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Reducing Emergency Services Response Time in Smart Cities: An Advanced Adaptive and Fuzzy Approach

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***Abstract*—Nowadays, the unprecedented increase in road traffic congestion has led to severe consequences on individuals, economy and environment, especially in urban areas in most of big cities worldwide. The most critical among the above consequences is the delay of emergency vehicles, such as ambulances and police cars, leading to increased deaths on roads and substantial financial losses. To alleviate the impact of this problem, we design an advanced adaptive traffic control system that enables faster emergency services response in smart cities while maintaining a minimal increase in congestion level around the route of the emergency vehicle. This can be achieved with a Traffic Management System (TMS) capable of implementing changes to the road network's control and driving policies following an appropriate and well-tuned adaptation strategy. This latter is determined based on the severity of the emergency situation and current traffic conditions estimated using a fuzzy logic-based scheme. The obtained simulation results, using a set of typical road networks, have demonstrated the effectiveness of our approach in terms of the significant reduction of emergency vehicles' response time and the negligible disruption caused to the non-emergency vehicles travelling on the same road network.**

***Keywords* – Traffic Management Systems (TMS), Smart Transport, Smart Cities, Emergency Services, Road Traffic Congestion.**

I. Introduction

The fast emergence of Smart Cities concept as a futuristic vision of today's cities promises to significantly change our lives and offer novel unprecedented services. These services and the underlying advanced Information and Communication Technologies (ICT) supporting them will also help in solving a myriad of contemporary problems which are hard to overcome using current solutions and technologies. Road traffic congestion is among the most challenging issues that current road traffic authorities are facing due to its overwhelming impacts. Among these impacts, the delay of emergency services delivery to the emergency location is the most critical due to the incurred cost in terms of deaths, injuries and financial losses in case of fires, car crashes, terrorist attacks, etc. According to [1], in Ireland only an average of 700 fatalities are caused every year due to ambulances' late response. To reduce these fatalities, Smart Cities and in particular smart transportation services are inherently an ideal platform for implementing ICT-based solutions, thanks to their rich technological resources.

In the case of fire emergencies, the response time requirements in the U.S indicate that the first fire fighter engine is expected to arrive at the scene of a fire within four minutes of a call in at least 90% of cases [2]. As a matter of fact, meeting this requirement increases the enormous cost of maintaining a functional fire response service, especially in populated areas experiencing heavy traffic congestion. The Fire Department of New York (FDNY) alone reported an expense budget of $1.671 billion in 2012, with approximately 1.43 million emergency medical service vehicles and 900,000 fire vehicles dispatched in the same year [3]. These statistics do not take into account the property damage and loss of life caused by fires. In 2013 there were more than 1.2 million fires in USA, with a fire department responding to a fire every 25 seconds. In the same year, fires caused 3,240 civilian deaths, 15,925 civilian injuries in addition to $11.5 billion in property damage [4].

The investment in Smart Cities at the moment is enormous, with both governments and large companies such as Siemens [5] and IBM [6] funding and researching initiatives to develop this revolutionary concept. Several cities around the world are already widely recognized to be the leading examples of Smart Cities such as Vienna, Amsterdam and Tianjin. According to [7], the number of Smart Cities is expected to quadruple from 2013 to 2025 with a staggering 88 Smart cities predicted at minimum by Information Handling Services (IHS) with 32 planned Smart Cities in the Asia-Pacific region, 31 in Europe and 25 in the Americas. Compared to 21 Smart Cities worldwide in 2013 it is very clear from the above information that there is both a pressing need for a more optimised ICT-driven emergency response system and a significant opportunity for its implementation with the upsurge of investment and interest in Smart Cities. To this end, we propose, in this paper, a system which could be widely deployed across Smart Cities worldwide to mitigate the devastating losses caused by emergency services delay. This is achieved by taking into account the severity of each occurring emergency event along with the traffic conditions and deciding which traffic control protocols and parameters should be changed to ensure the fastest journey of the emergency vehicle.

The remainder of this paper is organized as follows. In Section II, we present the literature followed by a detailed description of our proposed system in Section III. Section IV presents our evaluation methodology and metrics and discusses the obtained simulation results. Section V concludes the paper and presents some directions for its improvement. Finally, we present our vision on some future works that can build on this work and further generalize it to accommodate more use-cases and applications within the global spectrum of Smart Cities services.

II. Related Work

In recent years, many researchers from academia, industry and governmental agencies have attempted to design innovative dynamic emergency response and traffic management systems to reduce the impact of the increasing road traffic congestions. In fact, an adaptive system is already being deployed by the New Jersey Meadowlands Commission (NJMC) which received $10 million grant from the New Jersey Department of Transport to incorporate 144 traffic signals into a self-adaptive network [8]. The proposed system intends to build above an architecture similar to that of the Adaptive Traffic Management System (TMS) proposed in [9]. This paper outlines a theoretical system architecture for an advanced adaptive TMS deployment comprising of a Traffic Management Controller (TMC) which splits a large urban area into a set of heterogeneous sub-areas whereby each sub-area is controlled by a Local Traffic Controller (LTC). In this system, en-route events and traffic information are collected by various monitoring equipment and reported to the TMC through the LTCs. Based on this information, the TMC sends the appropriate decisions or recommendations to the LTCs which, in turn, apply the corresponding actions to the traffic light controllers within their sub-areas. Moreover, the LTCs can recommend some customized adaptation to smart vehicles within their transmission range.

In [10], the authors proposed a Traffic Decision Support System (TDSS) which tackles non-recurrent congestions caused by car accidents with a fuzzy case-based system. This fuzzy system analyses the state of the monitored road network in terms of various factors, such as traffic density and average speed of vehicles as well as optimization criteria including desired minimum waiting time and maximum throughput, to output a ranked list of optimal control measures which involve alterations to driving policies (e.g., lane closure, ramp metering etc.). There exist many works in the literature devising adaptive mechanisms for traffic light control [11- 13], which aim to dynamically change phase shift and duration of traffic lights rather than using fixed cycles. This is achieved by using WSNs and other road sensors to establish factors, such as vehicles' queue length, average crossing speed, traffic volume etc., to make decisions on how traffic lights should be altered.

It is clear that there is an increasing interest from the research community on designing advanced solutions to enhance the efficiency of the existing TMS models with special focus on its application in future smart cities. However, only few of those solutions are aimed specifically at the reduction of emergency services response time. In addition, they do not take into account the broad spectrum of relevant parameters to choose an ideal adaptation strategy, thus leaving plenty of motivation for the design of the TMS proposed in this work.

III. Proposed Solution

The proposed system aims to reduce emergency vehicles, such as ambulances, police and fire fighters cars etc., response time by means of certain actions which may involve either changing driving policies (e.g. speed limits, lane usage permissions etc.) or altering the state of objects in the road network (i.e. traffic lights and vehicles). The actions carried out depend mainly on the urgency of the situation being responded to and the level of traffic congestion in the road network, choosing the most appropriate response plan (i.e. a set of actions to be performed) for a given situation is obviously important as graver emergencies require a faster response and heavier traffic can severely impede an Emergency Vehicle (EV) and inflate its response time, thus requiring more efforts from the TMS to ensure rapid arrival.

The severity of the emergency situation should be provided by the emergency services authority in the form of a discrete value known as the Emergency Level (EL) as shown in Figure 1 to serve as a parameter for the TMS. Current traffic conditions are then acquired from the road network to evaluate certain traffic parameters which are then passed to the Fuzzy Logic controller. This latter returns a Congestion Value (CV) between 0 and 1 which is then converted to a discrete Congestion Level (CL) value that serves as a second parameter for the decision making system. The EL and CL are combined to choose an Emergency Response Plans (ERP). The ERPs can be represented by a vector of actions to be performed to reduce the emergency services response time.

Figure 1 provides further details on this process; once an emergency situation along with its emergency level are announced to the emergency service authority an Emergency Vehicle is immediately dispatched. The EV begins by contacting the TMS giving it the EL value and requesting a route to the emergency location. The TMS reads the Occupancy Level (OL) and Average Vehicle Speed (AVS) from the road network and forwards them to the Fuzzy Logic Controller to get the corresponding CV and CL value after assigning a route to the EV. Now that the TMS has both the EL and CL values an ERP is chosen and the relevant actions are applied to the network.

A. Actions Available

Several actions are available to the TMS to ensure the fastest possible response to an emergency, some of these can be performed at dispatch time whereas others must be performed dynamically while the EV is en route toward the emergency location. A list of these actions with a brief description follows below, each of which can serve as an element of an ERP vector. The identifier for each action will also be included in parentheses after their names as these are used to identify the actions in an ERP vector.

- **Traffic Light Change (TL)**: when the EV reaches a new road segment the current traffic lights phase can be changed or its duration extended to ensure that the EV

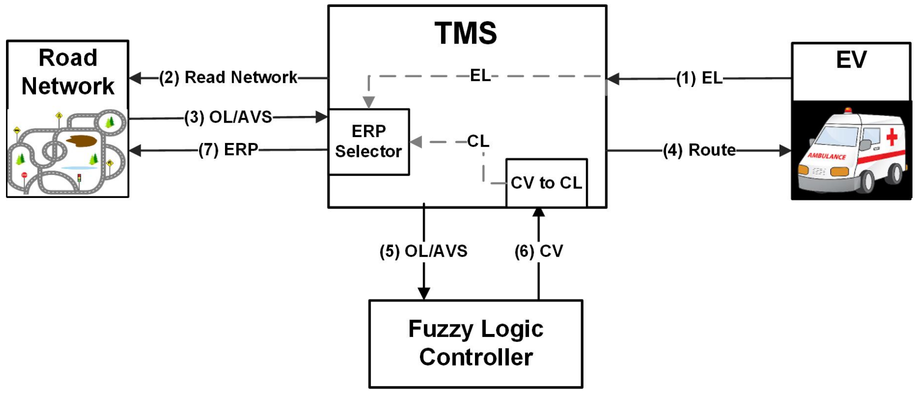


Figure 1: The proposed adaptive TMS architecture for emergency services

meets green lights only. A Vehicle to Infrastructure (V2I) like mechanism [20] can be used for efficient coordination between the EV and the traffic light controllers at each road segment/intersection.

- **Speed Limit Change (SL)**: when the EV is assigned a route the speed limit along this route can be, under some circumstances, temporarily raised by a value proportional to the original limit for each road segment.
- **Lane Clearance (LC)**: if the EV is on a road containing multiple lanes with other Non-Emergency Vehicles (NEV) directly ahead of it, these vehicles can be asked to move to another lane to create a clear path for the EV. In this case, robust inter-vehicles coordination and beacons congestion control protocols are required [19].
- **Permission to use Reserved Lanes (RL)**: this action complements lane clearance by temporarily allowing non-emergency vehicles to use reserved lanes (e.g. bus lanes, taxi lanes, truck lanes etc.).
- **Re-Routing (RR)**: vehicles along the EV route are re-routed away from this route to reduce the congestion and facilitate the EV's progress towards the emergency location. In this case, an advanced and fast re-routing protocol is needed [18].

B. Fuzzy Logic based System

The purpose of using a fuzzy logic based system is its ability to provide a representative output for a set of imprecise inputs, in addition to its flexibility and design easiness. Such system can be simply tuned by changing/upgrading the membership functions and the knowledge base rules in order to accommodate various road scenarios, making it very suitable for the highly changing traffic conditions in urban areas. Fuzzy logic is applied to determine the most appropriate (accurate) evaluation of the congestion level (i.e., Negligible, Low, Medium, High and Critical) corresponding to each pair (OL, AVS) as it is hard to define linear relationships between all possible values of inputs and corresponding outputs, especially the values which may change significantly when put in context with the values of other factors. For example, a higher lane occupancy may indicate higher congestion level but there is

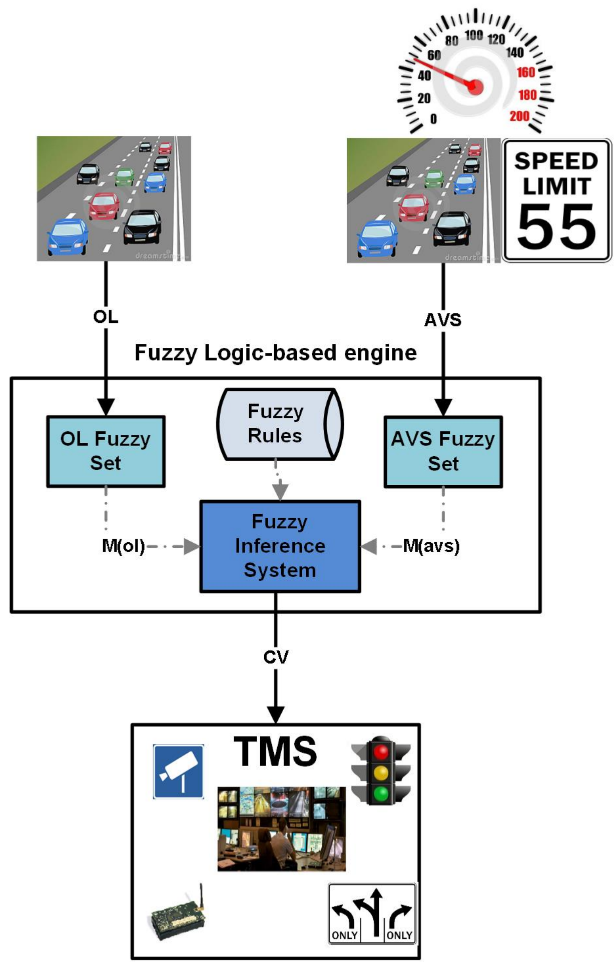


Figure 2: Fuzzy-logic-based engine for emergency services support

a huge distinction to be made between roads with high lane occupancy that have a steady throughput of vehicles going at a reasonably high speed and one where traffic is reduced to a standstill. Due to its non-discretised classification fuzzy logic allows for the compensation of any effects of external influences affecting congestion such as road conditions and speed limit since a discrete input is likely to have membership in more than one set, for example the OL of a lane may be 40% high and 60% medium which could perfectly describe an occupancy situation that would be considered ”medium” 60% of the time depending on other contextual factors.

The fuzzy logic controller, as defined in Figure 2, returns a congestion level given two key traffic parameters: Occupancy Level (OL) and Average Vehicle Speed (AVS) along the route of the emergency vehicle. As defined in the proposed conceptual architecture shown in Figure 1, the OL and AVS parameters are procured by the system from the road network and sent as inputs into the fuzzy logic controller which outputs a Congestion Value. The OL of each lane ($lane_i$) in the road network is calculated as follows [18]:

$$OL_{lane_i} = \frac{N_{lane_i} \times (\overline{Veh_{length}} + Veh_{gap})}{lane_{ilength}} \times 100\% \quad (1)$$

where N_{lane_i} refers to the number of vehicles running on the lane ($lane_i$), $\overline{Veh_{length}}$ is the average length of a vehicle, Veh_{gap} represents the minimum gap between two vehicles running on the road with respect to the required safety distance, and finally $lane_{ilength}$ is the length in meters of the lane ($lane_i$). An accurate estimation of N_{lane_i} can be achieved through a combination of various technologies such as induction loops, road sensors, CCTV cameras as well as GPS data as stated in [17]. The same technologies can be also used to determine the average speed of vehicles.

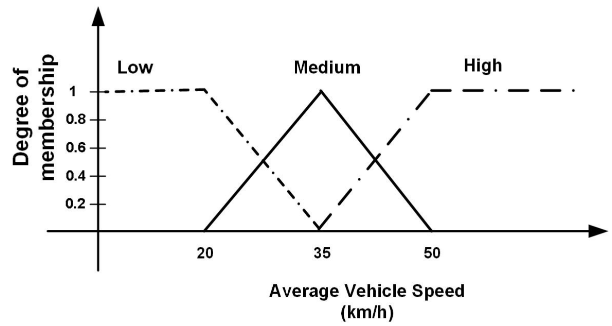
The CV is returned to the TMS and subsequently mapped to one of five CL values used to choose an ERP. Both parameters are fuzzified by the Fuzzy Logic Controller into their respective fuzzy set within the system, the membership function M(x) returns a vector of membership values of a fuzzy set for use in the defuzzification and rule application process.

Defuzzification is performed to get a final value based on the membership vector of a fuzzy set composed of membership values, as shown in Figure 3, for each class in the set. This is done using the Centre of Gravity (COG) method which uses the centroid along with the membership values of each class. The COG defuzzified value of a set A with regard to input x is given by (2).

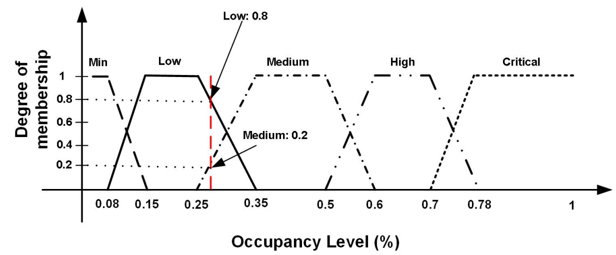
$$COG(A, x) = \frac{\sum_{i=1}^{n} c(i) \times M(x, i)}{\sum_{i=1}^{n} c(i)} \quad (2)$$

where n denotes the number of classes in a given fuzzy set, $c(i)$ is the membership function’s center of area corresponding to each class i of congestion level, and $M(x, i)$ refers to the membership level of an input x (i.e. road traffic conditions designated by the measured OL and AVS) to the class i.

Once the defuzzified values are obtained for both OL and AVS they are passed to a rule-block within the Fuzzy Logic Controller which defines the mapping to the final output of the system. This may seem like they would cause a linear input/output relationship at a glance, however it is not the case since the membership of a fuzzy set is not necessarily confined to one class, meaning that several rules could apply for each set of inputs.



(a) AVS membership function



(b) OL membership function

Figure 3: The AVS and OL membership functions used in the proposed system

Table I: Rule-base used in our system

Rules	Occupancy Level	Average Traffic Speed	Congestion Level
Rule 1	Minimal	High	Negligible
Rule 2	Minimal	Medium	Negligible
Rule 3	Minimal	Low	Low
Rule 4	Low	High	Negligible
Rule 5	Low	Medium	Low
Rule 6	Low	Low	Low
Rule 7	Medium	High	Low
Rule 8	Medium	Medium	Medium
Rule 9	Medium	Low	Medium
Rule 10	High	High	Medium
Rule 11	High	Medium	High
Rule 12	High	Low	High
Rule 13	Critical	High	High
Rule 14	Critical	Medium	Critical
Rule 15	Critical	Low	Critical

Table II: The corresponding ERP to each pair (CL, EL)

CL	EL	ERP
Minimal	Low	1
Minimal	Medium	1
Minimal	High	3
Low	Low	1
Low	Medium	2
Low	High	3
Medium	Low	1
Medium	Medium	2
Medium	High	3
High	Low	4
High	Medium	4
High	High	5
Critical	Low	4
Critical	Medium	5
Critical	High	5

Table III: An overview of the available ERPs

ERP	Actions list	Designed for
ERP 1	(TL)	Emergencies of low severity under low congestion conditions
ERP 2	(TL, **SL**)	Low to medium congestion with medium level emergencies
ERP 3	(TL, SL, **LC**, **RL**)	Severe emergencies in low to medium traffic congestion
ERP 4	(TL, SL, LC, **RR**)	Moderate emergencies in highly congested situations
ERP 5	(TL, SL, LC, **RL**, RR)	Severe emergencies in highly congested roads

C. Emergency Response Plans

Our designed adaptive TMS has five separate ERPs available to initiate changes in the default setting of the road network policies as well as vehicles driving rules and traffic lights default configuration. These changes are defined based on the specified ranges of EL and CL. Ideally these ERPs would be designed by traffic experts and be thoroughly evaluated before being added to any local traffic systems. As mentioned earlier ERPs can be represented by a vector of the actions to be performed and are designed for particular combined traffic/congestion situations and range the logical mappings accordingly. Table II gives a concise overview of how each ERP is chosen based on the input CL and EL values and Table III shows which actions are performed in each ERP and for which purpose this latter is designed. The set of actions performed at each ERP have been chosen based on a literature review of several reports from road traffic authorities and traffic experts suggesting the most appropriate actions to undertake in various congestion and emergency situations. However, more ERPs can be added with a customized set of actions depending on the city where our system is deployed, the road network characteristics, the drivers behaviours, and the specific driving policies set in some countries.

IV. Performance Evaluation

To assess the efficiency of our proposed TMS three metrics were used, the travel-time of the EV, the travel-time of NEVs which are directly affected by the actions performed by the TMS (i.e. the vehicles which have shared road segments with the EV or their routes get congested due to the applied re-routing action in ERP 4 and ERP 5) and the overall Traffic Load Balance (TLB). The system was tested using the SUMO [14] traffic simulator and the TraCI [15] client application to make the necessary changes dynamically to the simulation using Python scripts. To get a reasonable variation in results, three different and representative road networks were used in our evaluation. The first of these was a 10*10 square grid network with road segments lengths of 120 m, each with two lanes. The second network used was an area of lower Manhattan, this was the largest network used for testing. The last network used represents southern Ottawa. To effectively test the system every combination of EL and CL was tested, with the tests being carried out 10 times for each testing network, each time with a randomly selected emergency location and route for the EV. The scripts to implement system actions were written in python using the TraCi Python API and the Fuzzy Logic Controller was implemented using PyFuzzy [16].

A. Emergency Vehicle Travel Time

The graphs plotted in Figures 5, 6 and 7 show the average percentage of improvement (i.e. reduction) in the EV's travel-time when our system is used compared to the average travel-time achieved in the baseline system (i.e. currently used TMS in which no adaptation actions are applied and our fuzzy system is disabled). Each graph corresponds to one of the three testing maps and highlights the improvement for every combination of EL and CL.

From these histograms it is quite clear that our proposed TMS achieves a significant improvement in travel-time. The smallest observed improvement is still above 15% and the maximal is as high as 76% in NYC map (See the blue bar in Figure 6 for the combination (CL= Minimal, EL= High). The overall average improvement across all scenarios is approximately 46%. In almost every case we can see that the higher the emergency level is, the more the percentage improvement in travel-time will be. These results are justified by the fact that the higher the EL value the more elaborate the chosen ERP since there is a greater need for fast arrival and more actions are taken to reduce the journey time of the EV. It is worth to note that the only exceptions to this is the following combination in NYC map (NYC Critical Congestion, EL = Medium and EL = High) but the difference here is a small margin. The most likely reason for the lack of improvement in these cases is that ERP 5 is chosen here, which only adds the Reserved Lane action over ERP 4. The Reserved Lane action does not guarantee to reduce the travel-time of the EV since random routes are not likely to have many reserved lanes. The decrease in improvement can then be explained by the difference in routes that were selected for these tests rather than any deficiency in the chosen ERP.

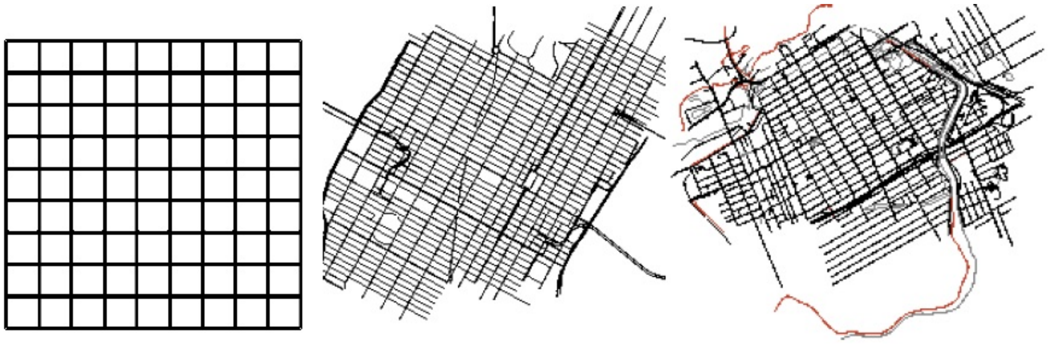


Figure 4: The road maps used in our simulation: Grid map (Left), Lower Manhattan map (Middle), South Ottawa (Right)

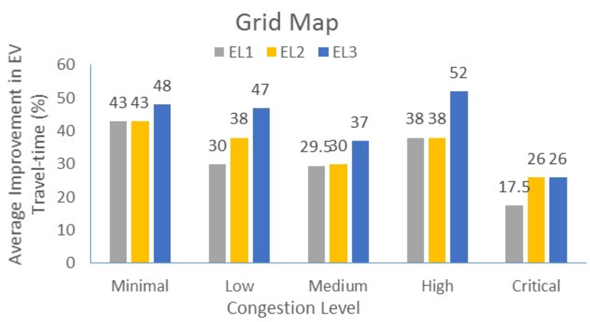


Figure 5: EV travel time improvement in Grid map

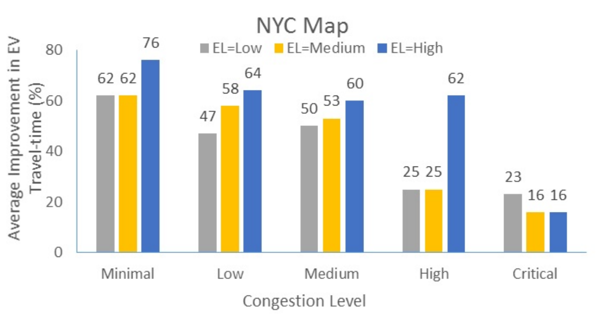


Figure 6: EV travel time improvement in NYC city map

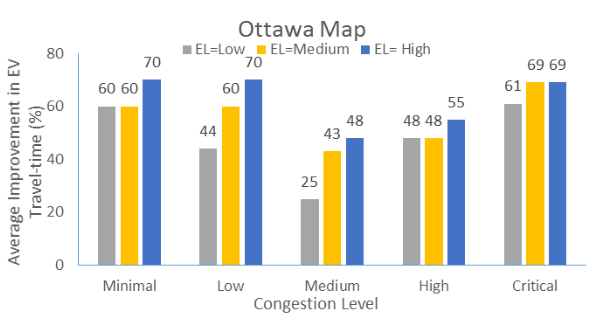


Figure 7: EV travel time improvement in Ottawa map

B. Non-Emergency Vehicles Travel Time

While the travel-time of Non-Emergency Vehicles (NEVs) is not quite as high a priority as the travel-time of the EV, it would be ideal for our TMS to not only speed up the EV arrival to the emergency location but to do so with a minimum disruption to other vehicles in the network due to the inherent cost and inconvenience caused by traffic delays. For this reason the travel-time of NEVs was considered as an appropriate secondary metric for the evaluation of our TMS efficiency. This was measured by tracking the journey time of vehicles travelling along the EV's route at dispatch, any vehicle requested to clear a lane during its journey and all vehicles re-routed or on the path of newly re-routed vehicles.

In most cases the actions taken by the system lead to an improvement in the average travel-time of NEVs since most of the tracked vehicles benefit from the same privileges as the EV (more green lights, higher speed limit etc.). The overall average change in NEV's travel-time was an improvement in journey-time equals to 14.8%. Occasional increase of NEVs travel time (i.e. the negative values, such as -3%, -30% and -23%, shown in Figures 8, 9 and 10, respectively) is also observed in the lower range of CL values, where the delay is presumed to be less significant since lower congestion means a shorter travel-time. It is also worth noting that, in our simulation, under lower congestion conditions less vehicles are tracked so the figures are more susceptible to be altered by a subset of outliers.

The reason for this decrease in improvement (i.e. increase in NEVs travel time) is that certain system actions led to slowing down NEVs. The primary culprit for this is the lane clearance action as it forces more vehicles to bunch up together on the same lane, thus augmenting the congestion on this lane and increasing the journey time. Speed limit change may also occasionally cause a negative impact on NEV's travel-time. The most likely reason for this is that these actions bring the vehicles through parts of the network shared with the EV's route faster but delivers them to other parts of the network at an increased rate, thus increasing congestion in the section of the network where they leave the EV's route. Re-routing has been observed to cause an improvement in high-congestion scenarios as it brings vehicles away from a highly-congested

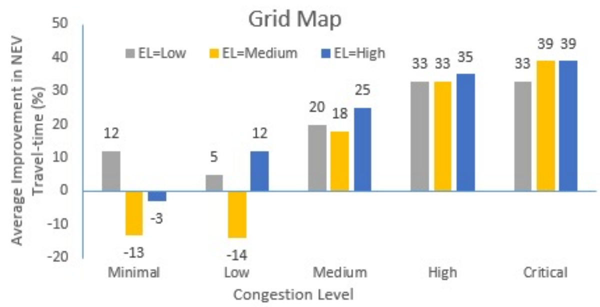


Figure 8: NEV travel time improvement in Grid map

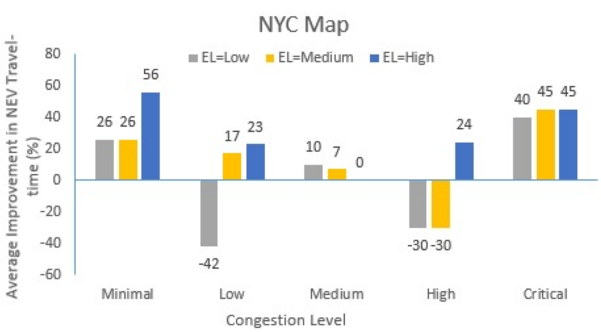


Figure 9: NEV travel time improvement in NYC city map

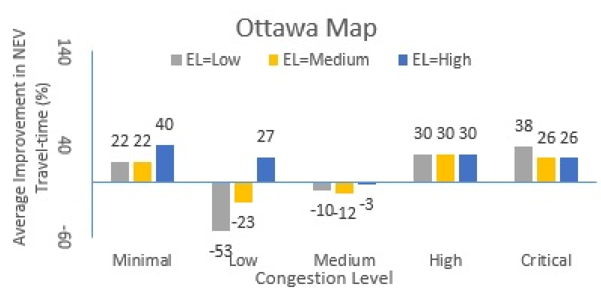


Figure 10: NEV travel time improvement in Ottawa map

EV's route and into potentially less congested areas.

C. Traffic Load Balance

Since the NEVs journey time metric is measured based on the subset of vehicles that come into contact with the EV in some way it does not necessarily reflect the overall impact on traffic within the network. To measure this the overall Traffic Load Balance (TLB) of the network is used as a final metric to analyse the impact on the distribution of the traffic in the road network. This metric is measured by means of the standard deviation of road lanes' occupancy across the network at 120 s intervals. The measured standard deviation was never particularly high in any of the tests run, with a maximum value less than 0.05. Small changes were measured but these were small enough to be insignificant and well within a reasonable margin of error. Thus the overall impact of the system on the network's TLB is negligible.

Table IV: The average improvement of traffic load balance degree in Grid map (%)

		Congestion level				
		Minimal	**Low**	**Medium**	**High**	**Critical**
Emergency level	**Low**	0	2.7	-0.3	-4.6	-2.5
	Medium	0	0	-0.6	-4.6	0.5
	High	2.7	0	-6.1	2.3	0.5

Table V: The average improvement of traffic load balance degree in NYC city map (%)

		Congestion level				
		Minimal	**Low**	**Medium**	**High**	**Critical**
Emergency level	**Low**	-0.6	-3.33	0	0	-2.7
	Medium	-0.6	-3.33	0	0	-2.7
	High	-0.6	0	0	-3.33	-2.7

Table VI: The average improvement of traffic load balance degree in Ottawa map (%)

		Congestion level				
		Minimal	**Low**	**Medium**	**High**	**Critical**
Emergency level	**Low**	0	-7.6	0	-7.6	0
	Medium	0	0	0	-7.6	0
	High	0	-7.6	0	-7.6	0

As shown in Table IV, the largest change in TLB on the grid network is a decrease of 6.1% in medium congestion situations. This slight change could be attributed to a low percentage of overall vehicles having their journeys sped up and leaving the network faster but the change is small enough to be equally caused by the variation in the routes chosen for the EV. In many cases the average percentage change in TLB is zero, meaning that there was no measured impact whatsoever on overall TLB. The same conclusions hold true for testing on the other two networks, as depicted in Tables V and VI where only a slight decrease is ever observed.

V. CONCLUSION

In this paper, we have proposed an adaptive Traffic Management System (TMS) combined with a fuzzy logic based scheme in order to take appropriate actions to speed up the progress of emergency vehicles while avoiding the creation of bottlenecks around their routes. This is achieved through the well-designed adaptation actions and emergency response plans chosen based on the emergency level advertised by the emergency vehicle and the output of the fuzzy system (i.e. the assessed congestion level). The proposed approach has significant potential to mitigate or at least alleviate the awful impact of road traffic congestion on emergency services delivery to emergency locations. Extensive simulations were carried out to assess the efficiency of the proposed system and analyse its impact on the non-emergency vehicles. The obtained results show a significant reduction in the travel-time of the emergency vehicle being dispatched with no remarkable adverse effects on traffic load balance and the journey time of non-emergency vehicles, thus achieving the primary goal of our system. The proposed system can be further improved to make it more tailored for use by local traffic experts by enabling the creation of additional specific ERPs and additional metrics used to choose them (e.g. weather conditions, time of the day, etc.).

VI. Future Works

We foresee that in the upcoming years the research activities dedicated to smart cities, and smart transportation in particular, will witness an unprecedented expansion with an emphasis on multi-disciplinary projects in both industry and academia. This is due to several factors such as the increasing interest of governments and big companies (e.g., IBM, Google, Intel, Microsoft, ...) to the concept of smart cities and the technologies required for its realization in real world (e.g., driver-less cars, electric vehicles, green transportation, smart building, smart e-healthcare, ...), and the expected economic gain and reduction in air pollution, and dramatic improvement of citizens quality of life. Therefore, our proposed system can be further generalized to accommodate more use-cases in order to maximize the utility of the available road infrastructure. This can be achieved by enabling an opportunistic usage, similar to the cognitive radio technology principle used in wireless networks, of reserved lanes on the roads (e.g. bus lanes, lanes for heavy or slow tracks, ”games lanes” reserved for accredited games and emergency vehicles etc.) whenever they are not occupied by the vehicles for which they are dedicated. The selection of vehicles that will be temporarily permitted to use a reserved lane is made based on their power source (i.e. electricity, fuel, hybrid, ...) and their trip length.

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