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Coalition Game for Emergency Vehicles Re-routing in Smart Cities

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Abstract—Traffic congestion is a serious problem in many cities around the world, due to the increasing number of vehicles using roads with limited capacity. Traffic congestion significantly affects mobility of vehicles in smart cities. However, the most important factor is the delay of emergency vehicles, such as ambulances and police cars, leading to increased road deaths and significant financial losses. To reduce this problem, we propose an advanced traffic control allows rapid emergency services response in smart cities while maintaining a minimum of congestion on the emergency lane. This can be achieved through a traffic management system capable of implementing path planning and driving the emergency vehicle in the best possible way to reach the hazard zone. The performance of the proposed algorithm is compared with two other algorithms over Birmingham city centre test scenarios. Simulation results show that the proposed approach improves traffic efficiency of emergency vehicles by an overall average of 21.78%, 29.32%, 32.79% and 46.77% in terms of travel time, fuel consumption, CO_2 emission and average speed, respectively.

Index Terms—Traffic congestion control, Cooperative game theory, Particle swarm optimization, IoV applications, Vehicular Ad hoc Networks.

I. INTRODUCTION

The increasing number of vehicles on urban road networks has caused serious traffic congestion problems, affecting travel time, travel costs, fuel consumption and air pollution. The most critical impact of traffic congestion is the delay of providing emergency services to unexpected events. This might lead to dangerous consensuses such as injuries, deaths and economic losses in case of car accidents, building fires and terrorist attacks, etc [1].

Emergency response systems and emergency logistics for general activities are considered as an important component in smart cities. After unpredictable events, we need to make sure that emergency vehicles can reach the destination area in a timely manner, survivors and properties have been moved in order to increase the capacity of emergency response and reduce the loss of life and property [2].

The authors in [3] have referred to other issues arising from delays of emergency vehicles in traffic congestion that are the disruption and selecting the wrong path to access the emergency site. This failure is attributed to the lack of drivers that are typically able to correctly identify the emergency vehicle approach and react appropriately. Recently, Intelligent Transportation Systems (ITSs) are considered as an effective solutions for improving mobility in smart cities [4]. ITSs has utilized Vehicular Ad hoc NETworks (VANETs) to broadcast messages between connected vehicles [5]. This helps Traffic Management Systems (TMSs) to control road traffic congestion, which improves the mobility of vehicles in the smart cities.

To address issues of emergency response time, this paper proposes an approach that is called Coalition Game Approach based on Particle Swarm Optimization (CGA-PSO) for emergency vehicles routing in smart cities to mitigate the devastating damage caused by delayed emergency services. This is achieved by taking into account different attributes for each emergency vehicle route driving along with the traffic conditions and distribute emergency vehicles into coalition to ensure the fastest drive to the hazard area. The main goal of CGA-PSO is to provide emergency vehicles with the optimal paths according to multiple criteria in order to meet the diverse navigation requirements.

The remainder of the paper is organized as follows: in Section II, details of the framework description are given. In Section III, a performance evaluation is provided. Finally, conclusions are drawn in Section IV.

II. FRAMEWORK DESCRIPTION

VANETs include Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication systems. Here, it is assumed that both systems utilize central access messages (CAMs) or beacon messages. CAMs are packets sent periodically between V2V or V2I communication systems that focus on monitoring traffic flow and congestion alleviation [6]. Fig. 1 illustrates the V2V and V2I structure. This enables them to select the optimal path to drive the vehicles to their destinations. This section describes the proposed framework by specifying the real-time data collecting methodology, the road network model and the coalition game of emergency vehicles.

A. Data Collecting

The data have been sent using beacon messages, and the proposed protocol works as follows: the vehicles transmit their average velocity and "roadId" to their neighbouring RSUs

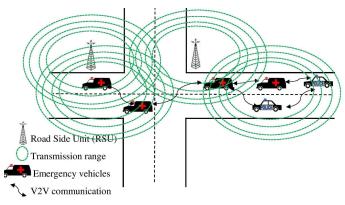


Fig. 1: Internet of Vehicles (IoV) road network infrastructure.

through beacon messages. Each RSU holds a data structure containing the average speeds, roadIds and roads length of all vehicles within its transmission range. The average speeds are found from the speed measurements over the previous five seconds (one measurement a second). If the average speed is less than or equal to a velocity threshold predetermined by the designer, the congestion detection is initiated, in which congested roads are identified. The RSU will then verify whether or not to broadcast the data from receiving beacon messages. The data will be used if the RSU does not receive a duplicate message with the same roadId. Whenever the RSU receives a new beacon, it updates its data structure and sends the data to vehicles within its transmission range. As a result, congested roads can be excluded from the map and a new routes are calculated at the RSU by using PSO algorithm and communicated to emergency vehicles as they approach the intersections.

B. Road Network

The road network can be modelled as a directed graph G = (V, E), where V corresponds to the intersections (nodes) and $E = \{e_1, e_2, \ldots, e_i\}$ corresponds to the road segments (edges). The road matrix H can be formulated as follows: suppose each intersection contains v roads; each of the roads contains the k attribute value in the road network:

$$H = \begin{bmatrix} T_L & R_L & D_L \\ H_1 & T_{11} & T_{12} & T_{13} \\ H_2 & T_{21} & T_{22} & T_{23} \\ \vdots & \vdots & \vdots \\ H_v & T_{v1} & T_{v2} & T_{v3} \\ w_1 & w_2 & w_3 \end{bmatrix}$$
(1)

The normalized road matrix has been obtained using the following equation:

$$r_{jk} = \frac{x_{jk}}{\sqrt{\sum_{j=1}^{v} (x_{jk})^2}}$$
 where $j = 1, \dots, v; \quad k = 1, 2, 3$

where $r = \{r_{jk} | j = 1, ..., v; k = 1, 2, 3\}$ are the normalized performance values of each T_L , R_L and D_L ,

respectively. $X = \{x_{jk} | j = 1, ..., v; k = 1, 2, 3\}$ denotes the set of performance values of each T_L , R_L and D_L , respectively. $w = \{w_k \mid k = 1, 2, 3\}$ denotes the set of weights; $EV = \{EV_1, EV_2, ..., EV_n\}$ is the set of emergency vehicles; and $A = \{A_v | j = 1, ..., v\}$ are the alternative roads for each emergency vehicle in EV. Every vehicle in the network periodically sends a message msg_j that contains $\{roadId_j, averagespeed_j, position_j, route_j, destination_j\}$ to the neighbouring RSUs.

Three parameters have been used in our optimization:

- 1) Road travel time $T_L = \{r_{jk} | j = 1, ..., v; k = 1\}$ represents the normalized travel time for each alternative in *H*.
- 2) Road length $R_L = \{r_{jk} | j = 1, ..., v; k = 2\}$ represents the normalized length in a directed graph G for each alternative in H.
- 3) Density of vehicles on the road, $D_L = \{r_{jk} | j = 1, \ldots, v; k = 3\}$, which is given as a normalized density in H and calculated as follows.

According to Greenshield's model, a linear relationship exists between speed and density, which has the following form:

$$V_r = 1 - D_r,\tag{3}$$

where D_r represents the density ratio and can be calculated as follows:

$$D_r = \frac{D_L}{D_q}.$$
 (4)

In (4) D_L is the current density of vehicles on the road and D_q is the maximum jam density, which is computed as follows:

$$D_q = g \frac{L_i}{A v g_L}.$$
(5)

Note, g is the number of lanes on the road, L_i is the road length and Avg_L is the average vehicle length plus the minimum gap between two vehicles. This work assumes Avg_L is 6.2m, as is done in [7] and [8]. From (3) and (4) D_L can be calculated as:

$$D_L = D_m (1 - V_r) \tag{6}$$

A multi-objective problem is often solved by combining the multiple objectives into one single-objective scalar function. This approach is in general known as the weighted-sum or scalarization method. In this paper, the cost function of the emergency vehicle has been formulated using the weighted sum method as below:

$$f = \operatorname{Min}\{w_1 T_L + w_2 R_L + w_3 D_L\},$$
(7a)
where $T_L = \sum_{j=1}^{v} r_{j_1}$, $R_L = \sum_{j=1}^{v} r_{j_2}$, $D_L = \sum_{j=1}^{v} r_{j_3}$.

(7b)

C. Coalition game of emergency vehicles

A normal form cooperative game is a couple (N, U) where:

- N is a set of players.
- U is a value function that assigns a real value to every coalition $C \in 2^N$.

In this paper, the Particle Swarm Optimization (PSO) [9] has been used in order to find m optimal routes as in algorithm 1 and we consider the EV as playing a coalition game on the basis of performance metrics and payoff function is defined. Here, the coalition formation game is defined by a set of EV rational players, denoted as a couple (N, U) where N = $EV = \{EV_1, EV_2, \dots, EV_n\}$ and U represent the coalition payoff. Each route in $R = \{a_1, a_2, \dots, a_m\}$ generated from PSO is considered as a coalition in the game and each EV in N will play a strategy $S = \{join, not join\}$ that is EV prefer to join for a certain coalition or not. The strategy profile for all players is $S = S_{EV_1} \times \cdots \times S_{EV_n}$. Here, eight of emergency vehicles N are assumed driving from the emergency center or start point through the city using the same route created by using Dijkstra algorithm towards destination or disaster area. Once the congestion is detected by RSU, the on-line phase is triggered automatically to determine alternative routes as follows: Once new data becomes available, the RSU updates the road costs. Based on this data the road matrix H for the RSU is updated. Then the RSU will identify congested roads in H and generates a set of congested roads contained in the matrix CR. Then PSO returns a set of m optimal paths.

Once emergency vehicles approach an intersection it will send a query message that contains $msgQ_i =$ $\{roadId, position, route\}$ to the RSU. The alternative routes will then be transmitted to the EV. This allows the emergency vehicles to select a coalition or optimal routes that increase its payoff function then each EV send the coalition name to each other using beacon messages in order to avoid selecting one optimal route or same coalition. Then each EV continue towards their destination with the coalition or the route that has been selected, avoiding the congestion that has formed. This procedure is repeated every time emergency vehicles approach an intersection and enter the RSU transmission range.

III. PERFORMANCE EVALUATION

A Veins simulator [10] which integrates the Simulation for Urban Mobility (SUMO) [11] with the network simulator OMNeT++ [12] has been used. This simulator is able to manage the mobility of vehicles and the communication between V2V or V2I communication systems. A realistic map has been imported from the Open Streets Map (OSM) tool [13] to evaluate and test the proposed method (the scenarios of Birmingham city in U.K.) as shown in Fig. 2. The CGA-PSO has been compared with the Original Dijkstra's Algorithm (ODA) and Dynamic Dijkstra's Algorithm (D-DA) which were implemented as in [14]. Table I shows the parameters that have been used in the simulation.

TABLE I: Simulation parameters

Simulation parameters	Value
Map dimension	3.5 km×2.5 km
Maximum allowed speed	32 m/s
Simulation time	1000 s
MAC/PHY	IEEE 802.11p
Max. transmission range	600 m
Number of emergency vehicles	8
Number of vehicles	1000
Number of simulation runs	10 times

Algorithm 1 The particle swarm algorithm.

Initialize the particle array with some random solutions.
 Loop

For each particle z with position p_z in S domain do Estimate the fitness function f for each particle as in 7.

If $f(p_z) < f(pbest)$, put $pbest = p_z$ where pbest is the location of the best fitness of all visited location. End If If f(pbest) < f(gbest), put gbest = pbestwhere gbest is the best location or solution found so far. End If

End For

3: Update particle velocity and position.

For each particle z in S do

$$vs = vs + e_1 rand()(pbest - p_z) + e_2 rand()(gbest - p_z)$$
(8)

$$p_z = p_z + vs \tag{9}$$

End For

Here, v is the particle velocity, p_z is the current solution. rand () is a random number between (0, 1). e_1 and e_2 are learning factors. Usually $e_1 = e_2 = 1$.

4: Exit the loop, if the terminating condition is met.

5: **End**.

Fig. 3 shows the average travel time of all of the algorithms. It is clear form the figure that the average travel time increases as the number of vehicles increases. This is because of the greater number of vehicles in the traffic jam, which increases the average travel time, as is shown for ODA and D-DA in Fig. 3. The CGA-PSO has significantly improved the average travel time since it distributes emergency vehicles into more than one group and over more than one route to avoid congested roads.

Fig. 4 shows the fuel consumption results obtained by the four algorithms. We can see the impact of taking the shortest congested route on the traffic efficiency and the fuel consumption. This figure shows that ODA consumes as much fuel as D-DA for low vehicle densities. The reason of that is the effect of choosing the shortest travelled path and waiting times taken by ODA and D-DA, respectively. According to

Birmingham New Street Train Station



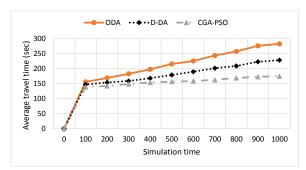


Fig. 3: Average travel time.

Fig. 2: Birmingham city centre Map that is imported into SUMO

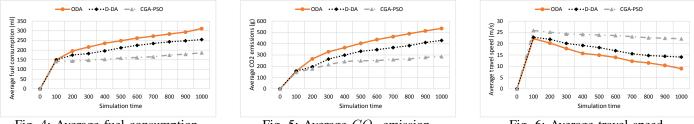
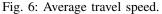


Fig. 4: Average fuel consumption.

Fig. 5: Average CO_2 emission.



this figure, CGA-PSO has better fuel consumption due to less waiting time, the best average speed and optimal paths that are selected based on the different navigation criteria. In addition, CGA-PSO pays attention to the congestion with the avoidance mechanism that helps to distribute the emergency vehicles on different routes to avoid the traffic jams and reach the hazard area much faster.

Fig. 5 depicts the CO_2 emissions recorded from all of the algorithms. It is clear from the figure that CGA-PSO has the lowest average CO_2 emissions compared to the other algorithms. This is due to it having the best average travel speed and the optimal paths (groups) being obtained by CGA-PSO. Both ODA and D-DA have the worst CO_2 emissions due to a large amount of fuel consumed by the emergency vehicles using them.

Fig. 6 illustrates the average travel speed obtained by all of the algorithms. CGA-PSO has recorded the best average travel speed compared to the other methods. This is due to the congestion avoidance mechanism and distribute the emergency vehicles on different alternative paths or groups to avoid the congested roads. Both ODA and D-DA have the worst average travel speed. This is due to emergency vehicles being stuck in the traffic congestion area.

IV. CONCLUSION

In this paper, we propose the CGA-PSO approach to emergency vehicle routing in smart cities. The novelty of this paper consists in the developed coalition game approach based on particle swarm optimization. The approach distributes dynamically the emergency vehicles moving at high speeds and affords to avoid congested areas. Simulation results show that our proposed CGA-PSO approach can successfully improve the performance of emergency vehicles by driving them with the least congested path. As reported from the Birmingham test scenario, it is shown that CGA-PSO can improve the traffic flow by an overall average of 32.67% in terms of travel time, fuel consumption, CO_2 emission and average speed, respectively, when compared to the original and dynamic Dijkstra algorithm.

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REFERENCES

- O. Rodríguez-Espíndola, P. Albores, and C. Brewster, "Disaster preparedness in humanitarian logistics: A collaborative approach for resource management in floods," *European Journal of Operational Research*, vol. 264, no. 3, pp. 978–993, 2018.
- [2] A. R. Abdelaziz, "A fuzzy-based power system reliability evaluation," *Electric power systems research*, vol. 50, no. 1, pp. 1–5, 1999.
- [3] C. Araz, H. Selim, and I. Ozkarahan, "A fuzzy multi-objective coveringbased vehicle location model for emergency services," *Computers & Operations Research*, vol. 34, no. 3, pp. 705–726, 2007.

- [4] C. Kan and J. Miles, "Its handbook 2000, recommendations from the world road associations (piarc)," ISBN 1-58053-103-2, Tech. Rep., 2000.
- [5] S.-h. An, B.-H. Lee, and D.-R. Shin, "A survey of intelligent transportation systems," in *Proceedings of Third International Conference* on Computational Intelligence, Communication Systems and Networks (CICSyN), 2011. IEEE, 2011, pp. 332–337.
- [6] Y. Yao, L. Rao, and X. Liu, "Performance and reliability analysis of ieee 802.11 p safety communication in a highway environment," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 9, pp. 4198–4212, 2013.
- [7] N. Parrado and Y. Donoso, "Congestion based mechanism for route discovery in a V2I-V2V system applying smart devices and IoT," *Sensors*, vol. 15, no. 4, pp. 7768–7806, 2015.
- [8] "Ministerio de Transporte de Colombia. Codigo de Trnsito de Colombia," http://www.colombia.com/noticias/codigotransito/, accessed: 2016-09-30.
- [9] R. Poli, J. Kennedy, and T. Blackwell, "Particle swarm optimization," Swarm intelligence, vol. 1, no. 1, pp. 33–57, 2007.
- [10] C. Sommer, R. German, and F. Dressler, "Bidirectionally coupled network and road traffic simulation for improved IVC analysis," *IEEE Transactions on Mobile Computing*, vol. 10, no. 1, pp. 3–15, 2011.
- [11] M. Behrisch, L. Bieker, J. Erdmann, and D. Krajzewicz, "Sumosimulation of urban mobility," in *Proceedings of the The Third International Conference on Advances in System Simulation (SIMUL 2011), Barcelona, Spain, 2011.*
- [12] "What is OMNeT++?., OMNet++discrete event simulator, opensimltd. web," https://omnetpp.org/, accessed: 2015-10-23.
- [13] M. Haklay and P. Weber, "Openstreetmap: User-generated street maps," *Pervasive Computing, IEEE*, vol. 7, no. 4, pp. 12–18, 2008.
- [14] S. Wang, S. Djahel, J. McManis, C. McKenna, and L. Murphy, "Comprehensive performance analysis and comparison of vehicles routing algorithms in smart cities," in *Proceedings of Global Information Infrastructure Symposium*, 2013. IEEE, 2013, pp. 1–8.