A Simulation Model for the Analysis of the Consequences of Extreme Weather Conditions to the Traffic Status of the City of Thessaloniki, Greece

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Abstract Natural disasters such as flooding and snow blizzards have evolved from a relatively rare event to a recurring concern for stakeholders, policy makers, and citizens. A special place in this debate is held by the transportation infrastructure; it provides services crucial to a society, and it can yield positive effects to the overall economy due to its interrelation with the urban activities. Finally, due to the increasing trend of urbanization, people are having an increasing dependence on urban transportation.

Consequently, extreme weather conditions could severely impact not only the operation of the transportation infrastructure (network and means) but also the economic activity of a city. Hence, there is the need for a framework that will allow decision-makers, on the one hand, to monitor in real time the status of the transportation network and on the other hand offer them insights on how a critical event, such as a flooding, could affect it before it does.

The purpose of this paper is to present such a tool that allows for efficient and effective monitoring of the status of the transportation network and crisis management in the case of a flooding.

To achieve the objective, two methodological frameworks will be combined: data analytics and simulation. Floating car data (FCD) from a fleet of taxis in the city of the Thessaloniki offer a glimpse on the status of the transportation network. The KPIs that are produced from the data are used as an input to a simulation model. The model has been developed with the methodology of system dynamics, because it allows for the adequate representations of complex systems (such as the transportation infrastructure), it offers a top-down view on the behavior of the system over time, and it can be easily communicated to non-experts.

The model also simulates the physical process of rain and snow, and the user can define how much rain and snow and at which times of the day it will fall. The water accumulates in the road network affecting the speed of the vehicles, and the larger

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the amount of water the more difficult it is for the sewage system to remove it, thus resulting in flooding roads.

Several scenarios were simulated, mainly trying to capture the dynamics of sudden rainfall and flooding. The results illustrate that there is a disproportional delay between the time that the rain stops and the time it is required for the system to bounce to an equilibrium.

Keywords System dynamics · Simulation · Flooding · Crisis · Urban transportation

1 Introduction

The city of Thessaloniki, Greece, is regularly suffering from flooding that makes traffic conditions dire and hinders the movement of passengers. The latest such event occurred on September of 2019 [6] when the streets flooded from an extreme and intense downpour. The event was not unique; similar situations happened on May of 2018. Furthermore, the event is limited neither in the city of Thessaloniki nor in the country of Greece. For example, Italy suffers from floods that cause traffic chaos and material damages and injuries [7], while human loss was the devastating effect of the catastrophic flood in Texas [22].

Thus, extreme weather conditions – such as flooding or snow blizzards – that were once considered events of low probability [17] have become a recurring concern for local authorities, high-level policy makers, and citizens alike [10].

A special place in this concern is held by the urban transportation sector due to its inherent importance; it provides services crucial to a society, and it can yield positive effects to the overall economy due its interrelation with the urban activities [1, 14]. This importance increases due to the increasing trend of urbanization, which will result in more and more people being dependent on an efficient urban transportation system [13].

Hence, there is the need for an extra level of preparedness since the ongoing climate change will result in more and more extreme weather conditions; decision-making on an urban environment needs to change from reactive to proactive and embrace crisis management as its core framework, in order to deal with potential consequences before, during, and after an extreme weather event [3].

The purpose of this paper is to present a decision support tool that allows for efficient and effective monitoring of the status of the transportation network and crisis management planning in the case of a flooding. To achieve the objective of the paper, a simulation model is developed and combined with real-time floating car data from a fleet of taxis in the city of Thessaloniki.

The rest of the paper is organized as follows: General information on such critical events, the methodology, and the simulation model structure are presented. Following in the next section, results are described and analyzed, while conclusions and future research directions are presented in the final part of the document.

2 Methodology

A flooding can be considered a crisis in general, in the sense that it may occur suddenly and with intensity, it requires one or more rapid decisions to avoid negative consequences, and there is no knowledge whether these particular decisions will have a negative or positive effect [17]. Thus, decision-making in such a context becomes even more complex than normal since the environment and the decisions are interrelated and subsequent changes may occur due to the decisions or independently [5, 9, 16].

Moreover, the complexity increases due to the inherent nature of the transportation system (or any urban system for that matter). It entails a large number of components that are connected causally, it involves different time scales and feedback loops, and finally, at its core it depends on the human behavior.

Thus, simulation can aid decision-makers with grasping the full scale of such a system and how it may be affected by a flood. Simulation models are representations of reality, which:

- Offer such insights
- Help decision-makers to gain experience in a consequence-free environment
- Allow the experimentation of different scenarios
- Can account for different perspectives [24]

Consequently, a search was performed in scientific databases using the terms "simulation," "transportation system," and "flooding" in different combinations and synonyms. The search was further refined by studying the abstract of the results to check for relevance with the subject matter. The final set includes the following papers.

Kermanshah et al. [12] used GIS data with a network science approach to simulate flooding scenarios and their effects for the city of Chicago. Armenia et al. [2] used system dynamics enhanced with a user interface to create an interactive learning environment to train managers on how a flooding can affect the energy, transportation, and telecommunication system of a city.

Jordan et al. [11] similarly used system dynamics, however including in their research the interrelation between the road and rail networks of an urban environment. The authors used simulation to estimate the times of appropriate closure and the subsequent costs of these closures on crossings and routes in case of a flood.

Armenia et al. [3, 4] used system dynamics to research the effects of critical events (including floods and terrorist attacks) on an urban transportation system and the domino effects that it might generate on the business community. Zhu et al. [25] on the other hand investigated the system from a bottom-up approach and, by using an agent-based model, investigated how drivers' behavior is affected by a flood and used the area of Lishui, China, as a reference.

Song et al. [19] used the qualitative branch of system dynamics, i.e., causal loop diagrams to research causal relations and resilience in the urban environment of Busan, Republic of Korea, among its various sectors. Yang et al. [23] utilized GIS data to identify how large-scale floods in the Arakawa River of Tokyo can affect inter-firm transactions in the area. Finally, Pyatkova et al. [15] used a microscopic traffic model to gain insights on the traffic disruption and its effects under different flooding scenarios.

No claim is made that the above research is exhaustive, nonetheless several interesting findings can be seen. First, the interactions between floods and the transportation system have not been extensively studied so far; a conclusion also held by Pyatkova et al. [15]. Furthermore, system dynamics is the methodology used in the majority of the papers, while only recently, with the increasing availability of data and advancements in computational power, (big) data are considered as a viable tool for this type of research. Consequently, the current paper contributes to the literature by offering a simulation model that combines big data and system dynamics to investigate the effects of different flooding scenarios in the city of Thessaloniki, Greece. It should also be noted that the simulation model relies on and expands the model developed by Armenia et al. [2].

2.1 System Dynamics

System dynamics [8, 20] is a computer-based methodology that uses ordinary differential equations to model the behavior of systems over time. It relies on the framework of systems thinking [18] to generate insights into how this behavior might be altered if different policies are applied to it [21].

The methodology offers further advantages as it can incorporate randomness, which characterizes the behavior of all transportation systems. Moreover, it can simulate the so-called soft variables – variables that are not easily quantified such as those associated with human behavior. Thus, system dynamics assumes that if the structure of the system under study is captured accurately enough, then the insights that will be provided by the simulation can be more helpful than a deterministic analysis. Finally, the qualitative arm of the methodology (causal loop diagrams) can be used as a communication tool to illustrate the decision-making process to non-experts.

2.2 Model Structure

The simulation model that was developed in the context of the paper combines data analytics and system dynamics simulation. Floating car data (FCD) from a fleet of taxis in the city of the Thessaloniki offer a glimpse on the status of the transportation network. The data are analyzed and two types of KPIs are produced: firstly, metrics such as average speed (real-time information from the taxis, aggregated) for the entire road network of the city, volumes of vehicles (inferred by combining average speed from the taxis and historical data), and a traffic KPI defined as the volume of vehicles in (every) part of the road network compared to the theoretical capacity of that particular part. Furthermore, the above KPIs can be combined to investigate the trends on a longer time horizon, which results in an origin-destination matrix for the various geographical zones of the city.

The KPIs that are produced from the data are used as an input to a simulation model. The simulated urban environment is divided into geographical zones, each of which has internal characteristics such as population density, area of the road network and its characteristic, public transport stops, extent of the sewage system, available parking spaces, etc. Thus, the simulated model accounts only for public means (mainly buses) and private transportation (cars, taxis) since the city of Thessaloniki does not yet have a metro network.

The KPIs from the data determine the behavior of the simulation model. The origin-destination matrix determines how people move among the various zones; the average speed and vehicles volumes determine the status of the road network and what remains from the population is using public means of transport. Furthermore, the model allows for the closing of roads in each geographical zone and the introduction or withdrawal of public vehicles. This allows for the dynamic allocation/movement of people: depending on the level of service of each available transport mode, a passenger may choose buses – if the service level is adequate – or use a private vehicle. The use of system dynamics also allows the incorporation of “soft factors” in that determination, factors such as habit, comfort, etc. As a result, the focus of the model is on the structure of the transportation system and how it determines the overall behavior. Figure 1 illustrates the main elements of the transportation part of the model.

In more detail, each geographic zone in the model entails a road network that is formed by major (large capacity of vehicles per kilometer) and minor (small capacity of vehicles per kilometer) roads. Important elements of the road network are those points that connect the zones. They can be considered as focal points

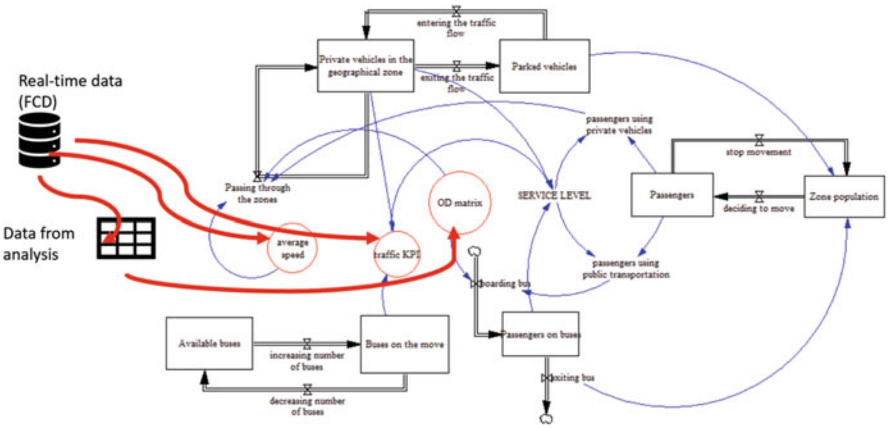

Fig. 1 General structure of the simulation model

in the network and their determination was performed manually with the map of the city. As a result, the movement of cars among the zones is determined by the origin-destination matrix (generated by the floating car data), the zone capacity (determined by the roads), and the percentage of cars that can pass per minute through the focal points.

Once inside the zone, a percentage of cars is moving to go to another zone, while the rest are looking for a parking place inside the zone. The parking capacity of each zone was determined by the available data from the municipality of Thessaloniki, multiplied by a random factor. Hence, vehicle movement is dynamic and dependent only by the internal structure of the model. This dynamic model allows the emergence of new behavior if, for example, new origin-destination matrices are generated by the FC data, due to an unexpected event.

Up until the development of the model, the city of Thessaloniki did not yet have a metro/subway network, and public transportation was performed only by buses. Thus, the buses' movement in the model is similar to that of the private vehicles.

Regarding the socio-demographic aspect of the model, each zone has a population, percentage of which travels either for leisure or business among the various zones. Data from the city of Thessaloniki was chosen as a reference case. Figure 2 below illustrates the travel demand derived from data from CERTH-HIT.

As it can be expected, two peaks are observed in the beginning of the day and early in the afternoon, coinciding with the general times that people move to and from their place of work. However, the figure below does not separate between the types of activity that might result in a trip. For that reason, in the context of the model, the above graph was separated into two, one for people that travel for business and one for people traveling for leisure (Fig. 3).

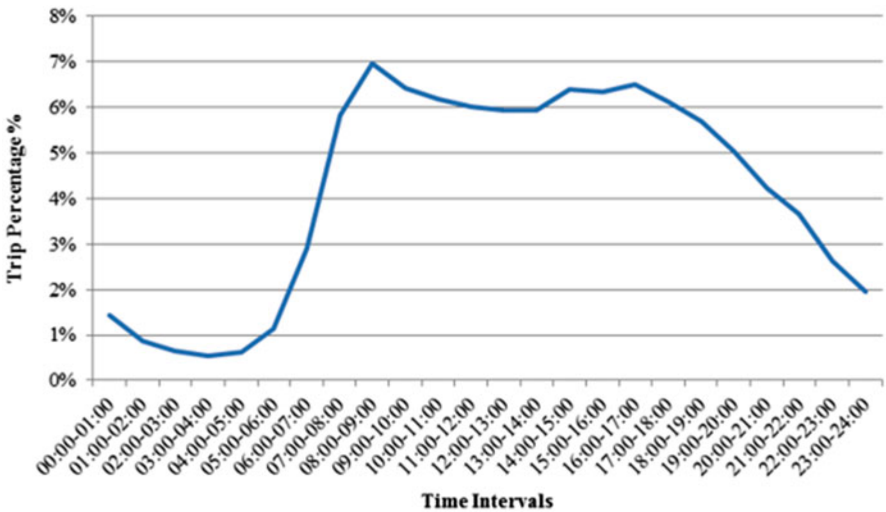

Fig. 2 Travel demand for the city of Thessaloniki

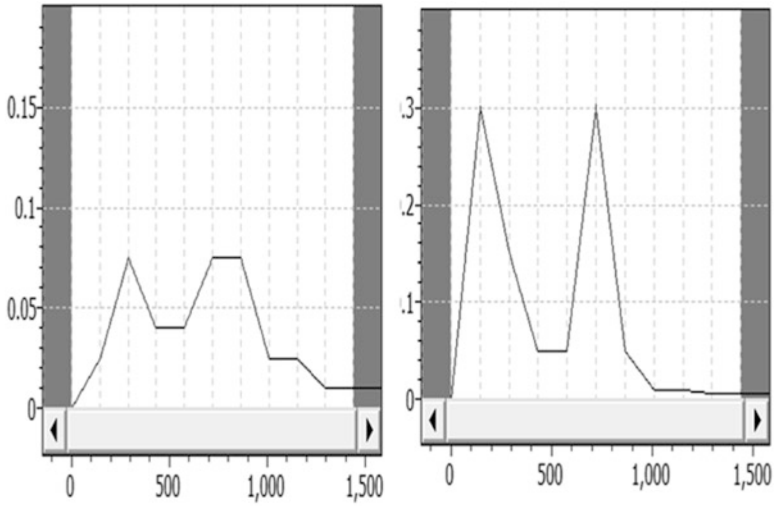

Fig. 3 Travel demand in the model for passengers traveling for leisure (left) and business (right)

Finally, the simulated passengers choose what means of transport they will use based on the utility of each one; the following factors are normalized to form the utility:

- Habit: a random number between 0 and 1.
- Road accessibility: counting the number of roads that are open compared to the sum of all roads in the zone.
- Perception of traffic KPI: a delayed number that is generated by the FCD.
- Parking availability: a delayed number that is generated by the number of empty parking spots compared to the total parking spots of a zone (multiplied to a random number).
- Comfort: a qualitative factor between 0 and 1. For private transportation it is a fixed number (above 0.5), while for public transportation it is calculated by the number of passengers on buses divided by their total capacity.
- Frequency of buses: it is used only when the utility of public transportation is calculated.

As a result, the choice of transport mean is dynamic and internal in the model, and it is decided by the current state of the system during the simulation steps. Finally, the model is simulated for 72 h.

In conclusion, the model attempts to capture the dynamics of the transportation sector of Thessaloniki during 3 (working) days. The model is assisted by data gathered from the city, but every “choice” that affects the overall behavior is decided internally based on the status of the model.

3 Results

The simulated model is tested under two different scenarios: In the first one (Scenario 1), the rain starts falling during the morning hours of the first day; it lasts for only a few hours and it stops. In the second scenario (Scenario 2), there is heavy rain from the beginning of the simulation that lasts for 1 full day. Figure 4 illustrates how the different types of rain are simulated in the model. The vertical axis depicts the mm of rain, while the duration is depicted at the horizontal axis.

Finally, the simulated city is separated into 15 zones, but for reasons of clarity only the results from zone that corresponds to the city center will be displayed.

3.1 Scenario 1 Results

The simulated result of the first "type of rain" is that the water level does not exceed an (hypothetical) alarm threshold that is used in the model to signal when the roads start to gather water. As a result, the water level on the road network persists – although at low levels – for the entire period of the simulation time, but it does not create significant problems (Fig. 5).

The result from that (persistent) low level of water is that the traffic is high during the hours that the demand for travel is high and falls otherwise (Fig. 6). This result does not differ from the "business as usual" scenario where there is no rain.

However, the travel times become slower which results in smaller periods of low traffic KPI (illustrated with the black circles on Fig. 6). The low water levels on the road network force the cars and buses to travel at lower speeds; thus more time is

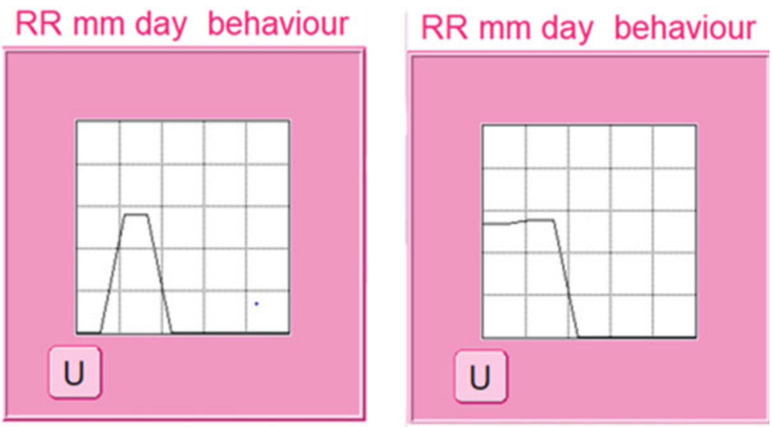

Fig. 4 Scenario 1 (left); Scenario 2 (right)

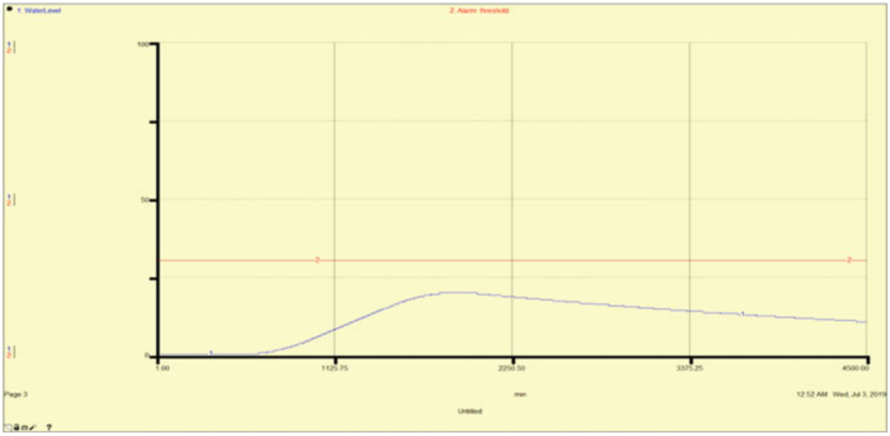

Fig. 5 Water level on the road network compared to the alarm threshold

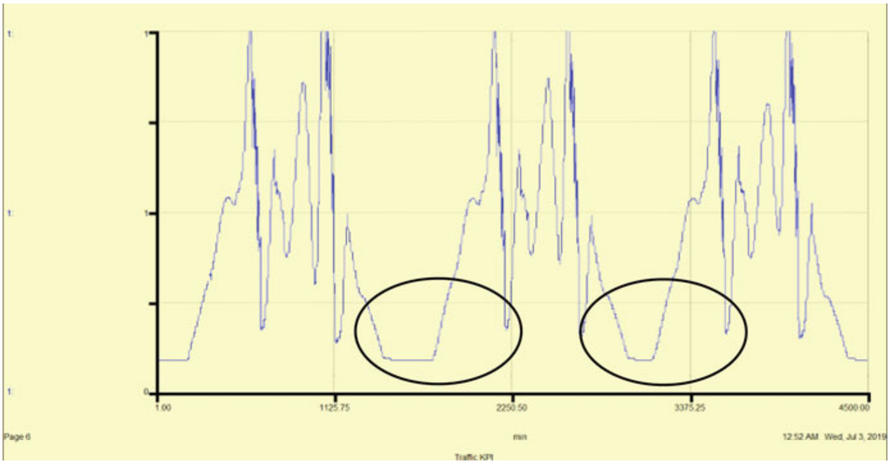

Fig. 6 Traffic KPI for zone 1 of the model (city center)

required to go from their origin to their destination. Consequently, more cars remain on the road for more time, which results in smaller periods of low traffic.

In conclusion, a "light" rain does not have significant effects on the transportation sector apart from larger periods of traffic. What is interesting is that the effects do not occur during the rain but persist after it has stopped.

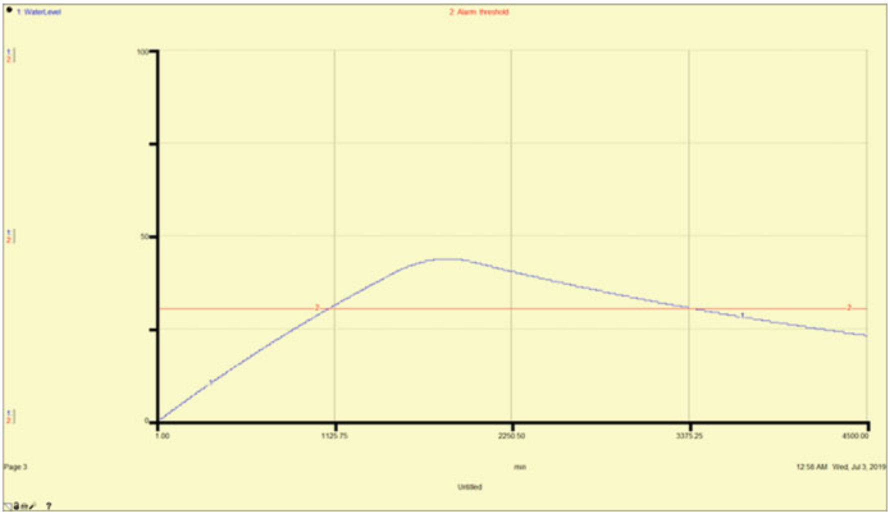

Fig. 7 Water level on the road network compared to the alarm threshold for Scenario 2

3.2 *Scenario 2 Results*

In the second scenario, "heavy" rain falls from the beginning of the simulation. This results in the water level being above the alarm threshold and the road network suffers from flooding. Figure 7 illustrates that the water level remains in high levels long after the rain has stopped and only at the latest stages of the simulation time it falls beneath the threshold. However, even then it is relatively high and, in any case, higher than any time of the first scenario.

The higher levels of water result in almost a standstill on the road network of zone 1. The network reaches almost its full capacity; similar to the first scenario, this occurs after the rain has stopped falling. Figure 8 illustrates the two scenarios that were simulated along with the "business-as-usual" scenario. The pink line of Scenario 2 shows that the traffic remains at alarmingly high levels until the end of the simulation time due to the water levels that take time to fall beneath the alarm threshold.

Compared to Scenario 1 (red line in Fig. 8), which resembles the basic scenario (blue line), Scenario 2 has the most severe effects on the road network, and since there is no subway, the effects do not concern only private transportation but public transportation as well. To illustrate the effect on buses, Fig. 9 below maps the service level of buses for the three scenarios.

The basic scenario (blue line) and Scenario 1 (red line) have similar results, with the service level being at its lowest during the peak of travel demand. Variations between the two results can be attributed to the slightly longer travel times that are observed in Scenario 1. However, in Scenario 2 the service level reaches the lowest

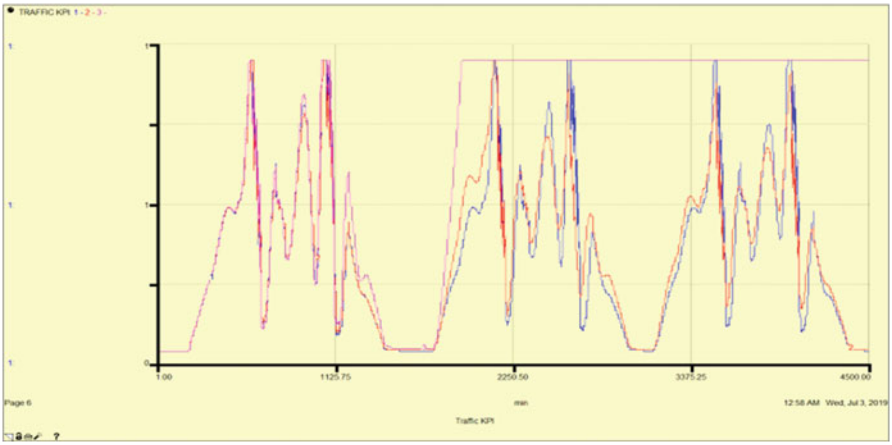

Fig. 8 Traffic KPI for business-as-usual scenario (blue), Scenario 1 (red), Scenario 2 (pink)

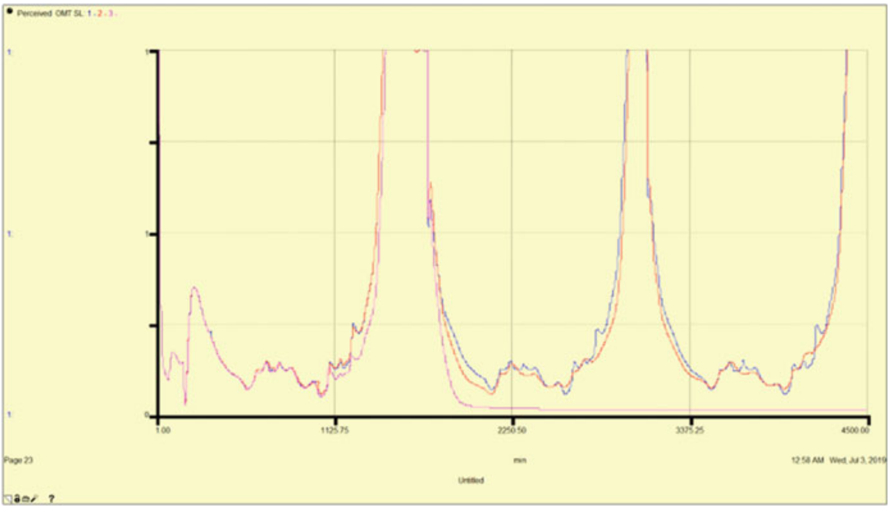

Fig. 9 Public transport service-level KPI for business-as-usual scenario (blue), Scenario 1 (red), Scenario 2 (pink)

point (for all three scenarios) and does not rebound to normal values during the remaining of the simulation time.

In conclusion, for both scenarios the most interesting results stem from the delay between the rain and the manifestation of the effects on the transportation network. Due to the slow descent of the water levels, the effects take time to manifest and to fade out completely. Comparing it with the real situation that occurred in Thessaloniki in 2018, the model reproduces the situation in the roads of the city

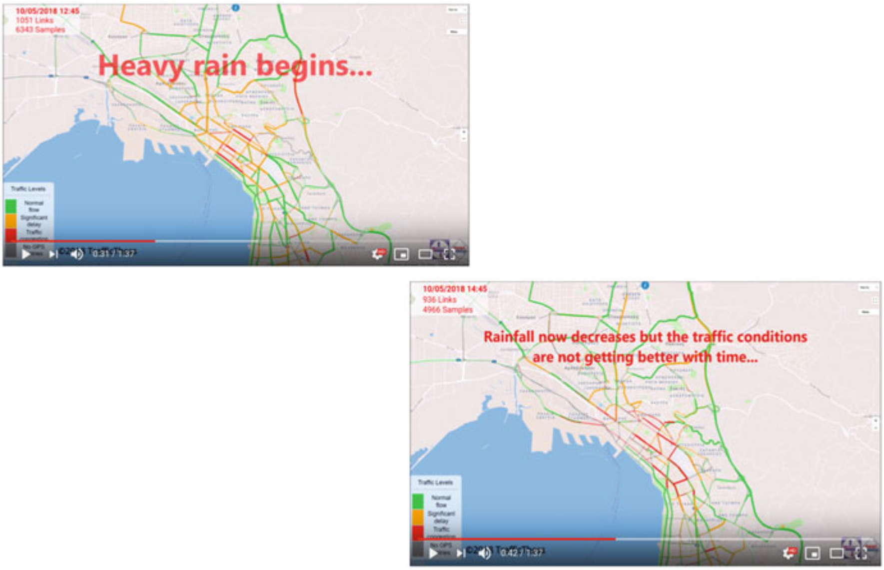

Fig. 10 How the flooding was captured by real-time data

center; despite the decrease in the amount of rain, the traffic conditions were not improving with time (Fig. 10).[1]

4 Conclusions

Floods in urban environments are becoming increasingly common phenomena around the world every year. Their consequences on the transportation sector can be severe and last for days, with the potential to create domino effects to other sectors and even lead to human losses. As a result, policy makers need to integrate their decision-making process regarding the transportation sector in a crisis management framework. This shift will assist them in reaching effective decisions before, during, and after a crisis (flood).

The purpose of this paper was to assist policy makers by proposing a simulation model that can act as a decision support tool and provide insights on the monitoring of the transportation sector during a flood. The model uses data from a fleet of taxis in Thessaloniki, Greece, as input and captures the dynamics of passenger movement in an internal way.

[1] https://www.youtube.com/watch?v=uX0o1kax8sU

The model was tested for two different scenarios that simulate different types of rain. The results indicate that the consequences can be seen long after the rain has stopped and can last for long periods resulting in a transportation system with extremely low level of service and in a state of disequilibrium.

Future directions of the current research include the studying of the effects to other zones of the simulated city, how the effects can move from one zone to another, etc., in other words, increasing the robustness of spatial dimension of the model. Furthermore, potential policies and countermeasures can be tested in the model and provide insights on which work (along with where in the city they work better) and which produce counter-intuitive results. Finally, a user interface and more interactive and intuitive graphical results would increase the communication value of the model and allow it to be used by non-experts. Finally, validation and verification efforts will continue to be indispensable parts of any direction that the model will follow.

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