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Input Data Selection for Road Traffic Control Systems

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Abstract

Emerging technologies in road traffic monitoring deliver communication solutions for wireless data transfers from mobile sensors. The availability of mobile sensors creates a huge opportunity to extend the road-side detection infrastructure of existing traffic control systems. The efficient use of the wireless communication medium is one of the basic issues in traffic monitoring systems development. In this paper a new method is proposed for input data selection in traffic control systems. The basic idea behind the input data selection is to recognise the necessity of data transfers through the uncertainty analysis of the traffic control decisions. The introduced algorithm selects time instances of input data that are transmitted from the traffic monitoring system to the control unit. The rejected measurement data are replaced by information granules produced by an on-line traffic simulation. If precision of the information granules decreases and the control decisions become uncertain then the current data readings have to be transferred. This principle enables a considerable reduction of the data volumes that have to be transmitted from traffic monitoring system. Processing of the measurement data is based on information granulation within fuzzy cellular traffic model. This technique allows the incomplete traffic information to be used for performance evaluation of control strategies and for uncertainty estimation of control decisions. Simulation experiments were performed to investigate the usefulness of this method for traffic control at signalised intersection.

1. Introduction

Recent developments of transport systems telematics provide effective techniques for traffic data acquisition and transfer [36]. Emerging technologies in road traffic monitoring (e.g. floating car data systems, and vehicular sensor networks) enable wireless communication between sensing devices installed in vehicles (mobile

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sensors) and the road environment for dynamic transfers of measurement data with a low cost and high accuracy [40]. The sensors available in vehicles can gather data sets including locations, speeds, directions, accelerations, etc. Thus, the vehicles can be used as the sources of information to determine accurately the traffic flow characteristics [18].

The road traffic control becomes an important application area of mobile sensors. This new technology creates a huge opportunity to extend the road-side detection infrastructure of the existing traffic control and monitoring systems [18]. A major drawback of the current-generation systems is a limited access to the traffic data that are usually registered only in few fixed positions [28, 29]. The coverage of these sensing platforms is narrow due to high installation and maintenance costs. It is expected that the mobile sensors will help to overcome these limitations as their remarkable feature is the capability to monitor every single vehicle dynamically.

Adaptive traffic control algorithms require real-time transfers of input data that describe current and predicted traffic state [14]. However, for many cases the scope of real-time measurement data available in traffic monitoring systems exceeds the requirements of particular traffic control implementations. Moreover, the transfer of all data records from vehicles to the traffic control unit is highly not advisable due to the bandwidth-limited wireless communication medium. Number of vehicles may use the same transmission medium for many applications of different purposes (e.g. control, safety, comfort). In dense road traffic the periodic transmissions may consume the entire channel bandwidth resulting in excessive congestion and delays in the communication network. Therefore the efficient use of the wireless communication channel is one of the basic issues in traffic monitoring systems development [18].

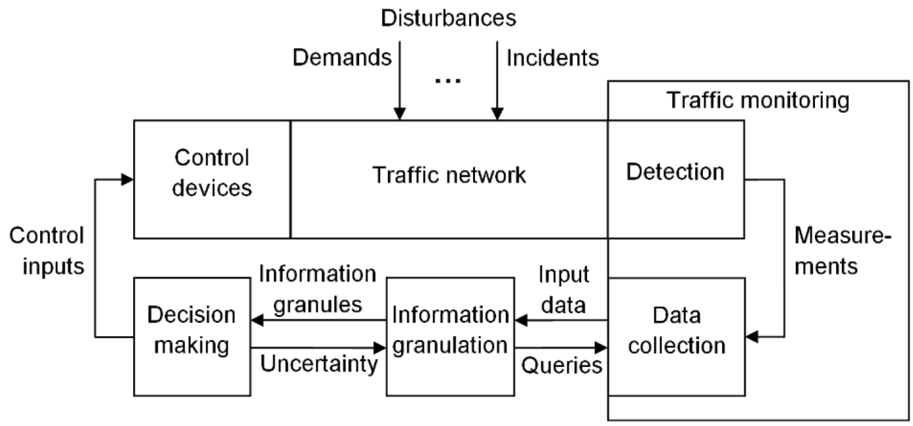

Fig. 1. Functional modules of traffic control system

The contribution of this paper is the proposal of a novel methodology of measurement data selection for traffic control systems, which provides a significant reduction in traffic data transmission. The underlying idea is to detect the necessity of data transfers on the basis of uncertainty determination of the traffic control decisions. Fig. 1 presents the overall design of the road traffic control system. This schema includes the data collection module, which processes queries and retrieves useful traffic data from the traffic monitoring system. The advantage of the introduced approach is that it uses on-time queries [39] instead of periodical data sampling. On-time queries are generated by the information granulation module only at the specific moments of time, when a high uncertainty level of the control decision occurs. The information granulation procedure involves on-line traffic simulation, which is performed using the fuzzy cellular model [25]. Result of the information granulation is a set of granules that describe current and predicted traffic states. A task of the decision making module is to use the available information granules in a selection of optimal traffic control strategy among several alternatives (e.g. optimal selection of travel route or traffic signal timing).

The uncertainty level of control decisions depends on the size (precision) of the traffic information granules [27]. If the precision of the resulting information is insufficient, the optimal control strategy cannot be derived without ambiguity. As a result the control decision becomes uncertain and it is a signal informing that new input data are necessary in the system to provide more precise traffic information and to reduce the uncertainty of decision.

The rest of the paper is organised as follows: Related works are reviewed and analysed in Section 2. Section 3 describes the method of traffic information granulation within fuzzy cellular model. An algorithm for performance evaluation of traffic control strategies is presented in Section 4. Section 5 discusses the basic steps of decision making and uncertainty calculation in the traffic control procedure. In Section 6, the algorithm of input data selection is introduced in details. Section 7 contains the results of an experimental study on input data selection for the traffic control at a signalised intersection. Finally, in Section 8, conclusions are given and some future research directions are outlined.

2. Related Works

Many research and implementation efforts have been involved recently in traffic monitoring technologies based on wireless communication e.g. [2, 11, 19]. The traffic monitoring platforms are typically implemented in client-server architectures. Such platforms usually consist of servers and vehicles equipped with mobile sensors (e.g. GPS modules) and the wireless communication interfaces, such as 3G or Wi-Fi networks. The sensed data (e.g. the speed and the position) are sent to the server for traffic monitoring. Clearly, with these input data, traffic state can be estimated without any aid of costly road-side detection systems. Using the communication capability of each vehicle, the traffic control applications are supplied with up-to-date information about particular events that effect control decisions.

The emergence of mobile sensing technologies has made it possible to introduce novel, more effective techniques of road traffic control. Several traffic control algorithms have been developed in this field of research for signalised intersections. Most methods are based on wireless communication between vehicles and road-side control nodes e.g. [1, 9, 43]. These adaptive signal control schemes use real-time sensor data collected from vehicles (e.g. their positions and speeds) to minimise travel time and delay experienced by drivers at road intersections.

Numerous works have been devoted to the problem of traffic control in road networks. In [6] a traffic management system has been introduced that includes a server-side decision making module for optimal route selection in urban network and enables the dissemination of instructions to vehicles. Wedde et al. [42] have proposed a routing scheme from multi-agent routing algorithm to control road traffic. In that approach vehicles are directed under decentralised control at each road intersection. The technique proposed by Inoue et al. [13] employs traffic information sharing and route selection procedures to address the problem of vehicle traffic congestion. On the basis of shared traffic information, congestion free routes are selected. In the Street Smart Scheme [8], each vehicle builds a speed map based on the speed of other vehicles in its vicinity and transmits it to the neighbouring vehicles. As a result, each vehicle is able to select the fastest route. In [22] an approach has been proposed to deal with the problem of traffic congestion using a congestion control algorithm designed for the Internet. A strategy developed by Wang et al. [41] attends the problem of traffic congestion in intersections where a ramp leads on to a highway. According to this proactive traffic merging strategy, vehicles share their velocity and acceleration information with other vehicles in the network. Each vehicle decides where and when it can merge onto the highway before arriving at the merging point. Another traffic control application enabled is dynamic speed control including speed warning, variable speed limits, and cooperative driving [4].

Although much work has been done to develop the road traffic control applications, little research has examined their requirements on input data. In most of the above cited studies, the real-time sensed data are assumed to be delivered continuously from all vehicles in a certain area to the control node. Such periodical data sampling scheme may cause excessive congestion and latency in the communication network due to the bandwidth-limited wireless communication medium. Therefore, more research is needed to determine required input data sets as well as sampling rates that are necessary for the decision making in traffic control applications. On-line evaluation of these characteristics will enable reduction in amounts of the transmitted data.

The problem of data congestion and transfer latency in vehicular ad-hoc networks (VANETs) has been addressed in many publications e.g. [7, 10, 12, 33, 34]. A way to avoid this problem is to increase the bandwidth but usually this is not cost-effective because quite often the congestion arises due to the inappropriate allocation or utilisation of resources [10]. Another approach is to fairly share the available bandwidth among the users without causing any congestion, i.e. congestion avoidance with efficient bandwidth management. Most of researches tend to find improvements using effective medium access control protocols [37], transmission strategies (e.g. data dissemination [7], data aggregation [33], self-organisation mechanisms [34]), and advanced wireless technologies [18] in order to reduce the congestion and latency. While above solutions focus on the expansion of the available network capacity, the input data selection methodology introduced in this paper contributes to reduction of data congestion in traffic monitoring systems by minimising the demand for data transmission.

In the literature several methods have been introduced for wireless sensor networks that enable the optimisation of data transfer for monitoring applications. Spatial and temporal suppression based techniques have been demonstrated to be useful in reducing the amount of sensor data transmitted for monitoring physical phenomena [17, 31, 38]. The underlying insight is that different observed states of the physical phenomena are in fact temporally as well as spatially correlated. Temporal suppression is the most basic method: sensor readings are transmitted only from those nodes where a change occurred since the last transmission [32]. Spatial suppression includes methods such as clustered aggregation [21] and model-based suppression [3]. They aim to reduce redundant transmissions by exploiting the spatial correlation of sensor readings. If the sensor readings of neighbouring sensor nodes are the same or similar, the transmission of those sensed values can be suppressed. In [38] a combined spatio-temporal suppression algorithm was introduced that considers the node readings and their differences along transmission paths to suppress reports from individual nodes.

The suppression based methods use a subset of sensor readings from selected nodes to derive actual values of the monitored parameters for all remaining nodes in the network. However, in those methods the data transfer procedure is executed at regular time intervals because the sensor readings have to be continuously analysed to suppress the unnecessary transmissions from particular nodes. The method introduced in this paper enables the time selective execution of the data transfers in traffic monitoring systems. According to the proposed approach, sensor data are transmitted from nodes (i.e. vehicles) to the control unit only at selected time moments. For the remaining time periods, the data transfer is ceased and the control unit approximates all the sensor readings on its own, using an information granulation technique. It should be noted here that in such time periods the control node does not communicate with other nodes (vehicles). This approach exploits the fact that traffic control algorithms can tolerate approximate (granular) traffic information. Nevertheless, the precision of traffic parameters approximation (granulation) has to be appropriately high to ensure the optimal performance of a traffic control system [30].

3. Traffic Information Granulation

According to the proposed approach, the traffic information granulation procedure requires an application of a traffic model to process the selected measurement data. The traffic model is necessary to use the incomplete data for producing traffic information granules that approximate the current and future traffic state. The resulting information granules are further used for performance evaluation of control strategies as well as for uncertainty estimation.

Traffic information granule *IG* is defined as a subset of universe of discourse $IG \subseteq R$, representing a group of traffic states that cannot be distinguished on the basis of available data [27]. The universe of discourse R is a multidimensional space of traffic parameters. In other words, the points in universe R correspond to all possible traffic states. This definition enables an arbitrary choice of formal method for representation of the information granules. The choice of formal method involves definition of theoretical framework for information processing (set theory, algebra of interval numbers, algebra of fuzzy numbers, etc.)

In the proposed information granulation method the fuzzy cellular model is applied to on-line simulation of traffic flow. The on-line simulation technique enables rapid evaluation of alternate courses of action in order to aid in decision making processes [16]. It allows us to determine the current traffic parameters (real time simulation) as well as to predict the future state of the traffic flow (faster than real time simulation). The term on-line means that the simulation is synchronised with real time and it is adjusted to data collected in traffic monitoring system.

The fuzzy cellular model of road traffic was intended for on-line simulation and satisfies specific requirements of traffic control applications [25]. This model is based on cellular automata approach to traffic modelling that ensures accurate simulation of the real traffic phenomena [20, 23]. To deal with nondeterministic traffic processes the uncertainty is described in the cellular model using fuzzy sets theory. All parameters of vehicles are represented individually by fuzzy numbers. These facts along with low computational complexity make the model suitable for on-line processing of traffic data.

A traffic lane in the fuzzy cellular model is divided into cells that correspond to the road segments of equal length. The traffic state is described in discrete time steps. These two basic assumptions are consistent with those of the Nagel-Schreckenberg cellular automata model. Thus, the calibration methods proposed in [23] are also applicable here for determination of the cells length and vehicles properties. A novel feature distinguishing this approach from the other cellular models is that vehicle position, its velocity and other parameters are modelled by fuzzy numbers defined on the set of integers. Moreover, also the rule of model transition from one time step to the next is based on fuzzy definitions of basic arithmetical operations.

In order to reduce the computational effort associated with on-line simulation, the fuzzy cellular model was implemented using the concept of ordered fuzzy numbers [15]. The algebra of ordered fuzzy numbers is a significantly more efficient tool than the solution based on classical fuzzy numbers and extension principle applied in [26]. Hereinafter, all the ordered fuzzy numbers are represented by four integers and the following notation is used: $A = (a_1, a_2, a_3, a_4)$. This notation is suitable for both triangular as well as trapezoidal membership functions. The arithmetic operations of addition and subtraction as well as the minimum function are computed for the ordered fuzzy numbers using the following definition:

$$o(A, B) = (o(a_1, b_1),\ o(a_2, b_2),\ o(a_3, b_3),\ o(a_4, b_4)) \tag{1}$$

where A, B are the ordered fuzzy numbers and o stands for an arbitrary binary operation.

Road traffic stream is represented in the fuzzy cellular model as a set of vehicles. A vehicle n is described by its position $X_{n,t}$, velocity $V_{n,t}$ (in cells per time step), maximal velocity V_n^{max} and acceleration A_n. All these quantities are expressed by fuzzy numbers. The position $X_{n,t}$ is a fuzzy number defined on the set of cells indexes. Velocity of vehicle n at time step t is computed as follows:

$$V_{n,t} = \min\{V_{n,t-1} + A_n(V_{n,t-1}), G_{n,t}, V_n^{\max}\} \tag{2}$$

Acceleration is defined as a function of velocity to enable implementation of a slow-to-stop rule that exhibits more realistic microscopic driver behaviour [5]. $G_{n,t}$ is the fuzzy number of free cells in front of a vehicle n:

$$G_{n,t} = X_{n-1,t} - X_{n,t} - (1,\ 1,\ 1,\ 1) \tag{3}$$

where $n-1$ denotes the number corresponding to the lead vehicle and n that of the following vehicle. If there is no lead vehicle in front of the vehicle n then $G_{n,t}$ is assumed to be equal to V_n^{max}.

After determination of velocities for all vehicles, their positions are updated. The position of the vehicle n at the next time step $(t+1)$ is computed on the basis of the model state at time t:

$$X_{n,t+1} = X_{n,t} + V_{n,t} \tag{4}$$

At each step of the simulation the traffic information granule is determined by a fuzzy relation: $IG_t \subseteq R$. The universe of discourse for the introduced traffic information granulation is defined as follows:

$$R = (D_X \times D_V \times D_A)^N \tag{5}$$

where D_P denotes the domain of vehicle parameter P (i.e. position, velocity and acceleration) and N is the total number of vehicles.

The preceding formulation of the fuzzy cellular model is illustrated in Fig. 2 a) – e), which shows the results of numerical motion simulation of two accelerating

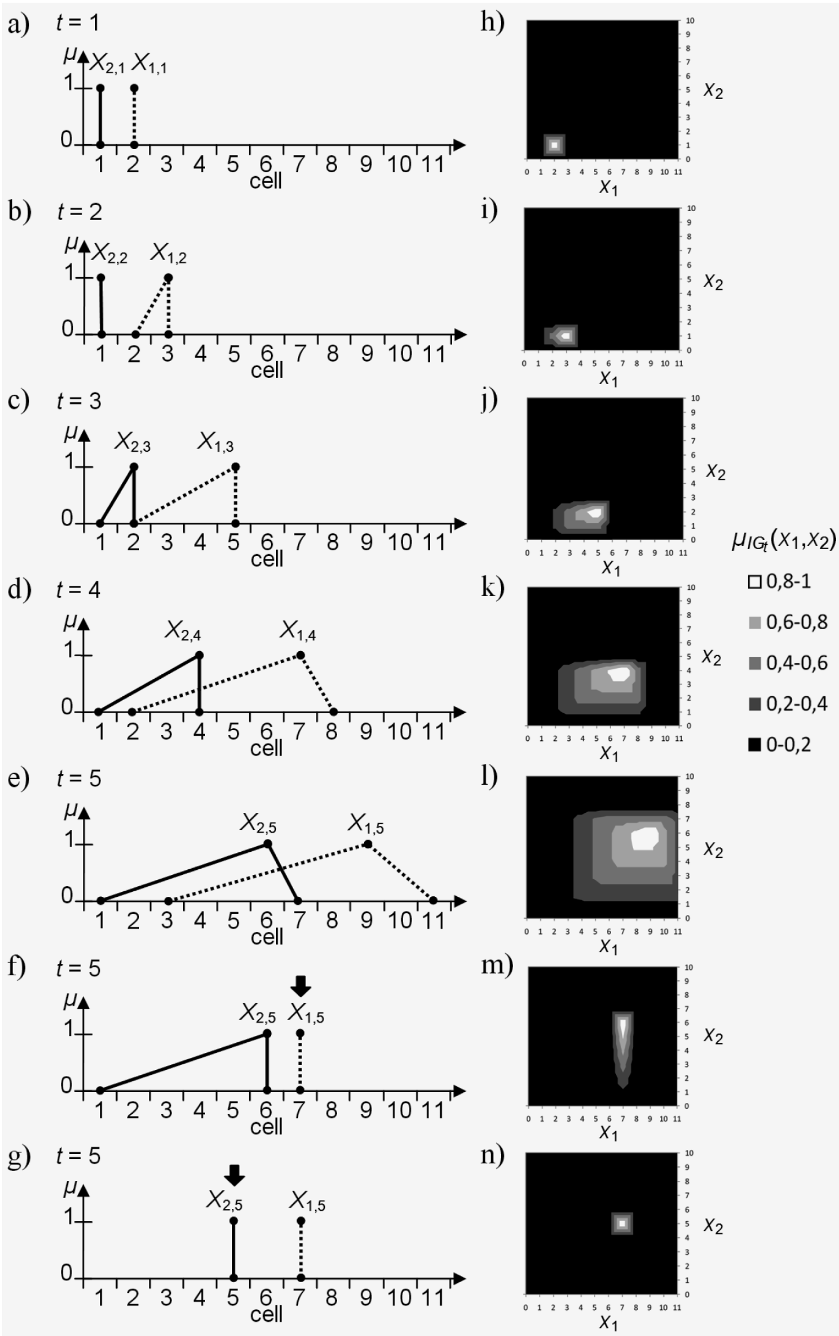

Fig. 2. Motion simulation of two vehicles

vehicles for five time steps. At the first time step of the simulation vehicles are stopped in the first and second cell. The maximal velocity of vehicles in this example is set as follows: $V_1^{max} = V_2^{max} = (1, 2, 2, 3)$. The acceleration for both vehicles can take two fuzzy values depending on the vehicle's velocity:

$$A_n(V_{n,t-1}) = \begin{cases} (1,\ 1,\ 1,\ 1), & V_{n,t-1} = V_n^{\max} \text{ or } V_{n,t-1} = V_n^{\max} - (1,\ 0,\ 0,\ 0) \\ (0,\ 1,\ 1,\ 1), & \text{else} \end{cases} \tag{6}$$

Based on the simulation results in Fig. 2 a) – e), the traffic information granules IG_t were determined and illustrated in Fig. 2 h) – l). A simplified definition of the universe of discourse was applied in this example. Due to illustrative purposes the two-dimensional space of parameters $R = D_X^2$ was considered i.e. only positions of the two vehicles were taken into account. Note that the domain of vehicle position D_X corresponds to the set of cell indexes. The membership function of information granules was computed using minimum t-norm:

$$\mu_{IG_t}(x_1, x_2) = \min(\mu_{X_{1,t}}(x_1), \mu_{X_{2,t}}(x_2)) \tag{7}$$

It was assumed in the discussed example that new localisation data are available at fifth time step of the simulation. According to these data the first vehicle is localised in cell number 7 and the second vehicle occupies cell number 5. Fig. 2 f) – g) and m) – n) present the model states as well as the traffic information granules that were adjusted to the input data delivered from traffic monitoring system. It can be observed from the presented example that the input data influence the size of traffic information granules and the precision of the traffic state determination.

The main advantage of the traffic model presented in this section relies on the fact that the traffic state estimation is computationally efficient and the uncertainty of the results is taken into account. Using this model the traffic state is estimated for the time steps when the measurement data are not available. The results are represented by means of information granules (fuzzy relations). As it is shown in the following sections, this representation is convenient for the traffic performance evaluation and determination of uncertainty in control decisions.

4. Performance of Traffic Control Strategies

There are several different measures available that can be employed for the evaluation of traffic control performance e.g.: average delay per vehicle, maximum individual delay, percentage of cars that are stopped, average number of stops, queue length, throughput of intersections, and travel time [25]. According to the proposed approach the on-line simulation is implemented for evaluating the performance of control strategies. In this section an algorithm is provided for computing the basic performance measures on the basis of information granules produced by the fuzzy cellular model. For the formal presentation of the algorithm a function *pm* is defined that assigns a value of performance measure to each traffic state in the universe of discourse R:

$$pm : R \to \mathbf{Z}, \tag{8}$$

where $\mathbf{Z}$ denotes the set of integers.

Let us consider again the simulation example in Fig. 2. In order to compute the stop delay of vehicles in this example the following form of function pm can be used:

$$pm(x_1, x_2) = \begin{cases} 2, & x_1 = 2 \text{ and } x_2 = 1, \\ 1, & x_1 > 2 \text{ and } x_2 = 1, \\ 0, & \text{else.} \end{cases} \tag{9}$$

Above definition corresponds to the assumption that the stop delay is encountered when the vehicles stay in their initial localisations. This simplification is a consequence of the fact that the two-dimensional space of parameters is considered.

In the general case, when the universe of discourse is defined by Eq. (5), the stop delay will be computed taking into account the velocity of vehicles:

$$pm(x_1, v_1, a_1, ..., x_N, v_N, a_N) = |\{n : v_n = 0, n = 1...N\}| \tag{10}$$

where $|.|$ denotes cardinality of the set.

Function pm can be formulated for different performance measures by inserting additional conditions into Eq. (10). E. g. if the number of stops has to be computed then the following formula will be used:

$$pm(x_1, v_1, a_1, ..., x_N, v_N, a_N) = |\{n : v_n = 0 \ \wedge \ a_n < 0, n = 1...N\}| \tag{11}$$

The performance has to be evaluated using traffic information granule IG_t defined in previous section. Thus, it is necessary to aggregate the performance values $pm(r)$ for all traffic states $r \in IG_t$ that are included in the information granule. The aggregated performance measure at time step t is computed as a fuzzy number

$$PM_t = (pm_{t,1}, pm_{t,2}, pm_{t,3}, pm_{t,4}) \tag{12}$$

using the following formulas:

$$pm_{t,1} = \min\{pm(r) : \mu_{IG_t}(r) > 0\}, \quad pm_{t,2} = \min\{pm(r) : \mu_{IG_t}(r) = 1\},$$

$$pm_{t,3} = \max\{pm(r) : \mu_{IG_t}(r) = 1\}, \quad pm_{t,4} = \max\{pm(r) : \mu_{IG_t}(r) > 0\} \tag{13}$$

Finally, the values of performance measure are summed up for all time steps t in the analysed period T:

$$PM = \sum_{t \in T} PM_t \tag{14}$$

Tab. 1 includes results of the stop delay evaluation for the simulation example which is illustrated in Fig. 2. The results were obtained by using Eq. (9) as a

Table 1

Stop delay estimation for the simulation example illustrated in Fig. 2

Figure	2 a)	2 b)	2 c)	2 d)	2 e)	2 f)	2 g)
Time step	1	2	3	4	5	5	5
PM_t[s]	(2,2,2,2)	(0,1,1,2)	(0,0,0,2)	(0,0,0,2)	(0,0,0,1)	(0,0,0,1)	(0,0,0,0)
PM [s]	(2,2,2,2)	(2,3,3,4)	(2,3,3,6)	(2,3,3,8)	(2,3,3,9)	(2,3,3,9)	(2,3,3,8)

definition of function $pm(r)$. Note that the unit of delay is equal to the time step of the simulation. It was assumed that single time step of the simulation corresponds to one second, thus the delays are also expressed in seconds. These results demonstrate the applicability of the fuzzy cellular model for processing the imprecise traffic information. The presented definitions allow the incomplete input data to be utilised for the evaluation of traffic control performance.

5. Decision Making and Uncertainty Estimation

Let us consider the road traffic control procedure as an iterative process that is based on control decisions making in successive time intervals. Each control decision determines the selection of control strategy, which will be implemented in a given moment of time. A set of consecutive decisions creates a traffic control programme for the defined time period T. The objective of traffic control procedure is to find an optimal programme, which minimises the objective function. The task of traffic control procedure can be interpreted as a problem of finding function $d(t)$:

$$d : T \to W \tag{15}$$

where $W = \{w_i\}$ is a set of all applicable control strategies. The function d takes integer values and it is referred to as control programme. Symbol $d(t)$ denotes the control decision, i.e. the number of control strategy selected for the time moment t.

The objective of traffic control is to find an optimal programme $d*$, which satisfies the following condition:

$$e(d*, f) \to \min \tag{16}$$

where e denotes the objective function of traffic control and f is a function describing parameters of traffic flow for the time period T:

$$f : T \to R \tag{17}$$

where R is the multidimensional space of traffic parameters (see Eq. 5). It should be noted that for practical applications the function f is difficult to be determined precisely. Therefore in the proposed method this function is replaced by a set of the traffic information granules IG_t.

The objective function of traffic control optimisation problem (16) can be any combination of the performance measures that were mentioned in the previous section. Prediction of the objective function values for all applicable strategies is required to decide the optimal control strategy. The objective function is evaluated (predicted) on the basis of two elements: the traffic model at hand and the input data on current traffic parameters. The input data necessary for this task are achieved from the traffic monitoring system. The traffic model includes knowledge about the control plant, which is used to estimate the traffic information granules (traffic state) and evaluate the performance of traffic control.

The performance evaluation is always uncertain due to the nondeterministic nature of traffic flow. The additional source of uncertainty in the traffic control is an estimation of the current traffic state. These two types of uncertainty affect control decisions.

Let e and e' denote respectively the values of objective function for control decisions $d(t)$ and $d'(t)$. We will say that the decision $d'(t)$ is more effective than decision $d(t)$ if the following inequality of probabilities holds:

$$P(e' < e) > P(e' > e) \tag{18}$$

To simplify notation, let $L[d'(t), d(t)] = d'(t)$ denote that the condition (18) is satisfied i.e. decision $d'(t)$ is more effective than $d(t)$. Uncertainty of this conclusion will be determined using the following formula:

$$UNC_{L[d'(t),d(t)]} = 1 - P(e' < e) + P(e' > e) \tag{19}$$

Conclusion $L[d'(t), d(t)] = d'(t)$ is certain if $P(e' > e) = 1$. Uncertainty is zero in that case, because $P(e' < e) + P(e' > e) \leq 1$ is always true. The uncertainty value increases when the probability $P(e' < e)$ falls, however this value is always lower than one since the condition (18) has to be satisfied.

A control decision $d^*(t)$ is an optimal one at a time moment t if

$$\forall d(t) \in W \ \ (d(t) \neq d*(t) \Rightarrow L[d*(t), d(t)] = d*(t)) \tag{20}$$

and uncertainty associated with this decision is given by:

$$UNC_{d*(t)} = \max_{d(t) \in W - d*(t)} \{UNC_{L[d*(t),d(t)]}\} \tag{21}$$

The control decision is based on evaluation of the objective function (16) for all applicable strategies. Fig. 3 presents three examples of performance prediction results that was obtained by using the algorithm discussed in Section 4. In order to illustrate the impact of input data transfers on the control decision uncertainty, the examples take into account three alternative control strategies denoted by A, B, and C.

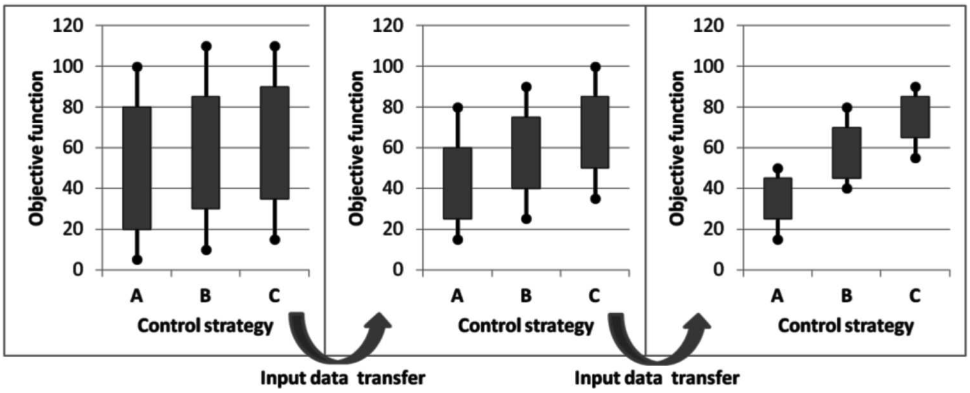

Fig. 3. Examples of performance evaluation results

For the first example (Fig. 3a) the corresponding predictions of the performance are represented by following fuzzy numbers:

$$E_A = (5,\ 20,\ 80,\ 100),\quad E_B = (10, 30, 85, 110),\quad E_C = (15,\ 35,\ 90,\ 110) \quad (22)$$

Using the method outlined in [35] the probabilities can be computed as follows: $P(e_A < e_B) = 0{,}62$ and $P(e_A > e_B) = 0{,}36$, where $P(e_X < e_Y)$ is the probability at which value of the objective function predicted for control strategy X is less than the value for strategy Y. Since the condition $P(e_A < e_B) > P(e_A > e_B)$ is satisfied, the control strategy A is decided to be more effective than strategy B. This conclusion can be written in equation form as $L(A, B) = C$ and its uncertainty is determined by: $UNC_{L(A,B)} = 1 - P(e_A < e_B) + P(e_A > e_B) = 0{,}74$. The strategies A and C have to be compared in the same way: $P(e_A < e_C) = 0{,}68$, $P(e_A > e_C) = 0{,}30$, thus $L(A, C) = A$ and $UNC_{L(A,C)} = 0{,}62$. In this example the result of decision making indicates that $d*(t) = A$ is the optimal control strategy. Using equation (21) the uncertainty of this control decision can be computed: $UNC_A = \max\{UNC_{L(A,B)}, UNC_{L(A,C)}\} = 0{,}74$.

Let us assume that the query is generated and the data collection operation is activated at the analysed time step of the control procedure. The new input data enable more precise evaluation of the control strategies performance, as shown in Fig. 3b:

$$E_A = (15,\ 25,\ 60,\ 80),\quad E_B = (25,\ 40,\ 75,\ 90),\quad E_C = (35,\ 50,\ 85,\ 100) \quad (23)$$

For this prediction the new values of probabilities are computed: $P(e_A < e_B) = 0{,}80$, $P(e_A > e_B) = 0{,}18$, $P(e_A < e_C) = 0{,}92$, and $P(e_A > e_C) = 0{,}07$. Therefore, the uncertainty of control decision $d*(t) = A$ is reduced in this example: $UNC_A = 0{,}38$. After the second transfer of input data (Fig. 3c) the uncertainty of control decision is further decreased to 0,01.

The above example presents the process of uncertainty analysis in the context of general definition of traffic control procedure. The uncertainty level of control decision is low if the objective function can be evaluated precisely. In most cases the uncertainty of control decision can be reduced by updating the available traffic information granules. The information updating operation involves query generation and input data transfer from the monitoring system. Input data are necessary to improve the estimation of the current traffic state within the traffic model. Moreover, the obtained information granule describing current traffic state is further used as a starting point of the traffic prediction. Higher precision of this information allows the prediction to be made with more confidence.

The main motivation for introducing the selection of input data for traffic control systems is the observation that different monitored parameters of the road traffic are temporally as well as spatially correlated. Hence, the collected traffic data do not change abruptly and randomly between two time steps of the traffic control procedure but instead changes occur in predictable patterns. The proposed method is based on an assumption that the input data transfers can be optimised using a predictive traffic model. The important insight is that the uncertainty of traffic prediction has to be appropriately low to ensure the optimal performance of traffic control procedure. Thus, the uncertainty estimation is necessary to select the input data accordingly.

6. Uncertainty Dependent Input Data Selection

The input data selection algorithm is discussed in this section as a component of a traffic control procedure. Scope of the input data depends directly on the traffic model used for traffic information granulation. In case of the fuzzy cellular model considered above it is required to provide data on the location of vehicles. Optional data that can be used to fine tune parameters of this traffic model include velocity and class of vehicles.

The operation of input data transfer is initialised by the information granulation module, which sends query to the traffic monitoring system (Fig. 1). The monitoring system processes the query and collects necessary data readings from detectors. Finally, the result of query (input data) is sent back to the information granulation module.

The proposed algorithm (Fig. 4) provides input data selection in the sense that queries are generated at selected time steps of the traffic control procedure. An uncertainty threshold is used to decide if new input data have to be delivered at a given time step. Namely, the transfer of input data is executed only when the level of uncertainty, evaluated using equation (21), exceeds a predetermined uncertainty threshold. This technique enables the considerable reduction of number of queries that are necessary to capture sufficient information for the traffic control optimisation.

After each new input data delivery from the monitoring system an information granule has to be created which approximates current state of the traffic. To this end the traffic model is appropriately adjusted to mirror the current traffic situation as

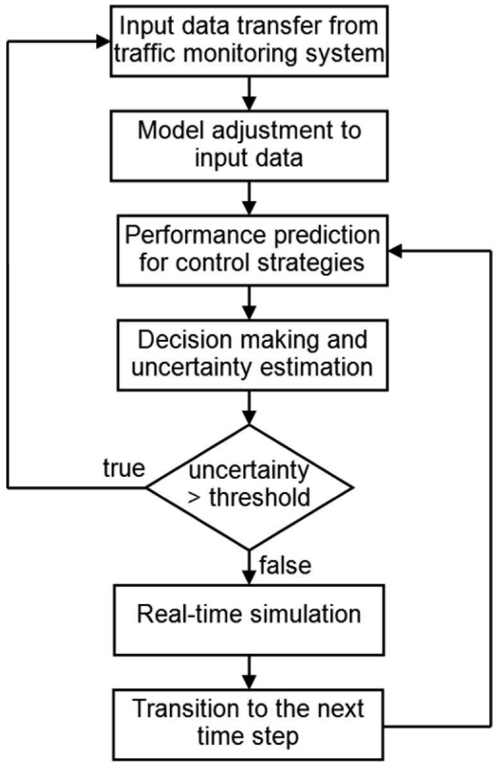

Fig. 4. Overview of uncertainty dependent input data selection algorithm

accurately as possible. The received input traffic data are processed to maintain consistency between simulated and measured traffic. The model adjustment operation includes the generation and removal of vehicles, adjusting their position, and fine tuning maximal velocity and acceleration parameters. The location data has to be translated into terms of cells that are basic units used to describe vehicles positions in the model. The modification of the maximal velocity and acceleration is based on statistics which aggregate the results of traffic measurements. Since the on-line simulation is implemented to evaluate the performance of traffic control strategies, the model adjustment operation has to take into account also the real-time status data of traffic control operations.

The traffic performance for all applicable control strategies is predicted by faster than real-time simulation using the approximation of current traffic state (traffic information granule) to determine initial conditions. The current traffic state is approximated directly on the basis of actual input data only at selected time steps. In remaining cases this approximation involves the information granulation procedure based on real-time simulation. The result of performance prediction obtained for each control strategy is an ordered fuzzy number representing a set of possible values of the objective function (16).

The optimal control strategy is selected among all alternatives during the decision making phase. The control decision is based on the evaluation of objective function (16) for all applicable strategies. The objective function can be defined as a combination of different performance measures. The basic issue of decision making is to select the control strategy which minimises the objective function. Thus, there is the necessity of comparing the ordered fuzzy numbers. For the proposed algorithm the probabilistic approach to fuzzy numbers comparison [35] is employed. This method estimates quantitatively the probability to which one fuzzy number is less or equal to another fuzzy number.

The proposed algorithm can be applied in traffic control systems of different types (traffic signals, variable speed limits, dynamic route guidance etc.). In the next section an experimental study is presented on signal control at an isolated intersection.

7. Experimental Results

The proposed input data selection algorithm was applied to traffic control at a signalised intersection. The signal phases as well as the topology of intersection are illustrated in Fig. 5. The traffic control procedure in this study is consistent with the general definition presented in Section 5. The procedure is executed in time steps of one second. At each time step a control decision is made regarding the selection of signal phase. The objective function used in this study is the average stop delay per vehicle. Thus, at each time step the signal phase is selected which minimises the delay predicted by the fuzzy cellular model.

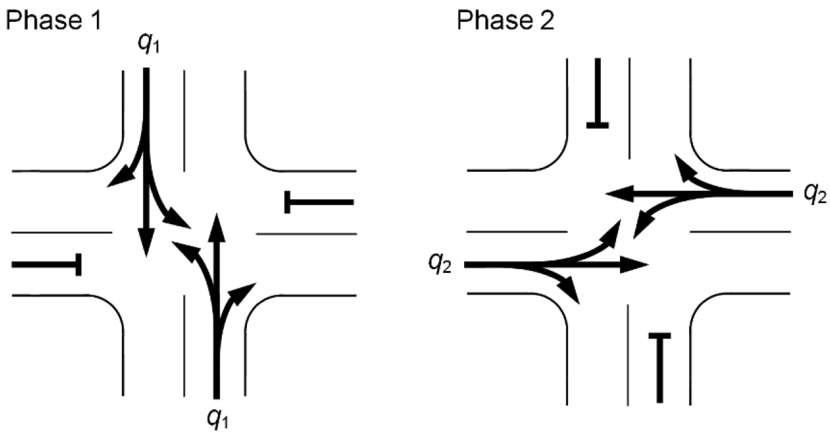

Fig. 5. Intersection topology and signal phases

The traffic control architecture consists of control unit installed at the intersection and traffic monitoring system, which communicates with mobile sensors in vehicles. The control unit sends queries, receives input data from the monitoring system and executes the traffic control procedure. Each vehicle in the system is equipped with a wireless communication unit and uses a GPS device to determine its position and speed. Every time a vehicle approaches the intersection, it has to register itself by sending a hello message to the traffic monitoring system. The input data transfers are initialised by the control unit which generates queries to retrieve locations and velocities of all registered vehicles.

The first analysed situation assumes that there is no selection of input data in the traffic control system. It means that queries are generated at each time step of the traffic control procedure, when the signal phase selection has to be made. A query has to be generated whenever there is a possibility to change the current signal phase (excluding the inter-green and minimum green time intervals). In the second setting, the input data selection is applied according to the algorithm presented in the previous section. Queries are generated only if the current uncertainty level of control decision exceeds the predetermined threshold. The analysis is focused on the reduction of number of queries as well as on performance of the traffic control

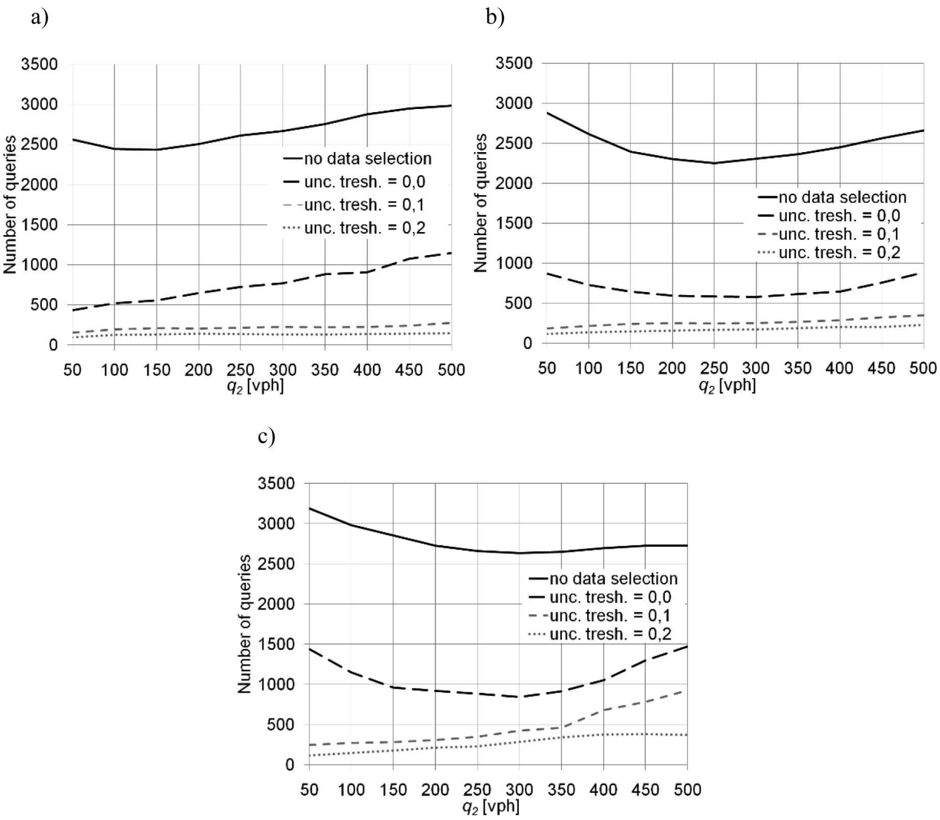

Fig. 6. Number of queries: a) q_1 = 100 vph, b) q_1 = 250 vph, c) q_1 = 500 vph

procedure in the examined scenarios. The effectiveness of the proposed solution was evaluated by using VISSIM software for traffic simulation.

Plots in Fig. 6 demonstrate the number of queries that were generated during one-hour traffic simulations. The solid lines show results obtained without input data selection, while dotted lines indicate results that were obtained applying the proposed algorithm. The effects of input data selection are illustrated for three different values of the uncertainty threshold (0, 0,1 and 0,2). It can be seen that the number of generated queries is substantially reduced through the input data selection. The simulations were performed for different combinations of the traffic flow volumes (q_1 and q_2) that correspond to a wide range of traffic conditions. The average reduction in number of queries reached 75% for the uncertainty threshold equal zero, 90% for threshold equal to 0,1 and 92% for the threshold equal to 0,2. These results confirm that the proposed method significantly decreases the volume of the transmitted data.

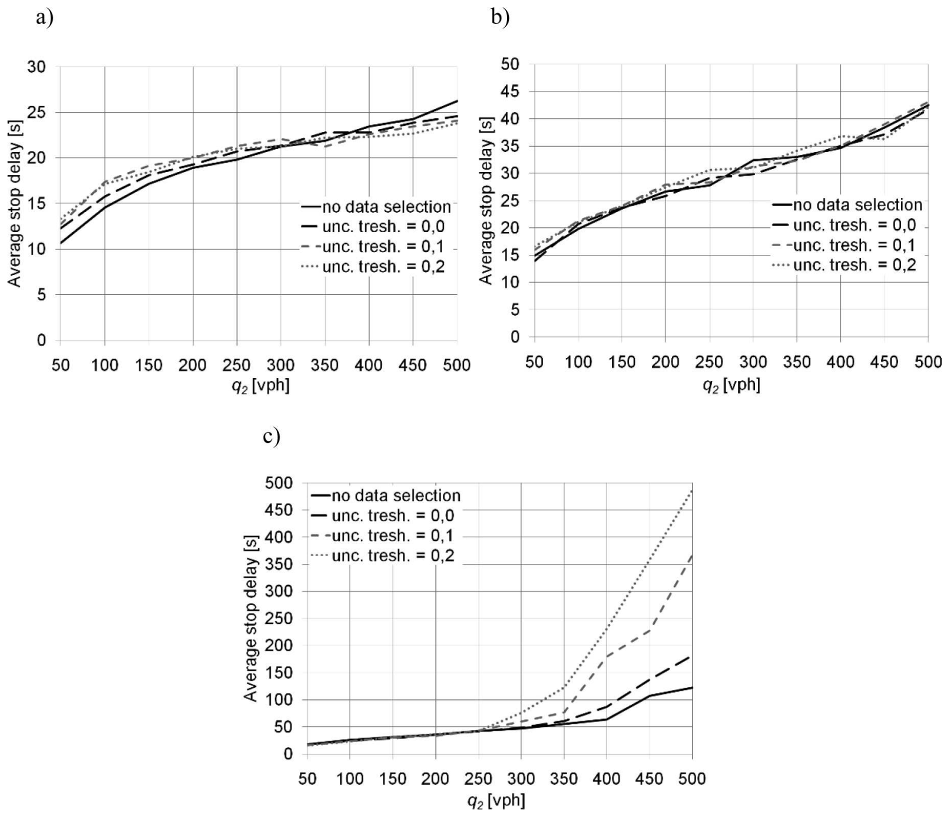

Fig. 7. Number of queries: a) q_1 = 100 vph, b) q_1 = 250 vph, c) q_1 = 500 vph

Further tests were performed to examine the dependency between input data selection and performance of the traffic control. To this end the average stop delays of vehicles were analysed. Plots in Fig. 7 illustrate the performance of traffic control using the same line styles as in Fig. 6. The experimental results show that the increase of delay for input data selection is negligible in most of the considered traffic conditions. The increased delays were observed only in case of the high traffic volumes (congested traffic state), particularly for the uncertainty threshold above zero.

It was observed for the analysed intersection that the uncertainty threshold values of 0,1 and higher cause a significant increase in the delay if the total traffic flow volume exceeds 1500 vph. This fact indicates that the uncertainty threshold has to be carefully determined for congested traffic conditions. Comparing the results in Fig. 6 with those in Fig. 7, it can be seen that there is a trade-off between the reduction of number of queries and the optimisation of traffic control performance. The trade-off can be obtained by suitably adjusting the uncertainty threshold.

Fig. 8 includes a histogram of time intervals between queries for the input data selection algorithm. The time intervals were registered for 100 successive queries during the traffic simulation. The uncertainty threshold was set to 0,1 in this case and the traffic flow volumes at the intersection were assumed as follows: q_1 = 100 vph and q_2 = 250 vph.

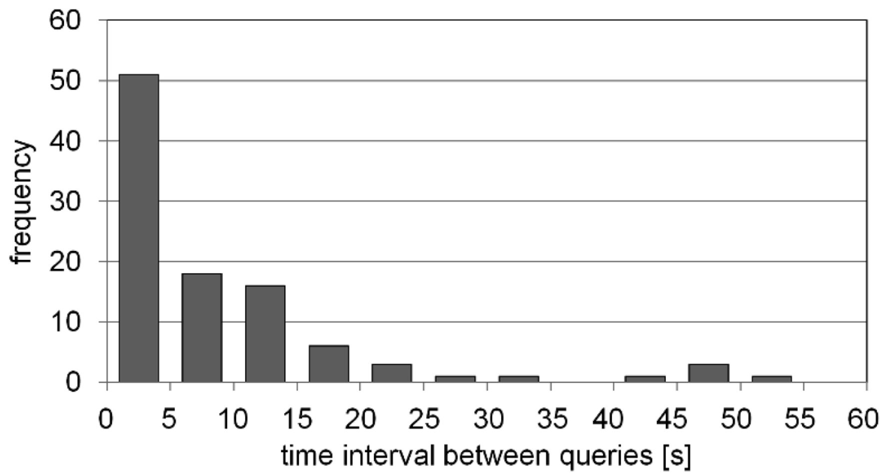

Fig. 8. Histogram of time intervals between queries

Fig. 8. shows that the time interval between queries varies in a wide range (1–54 [s]). The sampling period for the input data selection procedure is unstable as it is dynamically adapted to the current state of the traffic flow. Thus, the uncertainty dependent input data selection cannot be simply replaced by any periodical sampling method.

8. Conclusions

This paper introduces an approach for selecting the input data that are necessary to make control decisions in a traffic control procedure. The proposed method is based on the concepts of traffic information granulation and decision uncertainty. These concepts allow the traffic control procedure to be executed in situation of incomplete traffic information. The necessity of input data transfers is recognised through the uncertainty analysis of the traffic control decisions. It was shown that the uncertainty can be estimated on the basis of information granules. The traffic information granulation was carried out by means of fuzzy cellular model. In this solution, the ordered fuzzy numbers and fuzzy relations were used to represent the available granules of traffic information.

The introduced algorithm selects time instances of input data that are transmitted from detectors to the control unit. The rejected measurement data are replaced by information granules produced by an on-line traffic simulation. If precision of the information granules decreases and the control decisions become uncertain then the current data readings have to be transferred. This principle enables a considerable reduction of the data volumes that have to be transmitted from traffic monitoring system.

A traffic simulation environment was used to verify the effectiveness of the proposed method. Experiments reported in this study were performed for a traffic control system at signalised intersection. The experimental results confirm that the introduced algorithm is able to significantly reduce the number of input data transfers for various traffic conditions. Moreover, the average delays registered during traffic simulations show that the input data selection does not decrease the performance of traffic control for a wide range of traffic volumes. Results of application of this method for data collection in vehicular network and comparison with other data acquisition techniques can be found in [24].

Further tests will be necessary to examine the proposed approach in real-traffic conditions. The experiments should also take into consideration various measures of traffic performance (e.g. travel times, queue lengths, stop counts) and potential sources of errors, i.e. detection accuracy and quality of communication channels. Another interesting issue for future studies is the possibility of using the introduced method when a portion of vehicles are equipped with mobile sensors and communication devices.

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