Incidents detection on city roads

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Abstract. An important issue in traffic management is the timely and reliable incidents detection. The methods for detecting incidents are constantly being improved due to the intelligent transport systems’ development and the new sources of information emergence. Due to the incident detection tasks’ complexity, motion modeling is essential for testing various hypotheses. The article discusses the features of identifying incidents on the road network with traffic control. In the network sections, the occurrence of incidents of various durations and in different sections was simulated. The study aims to identify the minor incidents. Based on neural networks, the situations are classified and the possibilities of this approach are established. The incident detection results are presented.

Introduction
Actual problems of traffic management are the traffic jams and dangerous situations’ rapid detection possible determination on the road network based on the use of various types of technical means for monitoring the traffic flows’ characteristics in conjunction with the traffic mathematical modeling methods. There are various definitions of incidents from the detailed to the short ones. The first type includes the definition that traffic incidents should be understood as non-recurring events caused by various obstacles to traffic, weather conditions, stopped or slowly moving cars, road works, special events that lead to traffic jams or disruptions. A shorter one is an unforeseen event that affects the safety and throughput of the road network, which leads to additional delays for road users” [1, 2].

Incidents account for more than 50% of vehicle delays on the urban road network. According to various studies, reducing the incident duration to one minute depending on the situation complexity leads to damage reduction from 60 to 500 euros per incident [3]. Traffic incidents almost always lead to traffic jams, traffic delays and increased environmental pollution. Therefore, it is important to understand that the consequences of incidents vary depending on the time and place of occurrence, but are most often assessed by their existence duration.

According to the existence and consequences duration, transport incidents are divided into the following types [4]:
- serious transport incidents with a duration of more than 2 hours;
- incidents lasting from 30 minutes to 2 hours, which are classified as average in consequences;
- minor transport incidents lasting up to 30 minutes.

Typically, serious incidents are detected within 5-15 minutes of occurrence, however, the detection time for minor incidents can be delayed up to 30 minutes. This shows that the incident management systems have an important role to play in road safety ensuring. The functions of the incident management system include identifying incident signs, verifying the data accuracy, transmitting
information to relevant services and road users, coordinating the special services’ activities, supporting decision-making on traffic management in an incident.

To date, many countries have accumulated sufficient experience in operating the incident management subsystems. Basically, the object of control are the highways with a high degree of saturation with technical means for monitoring the traffic flows’ characteristics. In Europe, the incident management systems’ development is provided by the EasyWay project, which aims to coordinate such systems in the Trans-European Road Network (TERN) [2, 6]. The basis of the strategy is the formation of a unified policy in the functioning and development of incident management systems, increasing the efficiency of automatic incident detection methods, integrating the special services’ activities during the incident and eliminating its consequences and developing the cooperative intelligent transport systems. One of the priority areas is to reduce the time for detecting incidents and responding to them [7, 8, 9].

MIDAS (Motorway Incident Detection and Automatic Signalling) is an automatic incident detection system based on the traffic flow characteristics’ registration by the traffic detectors. The MIDAS system monitors the situation on the M25 J10-16, M42 J3a-7, M6 J4-5, M1 J10-13 and M6 J8-10a highways with a total length of over 1,500 km. For full coverage of road sections, installation of detectors every 500 meters is required. Due to such saturation with measuring instruments, it is possible to control the situation along the entire length of the road by comparing traffic intensity and traffic flows speed at the successive measurement points. Depending on the situation complexity, the system sets a speed limit and informs the drivers about the traffic jam (queue) formation at the incident highway section. The incident management system contributed to the traffic accidents reduction by 10-15% [10, 11].

The traffic management system on the ring toll road Attica Tollway in Greater Athens in Greece is focused on monitoring the traffic flow parameters, the rapid incidents detection and traffic management in incidents. The transport detectors are installed on the highway every 500 m, according to which every 20 seconds the intensity, speed and occupancy are averaged. On the highway, an average of 20,000 to 25,000 incidents per year is recorded [7].

The TransGuide Intelligent Transport System in San Antonio (USA), which controls traffic for approximately 160 km of highways, collects information from 2,500 detectors installed at 220 points with averaging information for every 20 seconds. Together with quite effective incident detection algorithms, this allowed to reduce the incident detection time by 20% [1].

During the ADVANCE project implementation, the possibilities of integrating the data from the stationary transport detectors, test vehicles and occasional messages to identify incidents, were determined. The output was the incident probability, their duration and the incident impact on the traffic conditions’ deterioration.

Incident Detection Methods and Models
The most effective are the methods for detecting incidents automatically using the appropriate data of the traffic flows parameters, which use the special algorithms for processing this data. However, sufficient saturation of the road network with detectors and additional means of collecting information are necessary. The development of these methods and models has the most important scientific and applied value and can be used to solve the following problems:

- improving the efficiency and reliability of incident detection based on the traffic parameters monitoring with determining the detectors’ optimal location, choosing the most informative parameters, assessing their values’ reliability;
- development and use of incident detection algorithms on a regulated urban street network;
- integration of data from various information sources (stationary detectors, mobile communications, satellite navigation systems) to identify incidents, the development of special models for bringing heterogeneous data into a single database;
- restoration of spatiotemporal patterns of changes in the traffic flows characteristics on the network sections between the stationary information sources;
- continuous replenishment of data to improve the traffic patterns’ calibration reliability for the specific sections of the road network.

The incidents’ automatic detection methods according to the registration of the traffic flows characteristics are divided into the following classes [1, 12, 13]:

- comparative algorithms based on the optimal solution trees that use a combination of traffic flow parameters and their threshold values to assess the traffic conditions and identify the incidents;
- statistical algorithms using the parameters of probability distributions, Bayesian algorithm, double exponential smoothing method, etc.;
- time series-based algorithms based on accurate models for forecasting the traffic flow parameters;
- artificial intelligence algorithms, usually based on fuzzy logic or neural networks;
- real-time traffic modeling algorithms.

Comparative algorithms are based on the principle that an incident is identified when the set of parameters selected for decision making exceeds their respective threshold values. The most famous of the comparative algorithms is the California algorithm, which was proposed by Payne and Tignor [14]. Incident detection is carried out according to the average busy condition for the time periods from 20 to 30 seconds for the adjacent points of the traffic flows’ characteristics measurement. The data obtained at each time step is compared with the pre-set threshold values for the change in busy condition to detect an incident. A set of threshold values allows to classify the various stages: incident absence; uncertain condition; incident occurrence; incident continuation. The initial information is the difference in the occupancy values of the sequentially located detectors:

\[ \Delta OC_i(t) = OC_i(t) - OC_{i+1}(t), \]  
\[ \Delta TOC_i(t) = OC_i(t) - OC_{i+1}(t - 1), \]

where \( OC_i(t) \), \( OC_{i+1}(t) \) – are the busy condition of detectors \( i \) and \( i+1 \) at time \( t \) accordingly;
\( \Delta OC_i(t) \) – is the difference in occupancy values of sequential detectors;
\( \Delta TOC_{i+1}(t) \) – is the difference in detector readings in successive time periods.

The relative difference in the occupancy values at successive detectors is also determined:

\[ \Delta ROC_i(t) = \frac{OC_i(t) - OC_{i+1}(t)}{OC_i(t)}, \]  

where \( \Delta ROC_i(t) \) – is the relative difference in occupancy values of sequential detectors.

Three thresholds for changing busy condition are used to make a decision: \( T_1 \) – is the maximum value \( \Delta OC \) under normal driving conditions; \( T_2 \) – is the maximum value of the temporary difference in detector occupancy under normal conditions; \( T_3 \) – is the maximum value of the relative difference in detector occupancy under normal conditions. However, the initial version of the California algorithm works satisfactorily only for a service level of at least \( C \).

To improve the California algorithm reliability, a statistical smoothing method was developed for the pre-processing busy condition data [15]. In this case, various statistical methods identify and remove sharp fluctuations in the traffic flows’ parameters. To do this, it is possible to use the methods of moving average, exponential smoothing and others. That is why this algorithm is known as DELOS (Detection Logic with Smoothing). DELOS uses the statistical smoothing method to remove sharp and high-frequency fluctuations in busy condition before comparing them with preset thresholds. Since they are based on static threshold values, comparative algorithms do not have sufficient flexibility when the situation goes beyond the previously obtained values. Despite these shortcomings, they are widely used due to their simplicity and ease of use.

Various smoothing methods (moving average, median, exponential smoothing) of the raw data are used as the first part before the algorithm calculation. There are four thresholds that need to be assessed: \( m, n, \psi 1, \psi 2 \). The integers \( m \) and \( n \) are calculated on the assumption that \( m * DT = 5 \) min and \( n * DT = 3 \) min, where \( DT \) – denotes the time elapsed between the consecutive measurements. Two other meanings \( \psi 1, \psi 2 \) are the upper bounds of functions 4, 5:
\[ U_i(t) = \frac{1}{\prod_{j=0}^{n-1} K_i(t)} \Delta OCD(i, t+j), \]
\[ \Delta OCD = OC(i + 1, t) - OC(i + 1, t + 1), \]
\[ W_i(t) = \frac{1}{\prod_{j=0}^{n-1} K_i(t)} \frac{1}{m} \sum_{j=1}^{m} \Delta OCD(i, t+j) - \frac{1}{m} \sum_{j=1}^{m} \Delta OCD(i, t-j), \]
\[ K_i(t) = \max \left\{ \frac{1}{m} \sum_{j=1}^{m} OC(i, t-j), \frac{1}{m} \sum_{j=1}^{m} OC(i + 1, t - j) \right\}. \]

For the urban roads, one of the first incident detection methods was based on the comparative data of intensity and occupancy. The actual data of the detectors in real time are compared with the standard for normal conditions for a given section of the network and on this basis the situation type is classified [16]. However, the incident detection methods’ development on the regulated road network remains a critical challenge.

**Regulated network incident modeling**

The simulation scheme includes a network section with traffic lights with a span of 300 m typical of the central part of the city. According to the research, in 86% of cases, the occurrence of an incident closes one lane and only 8% closes all lanes [8]. Therefore, during the simulation, the incident consisted of closing a 40-50 m stretch for the traffic road lane. The location and duration of the incident was randomly generated. Since the aim of the study was the ability to quickly identify an incident, the generated incidents were categorized as minor with a duration of up to 30 minutes. In order to be able to choose various options for recording the traffic flows’ characteristics, the detectors were provided at the beginning of the section, in the middle and at the end of the section. The movement intensity also changed during the simulation. Thus, the simulation scenarios were formed according to the following features:

- traffic intensity, two options 1000 vehicle/h and 1300 vehicle/h one direction on a two-lane road;
- the incident occurrence place, three options - closer to the stop-line (zone 1), in the middle of the section (zone 2), closer to the entrance to the section (zone 3);
- the duration of the incident from 10 to 30 minutes.

Naturally, for a lower traffic intensity, the change in the traffic flows’ characteristics is less pronounced, which makes it difficult to identify the incidents. Typically, when identifying the incidents, such indicators as speed, travel time of the road section, occupancy, and the difference between the incoming and outgoing flow are used. Table 1 shows the simulation data on changes in the speed and cars accumulation on a road section under normal conditions and incidents in various places of the section.

**Table 1.** Comparative values of traffic flow parameters for various situations.

| Simulation scenarios | Speed, km/h | Standard speed deviation, km/h | The maximum value of the difference between the incoming and outgoing number of cars |
|----------------------|-------------|--------------------------------|----------------------------------------------------------------------------------|
| Normal conditions    |             |                                |                                                                                  |
| 1000 vehicle/h       | 43          | 2.24                           | 6                                                                                |
| 1300 vehicle/h       | 34.7        | 6.83                           | 21                                                                               |
| Incident in zone 1   |             |                                |                                                                                  |
| 1000 vehicle/h       | 41.1        | 5.4                            | 6                                                                                |
| 1300 vehicle/h       | 29.2        | 13.6                           | 66                                                                               |
| Incident in zone 2   |             |                                |                                                                                  |
| 1000 vehicle/h       | 41.8        | 4.12                           | 18                                                                               |
| 1300 vehicle/h       | 19.3        | 11.1                           | 80                                                                               |
| Incident in zone 3   |             |                                |                                                                                  |
| 1000 vehicle/h       | 41.8        | 4.1                            | 12                                                                               |
These data show that with a relatively small increase in traffic on a regulated road network, when an incident occurs, the traffic conditions change dramatically. Therefore, it is especially important to use such incident detection methods that can work effectively with minor incidents and with as little traffic as possible. One of these methods is the use of neural networks. Neural networks are used to analyze, evaluate and predict the traffic flow state, based on the existing data [13, 17].

To train the neural network, we used the modeling traffic flows’ results in the regulated network section shown in Fig. 1. The initial data making up the training sample included the deviations from the normal conditions of the cars’ quantity, speed and occupancy over one-minute time interval. In the calculations, the database was divided into training, test and control samples. For this case, the architecture of the multilayer fully connected neural network MLP 9-4-2 was obtained, including 9 input parameters, 4 hidden and 2 output neurons. The input parameters include the difference in intensity, speed and busy condition between the actual and normal conditions. The obtained results indicate that the neural network model provides a satisfactory reliability of the situation classification under normal conditions and in incidents (Table 2).

### Table 2. Indicators of the resulting neural network.

| Situation name         | Neural network performance for the samples |
|------------------------|--------------------------------------------|
|                        | Training sample | Test sample | Control sample |
| Incident               | 95.000          | 80.000      | 85.714         |
| Normal conditions      | 98.437          | 100.000     | 90.909         |
| All situations         | 97.619          | 94.444      | 88.889         |

The total percentage of incorrectly classified situations was 2.381% for the training sample, 5.556% for the test sample and 11.111% for the control sample.

The traffic flows’ input parameters sensitivity analysis allows us to assess the degree of these parameters change when the situation changes and to conclude the importance of each parameter for a given neural network. In the case of sharp differences in sensitivity, it is necessary to conduct an additional analysis to obtain the objective data on changes in the input parameters’ set. In this case, the greatest sensitivity in detecting an incident is the speed in the middle of the section, and the least sensitivity is occupied and the speed in the first zone, busy condition and intensity in the third zone. If we determine the correlation between the input parameters, then the speed in the middle of the section has a significant correlation coefficient only with busy condition at this point. Obviously, the absence of dependence with other input parameters provides such a difference in the value of the speed sensitivity in the middle of the section when detecting incidents.

### Summary

The incident management systems are an important part of the intelligent transport systems, and their effectiveness affects road safety and traffic delays. Therefore, the methods and algorithms for automatically detecting incidents are constantly being improved, but in most works the objects of research are the highways. This article presents the results of modeling on a regulated network. To identify the incidents according to the traffic flows’ characteristics, neural networks were used. In general, the neural network indicators determine the possibility of using this method of detecting incidents. Further research will need to consider a more complex road network and the options for sharing the data from the stationary detectors and mobile information sources.

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