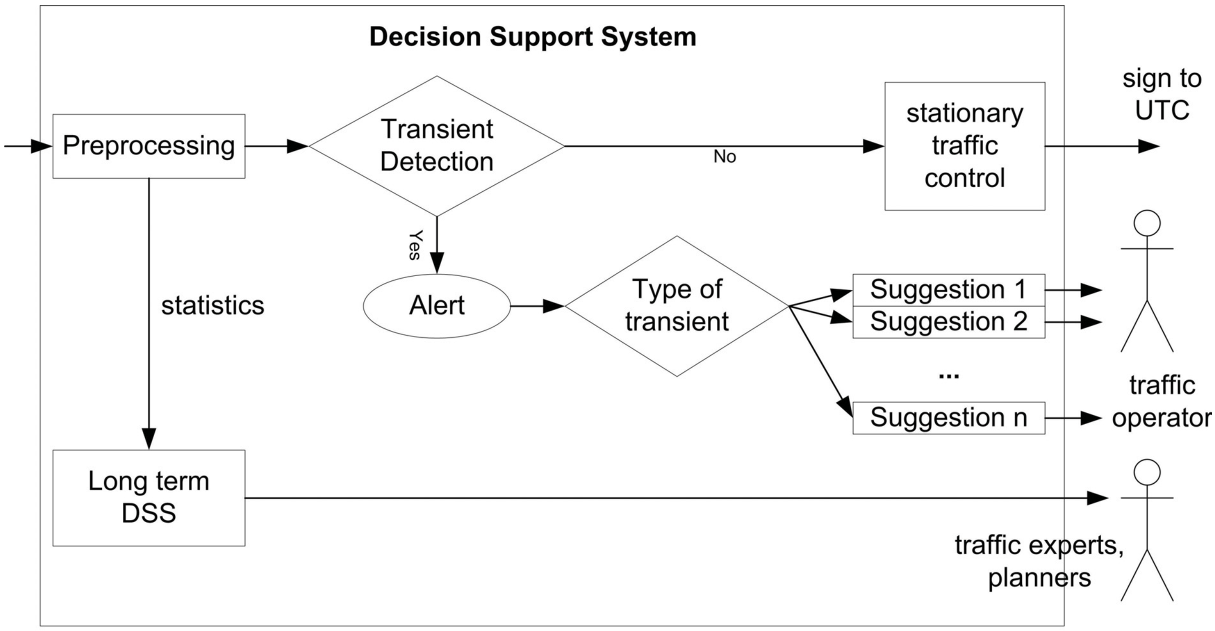


Figure 5. Decision Support System

### 4.1. Transient detection

DSS – as part of TCC – estimates the traffic demand for the next cycle of the traffic lights and investigate the time change possibilities of the signals, then predicts the effect of small changes of the current settings of the signals. DSS suggests the best split, offset and cycle time of the signals of traffic lights for traffic engineers in order to help in traffic management. The traffic management is based on data collected from detectors developed in the road network. These data are processed and used to establish the flow profiles – one for each link, divided into little time intervals. These flow profiles give the stationer state of the traffic, and the real time data are compared with them to calculate the differences. If the difference is larger than a predefined threshold, then the traffic is considered as transient, and this is a trigger event to begin gathering other information.

The stationary traffic can be finished by an incident. The incidents are nonrecurring events such as accidents, stalled vehicles, spilled loads, temporary construction and maintenance activities that disrupt the normal flow of traffic and may cause traffic congestion. Advanced ITS have Automated Incident Detection (AID) algorithms [31] to assist operators in efficiently detecting the incidents in order to minimize the traffic flow disruption [8][16][25][29]. The detection is done based on the spatial and temporal changes in the traffic pattern parameters which persist over a period of time.

In these detection problems the situations are defined by indicators, where the set of all conditions should meet to the predefined ones (e.g. a congestion on the given road is defined by two conditions: the average speed is lower than 10 km/h and the number of vehicles in the row is higher than 20). The common part of these incident detections is the well defined conditions. But in this paper the well defined conditions describe not the incident, but the stationary traffic state. If any of the conditions is not meet to the predefined range then the state is investigated: if the difference between the current and stationary values is larger the predefined threshold, then this situation is considered as a transient traffic. E.g. a stationary traffic on the given road is defined by two conditions: the average speed is higher than 25 km/h and the number of vehicles in the row is between 5 and 25. The reasons of the end of the stationary traffic may be different: congestion causes low average speed (below 25 km/h the original stationary traffic changes) or closing the road causes too few vehicles (on empty road the number of vehicles will be smaller than 5), etc. The stationary traffic can be defined by not only the vehicle flow, but by the composition of them (percentage of different vehicle types). There is an additional condition of traffic state in this case: the percentage of given vehicle type should be in a predefined range (e.g. percentage of trucks should be lower than 10%).

### 4.2. Managed information fusion for Decision Support System

In DSS there are some potential benefits of the combination of different sensor sources. E.g. the combination of the AC20 radar and the video sensing system via IFM can lead to an enhanced sensing solution, because of two complementary technologies. The success of this cooperation lays in the different sensing approach of sensors, and the complementary sensors capacity to fill the gaps of one another, which is solved in IFM.

Another example in this context is the collaboration between the inductive loop and video camera: the inductive loop sends its data to the DSS (via IFM), which shows a low speed incident and suggests to the operator to send the video camera to the target area to obtain more information. This additional information is sent to the IFM, which performs the information fusion obtaining more accurate and detailed information from the combination of the information coming from both sensors.

The DSS is able to suggest a specific action to the operator when DSS receives fused data from IFM. A good example for detection of transient traffic is the collaboration work between the inductive loop and the laser scanner. In this scenario DSS is able to detect the modification of the percentage of different vehicle types in traffic. The inductive loop detects a truck and informs that it is a 4 axle truck. This sends this information to IFM, at the same time the laser scanner placed at the same location with the loop also detects a truck and sends the information to IFM. Both data are fused and robust information is provided on the detection of four axle trucks. If the percentage of trucks is higher than 10%, then the stationary traffic changes into transient one. This information is sent by the IFM to the DSS, which shows an incident and suggests the update of the Variable Message Sign (VMS) at the entrance of the city forbidding the access of this type of trucks. This situation makes sense and is very useful when specific events take place in the city and traffic conditions are affected. The entrance of heavy vehicles would make the situation worse; this is why the traffic authorities forbid the entrance to the city.

These examples belong to short term strategies, but DSS provides further benefits about possibilities of developing long term, more strategic actions. This allows the traffic authorities to have detailed and robust information on the evolution of the information coming from the sensors installed in the road network, and hence, making decisions that will improve the traffic conditions acting directly on the areas where the major problems on a long term basis have been detected.

### 4.2. Example

In order to test the solution described above a test bed has been constructed from a little town (Székesfehérvár) in Hungary. The test bed contains the Székesfehérvár's road network with more than four-thousand points. The graph of the transport networks has contained 4111 nodes and 5443 edges. A row (representing a given edge) in the file (describing the network) stores 26 kinds of data, like quality of the road surface, which types of vehicles can travel on the road, what is the speed limit, etc. For the modelling the most relevant features are selected from 26 kinds of data:

- identity of the beginning point
- identity of the end point
- direction of the road
- average speed on the road
- number of the lanes
- length of the road

DSS parts for transient traffic have been implemented in C programming language. The next figure (Fig. 6) shows the graphical representation of the Székesfehérvár's transport networks. The six blue spots in the centre of the picture represent the rain-clouds, which cause modification of the stationary traffic because of wet roads. DSS detects the beginning of the transient traffic and suggests a good route (black bald line in the figure) in order to avoid this rainy area. The traffic operators set the green wave at traffic lights fitting in to this suggested route.

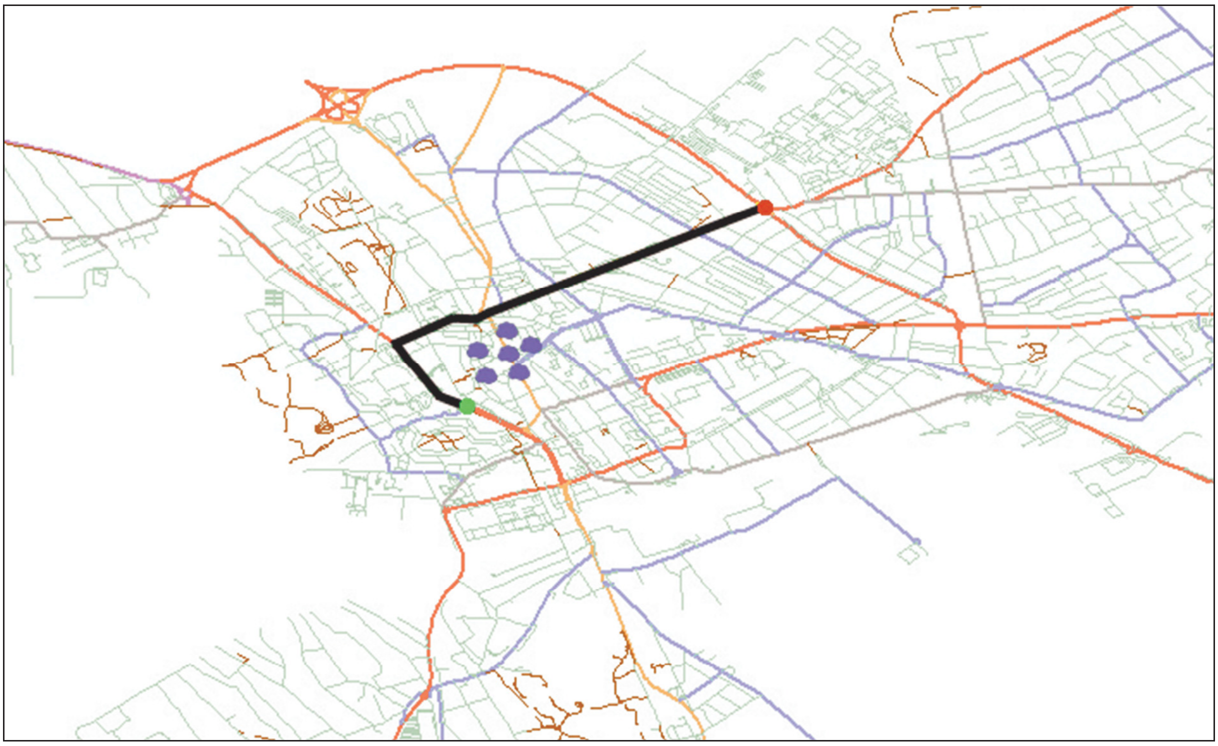

Figure 6. Székesfehérvár's transport networks

After a while rain has finished and lots of vehicles have travelled on the route represented by black bald line. The many vehicles cause congestion, as can be seen four cars in Fig 7. The consequence of this situation is a new transient phenomenon in traffic, which is recognized by DSS again. The new suggestion for alternative route is a black bald line in Fig 7.

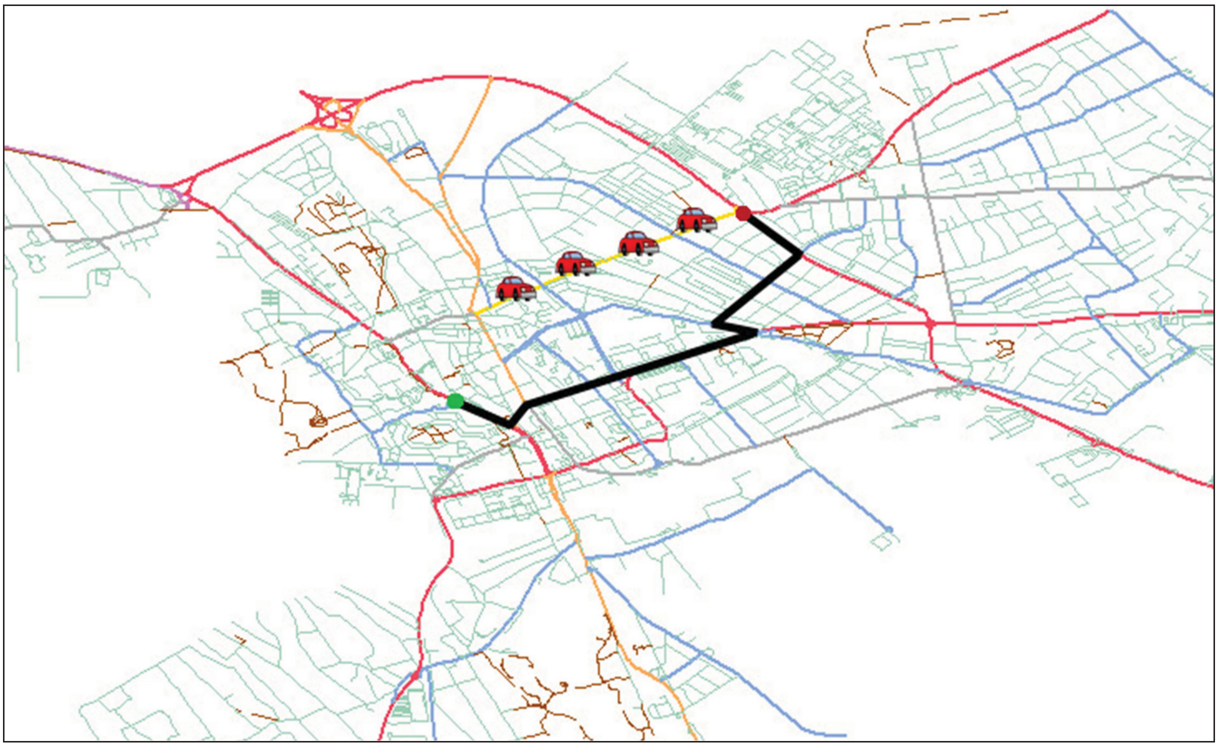

Figure 7. Alternative route suggestion

## 5. Conclusion

At stationer traffic the traffic engineers are monitoring the traffic, and they usually take only little and/or usual interventions. Traffic management at transient traffic is a more complex problem, where the control is crucial; because it can not be exactly planned for transient phenomena. This paper has presented a half-automatic solution for this, where Decision Support System helps with engineers in suggestions of interventions based on real time traffic data. The novelty of this paper was the gathering of information – triggered by the state changing from stationer to transient – from ad hoc channels and combining them with information from developed regular channels. This information fusion has benefits at DSS. One of the possible benefits can be seen at combination of different sensing approach of sensors, where the complementary sensors fill the gaps of one another (like AC20 radar and the video sensing system or inductive loop and video camera). There is another benefit at the scenario of detection the changing of percentage of different vehicle types in traffic. The detection of transient traffic is based on the collaboration between the inductive loop and the laser scanner. This situation may useful when specific events take place in the city and traffic conditions are affected. The traffic authorities forbid the entrance to the city because the entrance of heavy vehicles would worse traffic situation. An example of detection and DSS suggestion about transient traffic on Székesfehérvár's transport networks is presented at the end of the paper.

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