Geo-Dynamic Decision Support System for Urban Traffic Management

**Jan Kazak, Mieczysław Chalfen, Joanna Kamińska,
Szymon Szewrański and Małgorzata Świąder**

Abstract The paper presents the geo-dynamic decision support system (DSS) for urban traffic management issues. For this purpose, ArcGIS and Tableau softwares were used. Additionally, a self-defined transportation model based on Dijkstra's algorithm was created. The use of our own calculation model allowed for the full accessibility to all parameters of the analysed scenarios which was one of the key assumptions of the research. Functionality of the proposed DSS was tested on three scenarios. Each scenario presents congestion on the road network after the conclusion of events in main landmarks in Wrocław (Poland): the city stadium, the National Forum of Music and the Centennial Hall. The proposed DSS allows for dynamic analysis of urban traffic, including recalculation processes according to the changing congestion on a road network. Moreover, cumulative urban traffic assessment allows you to define hot spots on a network, which should be especially monitored by public services. An interactive dashboard reduces technical details of an analysis which helps to avoid the cognitive problems of the decision making process for a layman. The results prove the feasibility of the integration of the ArcGIS, self-defined transportation model and Tableau. The proposed solution enables full access to the transportation analysis' assumptions, as well as the use of a simple and intuitive interactive dashboard for the decision making process.

Keywords Urban traffic modelling · Dijkstra's algorithm · Tableau · Decision support system · Visual data analysis

J. Kazak (✉) · S. Szewrański · M. Świąder
Department of Spatial Economy, Wrocław University
of Environmental and Life Sciences, ul. Grunwaldzka 55,
50-357 Wrocław, Poland
e-mail: jan.kazak@upwr.edu.pl

M. Chalfen · J. Kamińska
Department of Mathematics, Wrocław University of Environmental
and Life Sciences, ul. Grunwaldzka 53, 50-357 Wrocław, Poland

Introduction

Contemporary urban space management forces local governments to search for new tools and solutions for their problems. The implementation of the smart city concept is strongly connected with the use of new technologies and capabilities that bring sustainable development goals within reach at the local scale (Ahvenniemi et al. 2017). Parallel to increasing the amount of available spatial data (An et al. 2016) there is a need to discover our ability to harness and analyse this data. In such a reality, cities are gaining greater control over their development. However, it is worth taking this challenge because those cities which are well instrumented and are connected by core systems are able to use this data and become the most successful (Zhuhadar et al. 2017). Technical support in the city management process allows for the ability to find optimized solutions which fit to each analysed case study. It increases the efficiency of public policies implementation and plays a key role from the point of view of quality of life (Przybyła et al. 2014).

One of the most crucial problems in modern cities is the issue connected with traffic management. The constantly increasing mobility of users requires a better understanding of these processes, as well as an impact of public policies into that phenomenon (Maggi and Vallino 2016). Some aspects of urban traffic issues are the matter of scientific research and are already aided by decision support models, e.g. road traffic control coordination (Dahal et al. 2013), road incidents (Hashemi and Abdelghany 2016), environmental impact mitigation (Ruiz-Padillo et al. 2016), risks assessment of hazardous materials transportation (Torretta et al. 2017) or even tsunami risk mitigation (Ai et al. 2016). The results of all of the mentioned models are very precise and well described from the scientific point of view. However, as it was highlighted by the initiative for cleaner and better transport in cities—CIVITAS, the first step in transport management should be based on policy context (CIVITAS 2015). Thus, there is a need to create systems which are simple to understand and would avoid cognitive problems (Tremblay et al. 2017). To avoid the negative impact of the implementation of improper actions, the system should be able to analyse alternative scenarios. According to the business intelligence pyramid, what links data mining and the final decision making are simulation models which are based on What-if? analysis (Golfarelli and Rizzi 2009). Therefore, the system should provide feedback to decision-makers about the possible effects of their decisions and as a result allow them to make better decisions based on knowledge.

From the technical point of view it is important to use common and well established mathematical models of calculations. One of the well known methods in transportation issues is Dijkstra's algorithm (Dijkstra 1959), which helps solve time-dependent problems (Ayed et al. 2011) and can react automatically according to changing circumstances (Szücs 2015). Because of the fact that the algorithm responds to new situations and reanalyses the optimal solution in each case, it could

be the right mathematical model for a dynamic system. As a result, it not only gives the optimal path but the list of possible solutions (Caha and Dvorský 2015). Dijkstra's algorithm is commonly used together with GIS to include spatial data (Ortega et al. 2014; Siljander et al. 2015; Pamučar et al. 2016) and finally to support users with a spatial presentation to enable visual analytics on the modelled results. Therefore, the aim of the research was to create a user-friendly decision support system (DSS) for urban traffic management which would include dynamic and spatial parameters in the simulation process.

Materials and Methods

The main goal of the research was to create a DSS which includes geographical and time attributes to support urban traffic management. The study presents the possibilities of the results that could be obtained according to traffic modelling, as well as a visual presentation of these results. The case study is Wrocław (Poland). The city struggles with urban traffic problems and according to the mobile data analysis, in the group of the seven biggest Polish cities, the amount of delay caused by traffic jams during peak hours increased the most—from 7:05 in 2011 to 8:52 in 2015 (Deloitte and Targeo 2016). Wrocław was one of the European Capitals of Culture in 2016 and because of that everyday traffic wa was additionally influenced by the congestion caused by people who attended big cultural events in different parts of the city. For that purpose, three What-if? scenarios were created. All of the scenarios present possible variants of car departures after cultural events that can be organized in the city. The first scenario assumes the departure of 9000 cars from the city stadium (capacity approx. 43,000 people) which is located close to the highway. The second scenario assumes the departure of 900 cars from the National Forum of Music (capacity approx. 2600 people) and the Opera (capacity approx. 1600 people) which are located close to the city centre. The third scenario assumes the departure of 900 cars from the Centennial Hall (capacity approx. 8000 people) which is located on the island connected to the city centre by two bridges.

All the scenarios were tested in the proposed geo-dynamic decision support system which combine ArcGIS, the self-created mathematical model based on Dijkstra's algorithm, with Tableau, which is one of the business intelligence systems (Fig. 1). The model is able to analyze any theoretical scenario depending on the needs of the local government. The results are presented on an interactive dashboard which enables the layman to process them and assess the potential impact of all predefined variants.

The data source for the road network was OpenStreetMap (OSM). Traffic congestion was assumed as in the scenarios presented above. As the proposed model constitutes the important part of the research itself, more detailed descriptions of all the stages are presented in the following parts.
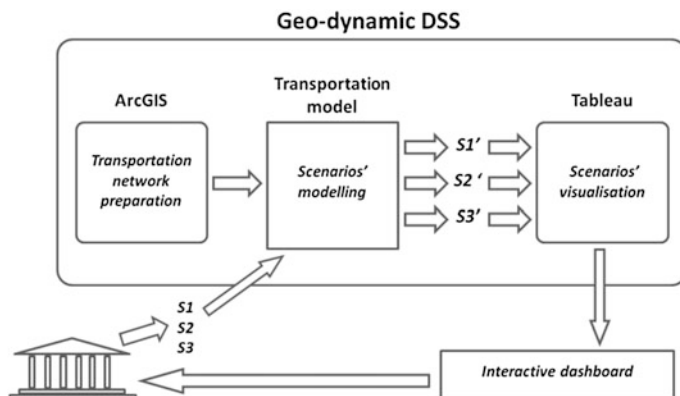
Fig. 1 Research conceptual framework

Geo-Dynamic DSS Components

Database Preparation for Linear Network Flow

The accuracy of transport network analysis depends directly on input data preparation. It plays a significant role on the effectiveness of linear network flow. The input data represents the linear layer of roads from the OSM source. As OSM data are open source and any user has the ability to update the data, there is a need for data verification in compliance with their plausibility and accuracy.

The first stage of the linear network preparation is the verification of data plausibility, which is connected with the linear objects updating. This stage involves creating the missing sections of the existing roads or removing objects that physically do not exist yet. At this stage, an important element is self-knowledge or the ability to use additional sources (i.e. WFS, other maps or database) by an analyst preparing the data.

The next stage of preparing the linear network is the verification of the data accuracy. This step is intended to ensure the completeness of the model, which should guarantee the complete database. The completeness of the database is tantamount to comprising all attributes describing each object. This database has to primarily contain information about road determinants i.e. one-way or maximum speed limits.

Subsequently, the verified and updated linear network has to be split into smaller lengths sections (i.e. 100 m). There is a need to create a set of points based on the specified distance along a linear network, then split the linear network with a generated set of points. This step allows the fragmentation of linear objects, which make the modelling flow of a linear network possible.

The final stage of data preparation for transport network analysis is to calculate the geometry (length) of linear objects from split analysis and calculate the coordinates of objects. It is crucial to calculate the start coordinates of the linear n-object (X and Y coordinates) and the end coordinates of the nearest linear object to the

linear n-object. These two pairs of coordinates allow to indicate the common point between two segments (which could be a node between them). The operation is necessary to determine the sequence of network segments.

Dijkstra's Algorithm for Traffic Modelling

For modelling purposes, the original, self-defined, macroscopic, continuous and random-deterministic model of urban traffic was created. The model enables to simulate traffic in an optional time step. In contrast to cellular automata models, the position of vehicles is described in a continuous movement. Random elements are the starting points and destinations. In a graph in a deterministic manner, the streets and trajectories of moving vehicles are defined. The model consists of three basic parts: a network of streets, characteristic of the behaviour of the vehicle in traffic and the algorithm selecting the routes for vehicles.

A network of streets is represented as a directed graph. The nodes of the graph correspond to crossroads and additionally are also located in the characteristic points of the street (turns, changing the parameters of the street, etc.). Each node has a specific name, location in the local coordinate system and in the geographical coordinates system, as well as a list of nodes with which it is directly connected. The edges of the graph correspond to the sections of the streets. Each section has a defined capacity based on a number of lanes in each direction and the maximum permissible speed limit.

Each vehicle in the model has a predetermined maximum speed limit, which can not be exceeded even if the parameters of the road allow that. However, in current research it was assumed that each vehicle travels on a road section with a maximum speed limit on each section of the network. No distinction between types of drivers was made (aggressive, average, insurance or other type of driving style).

The algorithm of traffic modelling comprises the following components:

- selection/determination of the starting and target nodes—can be given as a node_ID or randomized with a defined two-dimensional density function,
- determination of the trajectory of motion of each vehicle from the starting point to the destination point according to the established criteria by using Dijkstra's algorithm (Dijkstra 1959) to find the shortest path in the graph,
- modelling variable speed of traffic during the simulation.

The movement of vehicles in the model is based on the following elements:

- t_i—distance between the i-th vehicle and the previous one, measured in time unit [s],
- l_i—length of the i-th vehicle [m],
- k—density of vehicles on the analysed road section [vehicle km^{-1}],
- v_i—velocity of the i-th vehicle on the analysed road section [km h^{-1}].

By t_i distance, it is meant the time that the i-th vehicle (specifically, the farthest point in the direction of movement) needs to overcome the distance to the previous vehicle (specifically, it is the most extended point in the direction opposite to the direction of movement) in the direction of movement. Considering the movement of the vehicles in a microscopic scale on the road with a length of S (assuming no possibility of exit or entry on this road during the trip on each road section) the length occupied by one i-th vehicle was determined, where the distance between the vehicles can be described by the formula:

$$s_i = v_i \left[\text{km h}^{-1}\right] \cdot t_i[\text{s}] = v_i t_i \frac{1}{3600} [\text{km}] \tag{1}$$

Taking into account the length of the vehicle and the distance between the vehicles described above (1), we can set inequality:

$$\sum_{i=1}^{n} \left(\frac{l_i}{1000} + v_i \frac{t_i}{3600} \right) \leq S \tag{2}$$

The road section with a length S in the inequality (2) is presented as the sum of lengths of all n vehicles on the road, taking into account both the length of the vehicles and the distances between vehicles. Knowing that the speed of vehicles on the road section depends on the current traffic density k, it is assumed that the speed of each vehicle is equal to the maximum which is able to be achieved with the current density.

$$v_i = v(k) \text{ for each } i = 1, 2, \ldots, n \tag{3}$$

The formula (2) then takes the form:

$$\sum_{i=1}^{n} \frac{l_i}{1000} + v \sum_{i=1}^{n} \frac{t_i}{3600} \leq S \tag{4}$$

By setting the average length of a moving vehicle in meters:

$$\bar{l} = \frac{1}{n} \sum_{i=1}^{n} l_i \tag{5}$$

we get:

$$n \frac{\bar{l}}{1000} + \frac{v \cdot n}{3600} \sum_{i=1}^{n} \frac{t_i}{n} \leq S \tag{6}$$

Appearing in formula (6) the sum of t_i/n represents the mean arithmetic value of the distance (measured in time units) between vehicles, which is an estimator of the

expected value of the probability distribution of distances between all vehicles on the road section.

In natural traffic, the ability for a safe distance between all vehicles can be maintained only in a few conditions, e.g. calm and steady traffic on a highway. In other cases, especially in urban traffic, the distance between vehicles depends on many factors. In this study it is assumed that the distance between vehicles is a random variable based on a priori distribution and well-known parameters. Assuming that the probability distribution of distances between vehicles is known (*T*) and its finite expected value $E(T)$, the formula (6) is presented as follows:

$$n\frac{\bar{l}}{1000} + \frac{v \cdot n}{3600}E(T) \leq S \tag{7}$$

Hence:

$$v(k) \leq \frac{1}{k} \cdot \frac{3600}{E(T)} - \frac{3.6\bar{l}}{E(T)} \tag{8}$$

Based on other studies $E(T)$ was set as 2 s and l was set as 5 m (Kamińska and Chalfen 2016). The proposed model was verified by the case study of urban freeway traffic in Atlanta (Wang et al. 2011). In the same traffic conditions the vast majority of the distances between vehicles was in the range between 1.2 and 2.2 s (Fig. 2).

Theoretical speed calculated according to the formula is limited by the maximum permissible speed limit on the network section and for each car. At the start each vehicle trajectory to the destination point is determined. Trajectory for each vehicle is determined by the current density at the network at the moment of entering the roads. As a result the speed of movement throughout the city at each section is calculated.
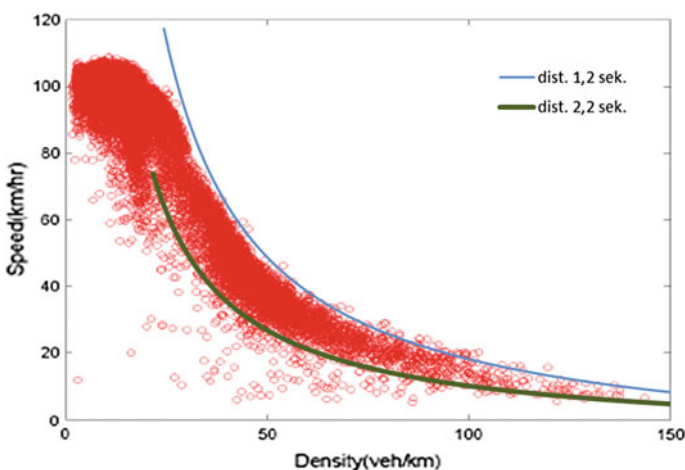

Fig. 2 Figure of empirical data of Wang et al. (2011) and designated $v(k)$

However, when the vehicle actually comes to each section of the street, the speed on this section is recalculated taking into account new traffic density (based on the new allocation of all vehicles on the model). The vehicle moves along a predetermined trajectory by uniform motion, i.e. place where the vehicle reaches in a fixed period of time Δt is calculated. The Δt time step in the simulation is optional, usually used $\Delta t = 1$–10 s. It is allowed to change the predefined trajectory in the model (at the start of each journey) so that the time-varying traffic density in a city is taken into account. Such a possibility of trajectory change is allowed only when the vehicle passes through the node having more than two neighbours. As a result of the simulation the model calculates the location of all vehicles in motion and the load on the network (e.g. the number of vehicles within the various edges of the graph or the average moving speed).

Data Visualization

Simulation data was visualised in Tableau Desktop. Raw data files contain id, path sequence, nodes coordinates as well as the number of cars per 5 min, and cumulative number of cars. The street names were coded. There were from 13,936 to 62,712 records in each simulation. Tableau provides a live connector to many data sources so it is possible to work directly with the data online. However, in predefined scenarios there is no need to work on online databases, as the only information that could be updated is a road network (where changes are not that dynamic). After connecting to the data source, the raw data was recognized as an attribute table and could be opened and processed in Tableau. All data were divided into measures and dimensions. Dimensions are used for categorisation, breaking down and grouping. Measures enable to sum, count and calculate the average value of objects. Both measures and dimensions can be discrete or continuous.

The raw data interpreter was used to set up geographical roles: latitude and longitude. Path sequence was applied to describe the directed edges between the nodes. Time data had been used as a parameter for time series mapping. Originally, a fully animated dashboard was built. To avoid misinterpretation problems, the filters for the minimum car number which should be mapped were used. Dynamic mapping of the car traffic simulation was built with the use of the original WMS Tableau basemap. All analyses, as well as data exploration, have been carried out with the use of VizQL—formal language for describing tables, charts, graphs, maps, time series, tables and visualizations.

Scenarios' Analysis

The use of DSS allowed for a spatio-dynamic model for each predefined scenario. Due to time steps in the procedure it was possible to create animations for a better visualization of urban traffic flows. However, in the paper, the following twelve

time steps are presented in a small multiple picture (Fig. 3). Such a method of visualization shows the rhythm of urban metabolism. The results of scenarios modelling potentially highlighted the most common problems in the organization of events in the analysed localizations in Wrocław.

As it was mentioned in Section "Dijkstra's algorithm for traffic modelling", the destination points in the simulations are chosen randomly. However, the structure of the road network on a case study is characterised by a higher density of nodes in the core of the city than on the outskirts of the city (Fig. 4). Therefore, the result of the random allocation of destination points will also influence a higher density in the city centre.

The first scenario shows that even the location close to the highway does not solve most of the traffic problems. As the route of the highway is rather a bypass of Wrocław for transit traffic, destination points outside of the city are served by this road. In hardly any case did it seem useful for urban traffic needs. However, a significant share of vehicles used one of the urban streets (Legnicka Street). Many cars (additional to regular traffic) entering one section of the street in one moment may impact a higher risk of accidents. That is why in the first scenario, a possibility of redefining the optimal trajectory to the destination point according to changing conditions was extorted. An accident was located on one of the most congested roads due to check the mechanism of the recalculation of trip trajectories for each vehicle.

The second scenario shows that the location in the city centre with a high density of road network with comparable parameters influence a rather regular distribution of vehicles. In that case it is especially important to remember that the results of the simulations present additional value to regular traffic congestion which is quite a problematic issue at certain moments of a day. Identification of regular peak hours and traffic flows at each part of the city is possible from the data collected by intelligent transportation system (ITS) which was applied in the city between 2008 and 2015. Knowing the cycles of traffic flows enables, for instance, to cooperate between municipal services responsible for cultural events and traffic management units to avoid an accumulation of vehicle congestion.

The third location is the Centennial Hall which is placed on an island. There are two bridges connecting the island to the city centre, however, one of them is close to the object. Therefore, the third scenario shows the so-called bottleneck issues in the network. In a short term management it might be rational to analyse a temporal reorganization of traffic in that neighbourhood to decrease the congestion. Such actions are already implemented in many cases and they are the elements of Active Traffic Management, e.g. closing street lanes, changing direction of lanes, changing traffic light priorities, etc. (Karoń 2016). Taking into account that in the same neighbourhood the ZOO and open exhibition area are also located, which influences traffic problems regularly, in long term management it might be necessary to analyse an option for the construction of a new bridge to divert directions.

All of the above case study conclusions were possible to identify because of the use of an interactive dashboard (Fig. 5). The final dashboard was composed with a standard bar and line charts, interactive filters and highlights. The data was broken down by the street name, so the operator is able to indicate which roads have the
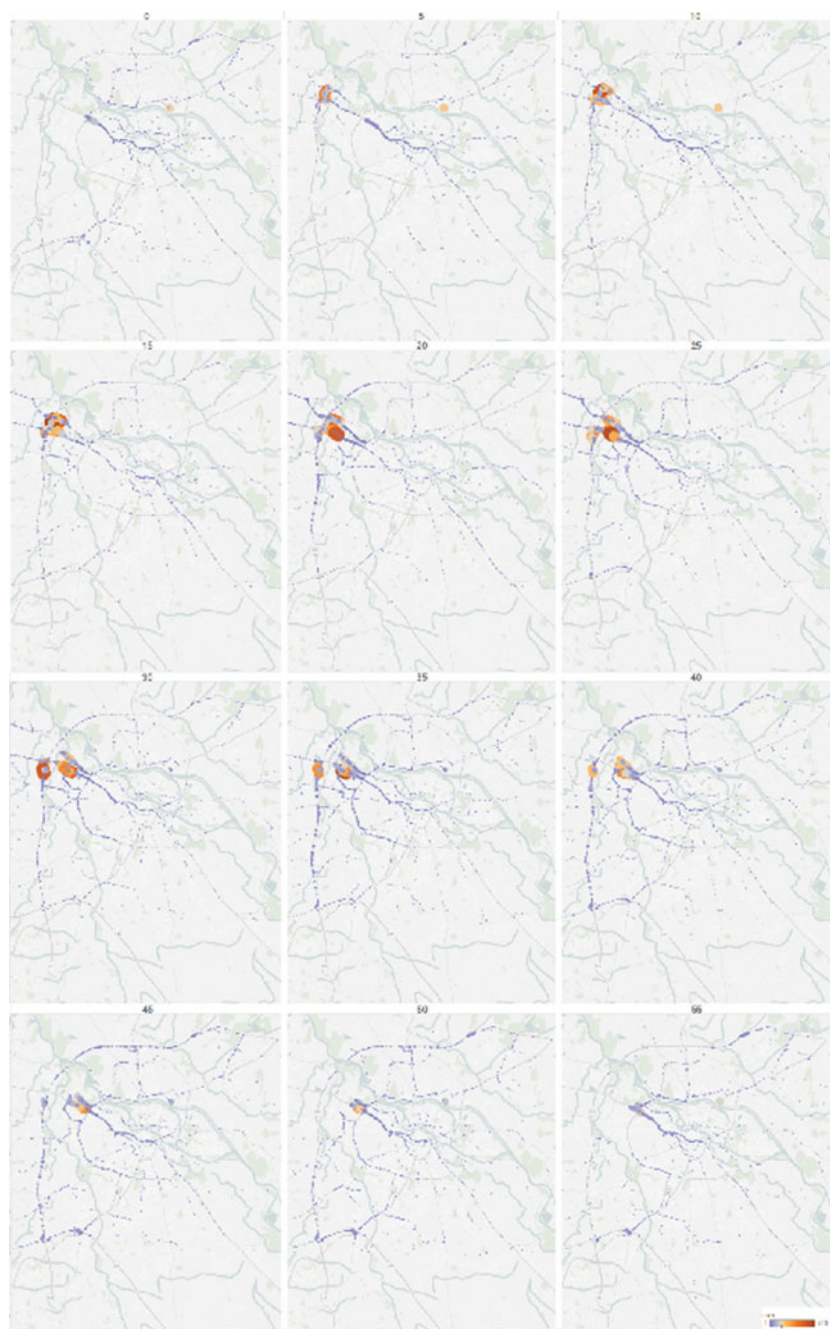
Fig. 3 Dynamic changes of network congestion in scenario no. 1

Fig. 4 Density distribution of road network nodes

Fig. 5 Interactive dashboard

highest car congestion during each simulation. Moreover, to visualize the dynamic character of the data, a time series line chart was applied. The dashboard is fully interactive, so one can select any number of nodes on a map and indicative charts will show summaries for only the selected items. As the date and time filter is

active, it is possible to follow the data within the time frame. The dashboard can be published in a cloud service and accessed by anyone who is interested. Such a way of publishing results enables a layman who has no experience with spatial or transportation modelling, as all available functions give him access to time slider, charts and the ability to select a specific area on the map.

Conclusions

The presented DSS aims to provide geo-dynamic analysis of urban traffic congestion on a road network. The applied solution enables to recalculate transportation trajectories according to time-varying traffic density on each section of a network. The use of Dijkstra's algorithm allowed to store the information about the spatial distribution of all the modeled vehicles and to optimize trips to destination points. The knowledge of possible traffic flows is crucial for the effective management of those processes. It could be used, for example, to support intelligent transportation systems which have become more and more popular. The proposed solution also gives information about cumulative congestion assessment. Such information might support not only traffic lights management but also temporary changes in traffic organization (e.g. closing street lanes, changing direction of lanes, changing traffic light priorities, etc.).

Besides transportation model for traffic calculations, the DSS presents the results in an interactive dashboard which limits variables to those which could be easily changed by users by intuitive functions. It is possible to get such outputs like cumulative load of vehicles, traffic congestion in each simulation time step, summary or average value of cars at each node or road section depending on a selection, etc. The time necessary for reporting the outcomes is reduced to a minimum (real-time reporting) which allows for better decision making based on knowledge. The Interactive dashboard enables to visualize the dynamic attributes as animation which helps to better understand traffic flows. The proposed solution reduces the cognitive problems with the use of DSS which is possible due to the limited accessibility to modeling results. Besides the transportation model, the elements used for DSS already exist. Therefore, the proposed concept fulfills the idea of diffusion of innovation which is based on defining new connections between existing solutions to improve the analysed issue.

References

Ahvenniemi, H., Huovila, A., Pinto-Seppä, I., & Airaksinen, M. (2017). What are the differences between sustainable and smart cities? *Cities*, *60*(Part A), 234–245. https://doi.org/10.1016/j.cities.2016.09.009.

Ai, F., Comfort, L. K., Dong, Y., & Znati, T. (2016). A dynamic decision support system based on geographical information and mobile social networks: A model for tsunami risk mitigation in Padang, Indonesia. *Safety Science, 90,* 62–74.

An, S., Yang, H., Wang, J., Cui, N., & Cui, J. (2016). Mining urban recurrent congestion evolution patterns from GPS-equipped vehicle mobility data. *Information Sciences, 373,* 515–526.

Ayed H., Galvez-Fernandez C., Habbas Z., & Khadraoui D. (2011). Solving time-dependent multimodal transport problems using a transfer graph model. *Computers & Industrial Engineering, 61*(20), 391–401.

Caha, J., & Dvorský, J. (2015). Optimal path problem with possibilistic weights. In I. Ivan, I. Benenson, B. Jiang, J. Horák, J. Haworth, & T. Inspektor (Eds.), *Geoinformatics for intelligent transportation* (pp. 39–50)., Lecture Notes in Geoinformation and Cartography Cham: Springer International Publishing.

CIVITAS. (2015). *Policy note: Intelligent transport systems and traffic management in urban areas.* CIVITAS WIKI consortium.

Dahal, K., Almejalli, K., & Hossain, M.A. (2013). Decision support for coordinated road traffic control actions. *Decision Support Systems, 54*(2), 962–975.

Deloitte and Targeo (2016) *Raport o korkach w 7 największych miastach Polski.* Warszawa: Deloitte Polska.

Dijkstra E. W. (1959). A note on two problems in connection with graphs. *Numerische Mathematik, 1,* 269–271.

Golfarelli, M., & Rizzi, S. (2009). What-if simulation modeling in business intelligence. *International Journal of Data Warehousing and Mining, 5*(4), 24–43.

Hashemi, H., & Abdelghany, K. F. (2016). Real-time traffic network state estimation and prediction with decision support capabilities: Application to integrated corridor management. *Transportation Research Part C, 73,* 128–146.

Kamińska, J., & Chalfen, M. (2016). An influence of safe distance between vehicles on traffic speed and density. *Autobusy: technika, eksploatacja, systemy transportowe, 17*(6), 578–582.

Karoń, G. (2016). Strategies of Active transportation and demand management. *Komunikacja publiczna, 3*(64), 39–46.

Maggi, E., & Vallino, E. (2016). Understanding urban mobility and the impact of public policies: The role of the agent-based models. *Research in Transportation Economics, 55,* 50–59.

Ortega, E., Otero, I., Mancebo, S. (2014). TITIM GIS-tool: A GIS-based decision support system for measuring the territorial impact of transport infrastructures. *Expert Systems with Applications, 41*(16), 7641–7652.

Pamučar, D., Gigović, L., Ćirović, G., & Regodić, M. (2016). Transport spatial model for the definition of green routes for city logistics centers. *Environmental Impact Assessment Review, 56,* 72–87.

Przybyła, K., Kulczyk-Dynowska, A., & Kachniarz, M. (2014). Quality of life in the regional capitals of Poland. *Journal of Economic Issues, 48*(1), 181–196.

Ruiz-Padillo, A., Ruiz, D. P., Torija, A. J., & Ramos-Ridao, Á. (2016). Selection of suitable alternatives to reduce the environmental impact of road traffic noise using a fuzzy multi-criteria decision model. *Environmental Impact Assessment Review, 61,* 8–18.

Siljander, M., Venäläinen, E., Goerlandt, F., & Pellikka, P. (2015). GIS-based cost distance modelling to support strategic maritime search and rescue planning: A feasibility study. *Applied Geography, 57,* 54–70.

Szücs, G. (2015). Decision support for route search and optimum finding in transport networks under uncertainty. *Journal of Applied Research and Technology, 13*(1), 125–134.

Torretta, V., Rada, E. C., Schiavon, M., & Viotti, P. (2017). Decision support systems for assessing risks involved in transporting hazardous materials: A review. *Safety Science, 92,* 1–9.

Tremblay, S., Gagnon, J.-F., Lafond, D., Hodgetts, H. M., Doiron, M., & Jeuniaux, P. P. J. M. H. (2017). A cognitive prosthesis for complex decision-making. *Applied Ergonomics, 58,* 349–360.

Wang, H., Li, J., Chen, Q.-Y., & Ni, D. (2011). Logistic modeling of the equilibrium speed–density relationship. *Transportation Research Part A: Policy and Practice, 45*(6), 554–566.

Zhuhadar, L., Thrasher, E., Marklin, S., & Ordóñez de Pablos, P. (2017). The next wave of innovation—Review of smart cities intelligent operation systems. *Computers in Human Behavior, 66,* 273–281.