A Multi-Agent Based Vehicles Re-routing System for Unexpected Traffic Congestion Avoidance

Shen Wang, Soufiene Djahel and Jennifer McManis

Abstract— **As urbanization has been spreading across the world for decades, the traffic congestion problem becomes increasingly serious in most of the major cities. Among the root causes of urban traffic congestion, en route events are the main source of the sudden increase of the road traffic load, especially during peak hours. The current solutions, such as on-board navigation systems for individual vehicles, can only provide optimal route using current traffic data gained just before the start of their journeys. Those solutions are thus unable to provide a better alternative route quickly enough if an unexpected congestion occurs. Moreover, using the same alternative routes may lead to new bottlenecks that cannot be avoided. Thus a global traffic load balance cannot be achieved. To deal with these problems, we propose a Multi Agent System (MAS) that can achieve a trade-off between the individual and global benefits by giving the vehicles optimal turn suggestions to bypass a blocked road ahead. The simulation results show that our strategy achieves a substantial gain in average trip time reduction under realistic scenarios. Moreover, the negative impact of selfish re-routing is investigated to show the importance of altruism re-routing applied in our strategy.**

I. INTRODUCTION

Nowadays, most of the large cities in the world are witnessing ever-increasing road traffic congestion due to the worldwide urbanization that has been carried out for decades. According to the annual urban transportation report[1], the incurred economic loss in terms of both travel time delay and fuel consumption is estimated as $121 billion in 2011 and is expected to grow up to $199 billion in 2020. Moreover, among all factors that lead to traffic congestion, en route events (e.g. special events, unplanned road works, car crashes etc.) are the major cause of such loss due to their random nature. The above report reveals also that in order to get more reliable trips, drivers usually need to plan to spend three times more travel time by taking this unexpected congestion into consideration, especially during peak hours with heavy traffic load.

There are two main existing solutions categories for mitigating the huge traffic congestion loss. One is the dynamic optimization of traffic light phases. For instance, the most popular traffic control systems used by city planners are Sydney Coordinated Adaptive Traffic System (SCATS) [2] and Split Cycle Offset Optimization Technique (SCOOT) [3]. Both SCATS and SCOOT can optimize traffic light phases duration at each intersection by collecting real-time traffic information from the widely deployed infrastructure (e.g. induction loops, CCTV cameras, advanced sensors etc.) to reduce the travel delay at each intersection. Another solutions category is vehicular route assignment using shortest path finding algorithms. For example, the well-known vehicle navigation systems (e.g. TomTom, Google Navigation, etc.) can calculate "the fastest" route based on the current traffic conditions to reduce the travel time for a specific journey.

In this paper, we propose a new approach called Multi agent system based Next-Turn Re-routing (**MNTR**) from route assignment perspective to overcome the following limitations of the existing solutions in the second category:

- **Unpredictability makes the route unreliable:** the so-called "fastest" route cannot be always guaranteed the fastest as some future traffic variation cannot be predicted in advance, such as random incidents etc. Even though some solutions [6][7] can provide a route with guaranteed least travel time based on massive historical traffic data and prediction models, their low execution efficiency [18] makes them unsuitable for large-scale urban scenarios. Moreover, the unpredictability of the en route events impact on traffic flow makes the estimated travel time of the advised route unreliable.
- **Global benefit is ignored:** optimal routes are computed without considering any negative impact to other vehicles routes (i.e. assigning an optimal route to a given vehicle may create a bottleneck at one or more road segments common with several other routes). For example, for vehicles which need to be rerouted to bypass the en-route events, it is more likely that they will choose relatively similar routes for the subsequent few turns, thus new congestion will certainly occur.

Compared to the state-of-the-art, the contributions of our work are as follows:

- **Two-Step re-routing:** instead of calculating the entire route [4][5][6][7][8] at once, MNTR provides, as first step, the optimal next turns for the set of concerned vehicles to bypass the blocked road. Then, as a second step, when the vehicles enter in their assigned next road segment, they use the on-board navigation system to get the complete routes for the rest of their journeys. Among all the next turn choices, the optimal next-turn has the greatest potential to lead the rerouted car to its destination quickly and mitigate the negative impact on other vehicles. Furthermore, as the optimal next-turn

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S. Wang is with Lero, RINCE, School of Electrical Engineering, Dublin City University, Ireland. shen.wang4@mail.dcu.ie

S. Djahel is with Lero, School of Computer Science and Informatics, University College Dublin, Ireland. soufiene.djahel@ucd.ie

J. McManis is with Lero, RINCE, School of Electrical Engineering, Dublin City University, Ireland. jennifer.mcmanis@dcu.ie

computation is much faster than recalculating the entire route, this two-steps re-routing approach fits perfectly in this time-critical scenario in which the car needs to be rerouted before reaching its next intersection.
- **Efficient MAS architecture:** an intelligent agent in MNTR is defined as each traffic light and all the outgoing lanes that it controls. Compared to the vehicle-based MAS solutions [9][10][11][12], our system architecture has two advantages when applied into practice. First, traffic lights are easier to update. Rather than installing Vehicle-to-Vehicle (V2V) communication facilities, traffic lights in which most of MNTR's functionalities are implemented, have already been universally deployed in the existing road infrastructure. Second, the agents coordination mechanism in MNTR is concise and efficient. In contrast, the V2V protocols used in vehicle-based MAS solutions still need to overcome several unsettled theoretic and technical mobility issues. However, as the vehicles move from one intersection to another, this means that the exchange of traffic load information between agents is done automatically without any need of explicit communication among them (see Fig. 3). Therefore, when an MNTR agent reaches its optimal status, all its neighbouring agents will be optimized consecutively. Besides, even compared with region-based MAS [13] solutions, MNTR has much lower traffic information update frequency as it just refreshes the current traffic conditions after the traffic light receives the vehicular re-routing request, instead of applying a periodic update mechanism.
- **Global and individual benefits trade-off:** when an en route event happens, by using multi-objective next turn assignment, MNTR can not only achieve good traffic load balance (i.e. global benefit) but also can help all the vehicles to finish their trips as soon as possible (i.e. individual benefit). This next-turn decision considers traffic load and travel time in each agent and the destination location of the vehicle which needs re-routing. We also enhance the efficiency of the travel distance estimation in the re-routing scenario, by adding an angle similarity mechanism with respect to the blocked road.

We use SUMO[14] as our simulator with a scalable grid-map and a realistic urban scenario from the project TAPASCologne[15] to evaluate the performance of MNTR. The results show that when applying MNTR after en route event occurrence, up to 51.50% average trip time reduction can be achieved and the global traffic load can still remain balanced. We also present an evaluation of the negative impact of selfish re-routing to show the importance of altruism re-routing used in MNTR.

For the rest of this paper, we first describe and define the problem we solve formally in Section II. Then in Section III, the architecture and detailed operations of our new MNTR approach are illustrated. The evaluation methodology and the analysis of the obtained simulation results are outlined in Section IV and V respectively. Finally, we draw the conclusion and discuss our future work in Section VI.

II. Problem Definition

Given an urban road network, we denote it as a directed graph $G = (V, E)$ which consists of a set of intersections $V = \{V_1, V_2, \cdots, V_M\}$, ($M$ is the total number of intersections) and a set of road segments (unidirectional lanes), $E = \{E_1, E_2, \cdots, E_N\}$ (N is the total number of road segments). Each vehicle running on this road network, v_i ($i \in \{1, 2, \cdots, K\}$, such that K is the total number of vehicles in the observed scenario), has its own trip OD_{v_i} starting from the origin location $V_o^{v_i}$ and ending at the intended destination $V_d^{v_i}(V_o^{v_i}, V_d^{v_i} \in V)$. During this trip, the vehicle crosses a set of consecutive road segments of its chosen route $R_{v_i} = \{E_o, \cdots, E_i, E_j, \cdots, E_d\}$ (E_j is one of the road segments directly connected to E_i, and the lane E_o starts from $V_o^{v_i}$ while E_d ends at $V_d^{v_i}$). The corresponding travel time of this trip is defined as $T(R_{v_i}) = T_{v_i}^{E_o}+, \cdots, +T_{v_i}^{E_i} + T_{v_i}^{E_j}+, \cdots, +T_{v_i}^{E_d}$ where $T_{v_i}^{E_i}$ refers to the time spent by a vehicle v_i run through the lane E_i.

If we consider the urban road network with travel time information as a discrete time-dependent network, $\{t_1, t_2, \cdots, t_i, \cdots, t_J\}$ (J is the total number of time intervals in our observed scenario), with equal length time intervals $T^{'}$ ($T^{'} = t_{i+1} - t_i$), then we get the complete travel time information for each time interval $T = \{T_{t_1}, T_{t_2}, \cdots, T_{t_i}, \cdots, T_{t_J}\}$, such that $T_{t_i} = \{T_{t_i}^{E_1}, T_{t_i}^{E_2}, \cdots, T_{t_i}^{E_N}\}$.

Our target is to reduce the average trip time T_{avg} for all vehicles' trips:

$$T_{avg} = \frac{T_{sum}}{K} = \frac{\sum_{i=1}^{K} T(R_{v_i})}{K} \tag{1}$$

In an urban road network, all vehicles' movements are strongly correlated with each other, which consequently affects the evolution of traffic flow. The vehicles' movements we consider here are the routes that the vehicles are going to follow. Therefore, the solution we are aiming to find is a set of routes for each vehicle. However, due to the rapid variation of the traffic conditions, especially when unpredictable en route events occur, we need to adapt the route allocation to the current traffic conditions. Therefore, the route for one specific vehicle could be different during various time intervals. Hence, we define the solution as $R = \{R_{t_1}, R_{t_2}, \cdots, R_{t_i}, \cdots, R_{t_J}\}$ such that $R_{t_i} = R_{t_i}^{v_1}, R_{t_i}^{v_2}, \cdots, R_{t_i}^{v_K}$ ($R_{t_i}^{v_j}$ means the route for vehicle j at the ith time interval).

A greedy method could be used to find the best routes allocation in order to minimize our target T_{avg}. This greedy method consists in trying every possible routes allocation, run simulation to record the achieved average travel time for each route allocation, and then chose the best one. However, this approach is impractical due to the huge number of route allocation permutation and combination for each vehicle in each time interval. A similar reason hinders the application of existing Dynamic Traffic Assignment (DTA) [19] solutions in real world.

In this paper, the proposed MNTR reduces calculation complexity by focusing on updating the routes allocation only after the occurrence of an en route event by updating the routes of vehicles whose the current route includes the blocked road segment(s). It is worth to mention that MNTR uses two-step re-routing process as those vehicles will be re-routed only twice (i.e. next turn allocation, then complete route recalculation) as explained in next section. It is shown in Section V that MNTR can efficiently reduce the average travel time with minor change of routes allocation.

III. System Description

A. Re-routing Process

First of all, as shown in Fig.1, we describe the general seven steps of the re-routing process using "Level-0 MNTR". Notice that "Level-0 MNTR" means that the only traffic light activated to perform MNTR is the one located at the start of the blocked road segment.

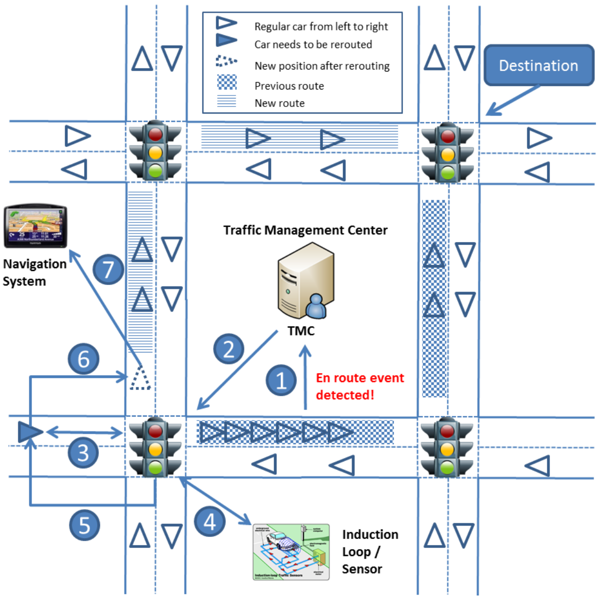

Fig. 1. Rerouting process in MNTR: driving on the left hand side as in Ireland

*1)*When an en route event happens, the Traffic Management Center (TMC) detects and verifies it by various means including road traffic monitoring infrastructures, such as the widely deployed monitors, sensors and induction loops.
*2)*TMC communicates this en route event (i.e. the location of the blocked road) to its closest traffic light which is the one located at the start junction of the affected road.
*3)*This step is a confirmation process of re-routing request using Vehicle to Infrastructure (V2I) communication. First, the traffic light sends "re-routing alert" with the location of the closed road to the first vehicle on each of the incoming lanes that it controls. Second, after receiving this "re-routing alert", the vehicle checks whether the closed road is included in its current route or not. If it is the case, the vehicle sends a "re-routing request" back to the traffic light along with its destination location information to confirm this re-routing.
*4)*When the traffic light receives this re-routing confirmation with specific destination location, it collects the current traffic information (i.e. occupancy and travel time) for all the available outgoing lanes that it controls (i.e. excluding the closed road), and then computes the optimal next turn for each particular re-routing request based on these up-to-date local traffic conditions.
*5)*Traffic light sends back the optimal turn to the corresponding vehicle.
*6)*The vehicle follows its next turn suggestion, enters into a new lane, and thus successfully bypasses the closed road.
*7)*Finally, this vehicle updates the whole route to its intended destination using its on-board navigation system (e.g. Tom-Tom, Google Navigation) according to the current global traffic conditions.

In addition, our proposed MNTR can also work in different levels to alleviate the congestion in the vicinity of the blocked road segment. As shown in Fig.2, we define Level-0 MNTR as the MNTR system with the closest traffic lights enabled only (i.e. the traffic light controlling the outgoing lane where the en route event has occurred). Without loss of generality, Level-$(i+1)$ MNTR means that based on the last MNTR enabled levels, we enable all of Level-i MNTR's neighbouring traffic lights. Here, "Level-i" denotes the traffic lights located "i" hops (i.e road segments) away from the traffic light at "Level-0".

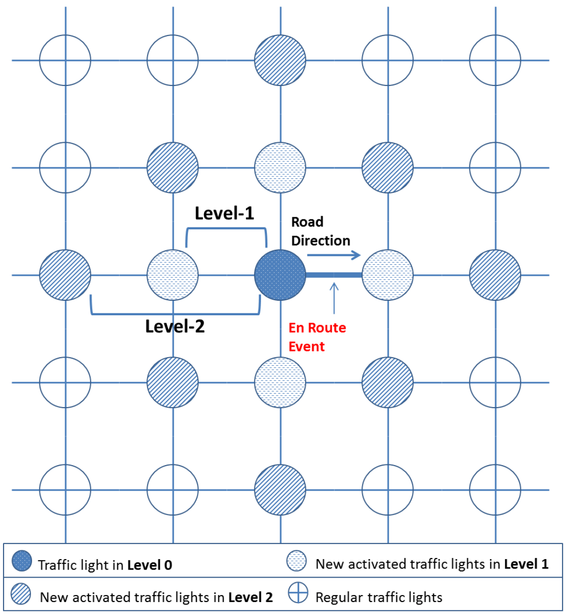

Fig. 2. Activated traffic lights in different MNTR levels

B. MAS Architecture in MNTR

In our MAS architecture of MNTR, we define an agent as the traffic light and the set of outgoing lanes that it controls. As depicted in Fig.3, the outgoing lanes of agent 1 are the lanes 1, 3, 5, 7 which are the only available options from which a vehicle to be rerouted can choose it next turn. This decision should be taken by collecting the current traffic information of these outgoing lanes. Notice that the vehicles' re-routing requests are received by the traffic light from the incoming lanes (e.g. lanes 2, 4, 6, and 8 in the case of agent 1).

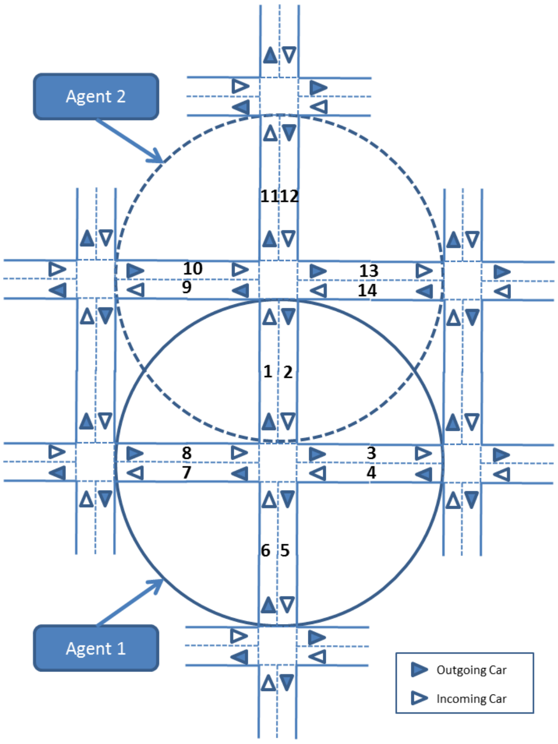

Fig. 3. MAS architecture in MNTR

There are two factors we consider for each agent in MNTR, traffic load and travel time of all outgoing lanes. The purpose of balancing the traffic load is to maximize the utility of the existing road infrastructure. The existing urban road infrastructure cannot meet the unpredictable and dynamic requirements of citizen's trips, and the cost needed for improving its capacity and efficiency is expected to be huge. Therefore, proposing a strategy that can balance the traffic load from global perspective is the most feasible and efficient way to make full use of the current road infrastructure, and thus the reduction of average trip time for all drivers can be achieved. In general, traffic load is a relative concept measuring the ratio of the number of vehicles in a specific road to its full capacity. In this paper, we consider the lane occupancy O_{E_i} as an indicator of traffic load in lane TL_{E_i}. The occupancy is defined as the ratio of the total length of all vehicles running in a particular lane plus the sum of minimum gap length between them to the total length of this lane. If we assume that the average length of each vehicle is L_v meters, K_{E_i} is the number of vehicles in lane E_i, the minimum gap is L_{gap} meters, and the length of lane E_i is L_{E_i} meters, then the occupancy of a lane E_i can be defined as:

$$TL_{E_i} = O_{E_i} = \frac{K_{E_i} \times (L_v + L_{gap})}{L_{E_i}} \times 100\% \qquad (2)$$

The travel time (i.e. the second factor considered by an agent) of one particular outgoing lane is directly related to our ultimate goal which is reducing the average trip time. Typically, the travel time on a specific lane T_{E_i} depends on both the vehicles speed and traffic light phase duration. In this paper, for the sake of simplicity, we calculate T_{E_i} as the ratio between the length of lane E_i and the average vehicles speed $Avg\_V_{E_i}$, measured in meters per second:

$$T_{E_i} = \frac{L_{E_i}}{Avg\_V_{E_i}} \qquad (3)$$

We evaluate the status[1] of each agent by combining both traffic load and travel time information. The lower difference among all lanes in one agent in terms of these two factors, the better status this agent has. More precisely, as shown in Fig.3, in urban road network, each vehicle travels from one junction to another, meaning that it roams between adjacent agents. Consequently, any change in both factors of one lane of a given agent will definitely affect the status of its neighboring agents due to the natural movement of vehicles in an urban scenario. Therefore, it is impossible to find two adjacent agents with similar status but their respective traffic load and travel time are significantly different.

One of the distinguishing features of our proposed MNTR is its automatic coordination mechanism explained below. For instance, in Fig.3, when the lane 3 is closed due to the occurrence of an en route event, our MNTR starts to guide the vehicles requesting re-routing to different turns to achieve the local optimum, thus the travel time and traffic load of all other three outgoing lanes will get higher. Each of the outgoing lanes in this agent is also incoming lane for another agent. In this case, lane 1, for example, is outgoing lane in agent 1 but also incoming lane in agent 2, thus the en route event will soon affect the status of agent 1 and the other agents follow because the heavy traffic in lane 1 will quickly increase the traffic on lanes 9, 11 and 13 as well. If we enable MNTR for all of its adjacent agents, the traffic load will be more widely balanced, leading to the reduction of travel time as well. For the sake of energy saving, we will not suggest the users of our system to enable MNTR for all agents, as usually only one level MNTR is sufficient, as shown in Section V.

C. Decision for the Optimal Next-Turn

The idea of next-turn re-routing comes from drivers' instinct when they are notified about a heavy congestion ahead. These drivers will choose a next turn to avoid the congested road instinctively first, and then start thinking about how to correct their previous routes to reach their intended destinations. We can see from the Graphical User Interface (GUI) of the popular navigation systems that they are all designed following the so-called "first-person view", because in a such time critical scenario the drivers care more about the alternative next turn rather than the entire new route that excludes the blocked road. Instead of making next turn decision instinctively, our proposed MNTR does

[1]The status of an agent is represented by the standard deviation of traffic load and travel time among all the outgoing lanes that it controls.

this intelligently by considering both traffic load balance and travel time reduction. In other words, this decision should lead to a better tradeoff between global and individual benefit.

In order to suggest the optimal next turn, MNTR needs to take the two aforementioned local parameters into account, traffic load TL_{E_i} and travel time T_{E_i} of a specific lane. However, such local information is not sufficient for choosing the optimal next turn to serve various re-routing requests; we thus need to introduce another parameter which is the geographic closeness. The lane with the least geographic closeness will have the highest probability to lead the rerouted vehicle to its destination faster. In general, the distance estimation in MNTR uses Euclidean distance, as most of the implementations of A*. Albeit the correctness and high efficiency of this metric have been proven over decades of practice in science and engineering, we still need to enhance it in re-routing scenario by taking the angle similarity into account. The concept "angle" here refers to the angle between the vector from the start junction to the end junction of the blocked road and the available next turn lanes. The one with the least similarity will be chosen to follow because the rerouted vehicle will have more chance to avoid the congestion in the surrounding caused by the blocked road.

Fig.4 illustrates how MNTR calculates the geographic closeness using Euclidean distance and angle similarity. Suppose a vehicle that needs to be rerouted is approaching its next junction $V_n(x_n, y_n)$, there are three roads in front of it, R_1, R_2, and R_c, where R_c is the closed road due to an en route event, while R_1 and R_2 are available roads for this vehicle to make progress in its trip. The end junctions of these three roads are denoted as $V_1(x_1, y_1)$, $V_2(x_2, y_2)$ and $V_c(x_c, y_c)$, respectively, with their coordinates provided, and the realistic length of the two available roads are denoted as L_1, L_2. Besides, MNTR is also aware of the destination location, $V_d(x_d, y_d)$, sent by the vehicle. All the information mentioned above are available to the traffic light at junction V_n before the calculation process.

First, the traffic light computes the estimated Distance (D_i) based on which the best road will be chosen from $R_i, i \in \{1, 2\}$. This distance is calculated by adding the realistic lengths (L_i) of these roads to the Euclidean Distances (ED_i) from their end points to the vehicle's destination, as described below:

$$D_i = L_i + ED_i = L_1 + |\overrightarrow{V_i V_d}| = L_i + \sqrt{(x_d - x_i)^2 + (y_d - y_i)^2}$$

Second, the Angle Similarity (AS) can be obtained by the law of cosine using the following equations:

$$\overrightarrow{V_n V_c} = (x_c - x_n, y_c - y_n), |\overrightarrow{V_n V_c}| = \sqrt{(x_c - x_n)^2 + (y_c - y_n)^2}$$

$$\overrightarrow{V_n V_i} = (x_i - x_n, y_i - y_n), |\overrightarrow{V_n V_i}| = \sqrt{(x_i - x_n)^2 + (y_i - y_n)^2}$$

$$AS_i = 1 + \cos\theta_i = \frac{\overrightarrow{V_n V_c} \cdot \overrightarrow{V_n V_i}}{|\overrightarrow{V_n V_c}||\overrightarrow{V_n V_i}|}$$

where $\theta_i \in [0, \pi]$

Therefore, $AS_i \in [0, 2]$, and the higher the value of angle similarity, the smaller the angle separating the two vectors and thus the more similar they are.

Third, we compute the Geographic Closeness (GC) in MNTR using the following equations:

$$GC_i = w_D N_{D_i} + w_{AS} N_{AS_i}, \;\; w_D + w_{AS} = 1$$

where w_D,w_{AS} are weight values assigned to the estimated factors distance and angle similarity, respectively. N_{D_i},N_{AS_i} are normalized values of the aforementioned two factors calculated as:

$$N_{D_1} = D_1 / \max_{i \in 1,2} D_i, N_{AS_1} = AS_1 / \max_{i \in 1,2} AS_i$$

Finally, the utility function that the final optimal next turn decision needs to use is:

$$U_i = w_{TL} N_{TL}^i + w_T N_T^i + w_{GC} GC_i \tag{4}$$

such that $w_{TL} + w_T + w_{GC} = 1$.
Where w_{TL}, w_T and w_{GC} are weight values assigned to the normalized traffic load (N_{TL}), normalized travel time (N_T) and normalized geographic closeness (GC), respectively. Notice that all variables are in the range of $[0, 1]$, and the lane with the least utility value will be suggested as the optimal next turn for the vehicle.

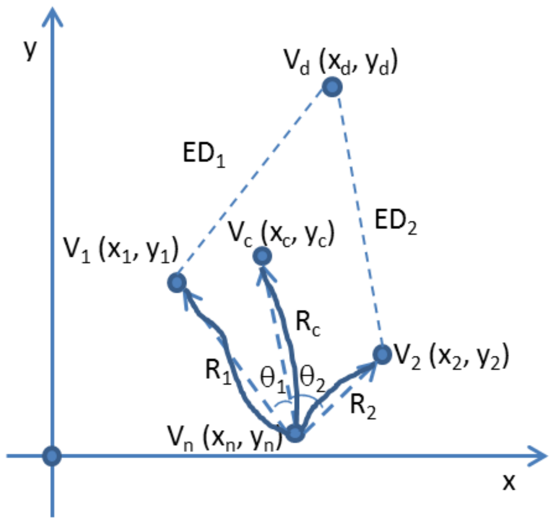

Fig. 4. Illustration of angle similarity mechanism

IV. System Evaluation Methodology

A. Simulation Setup

We use Simulation of Urban Mobility (SUMO) as our simulator combined with Traffic Control Interface (TraCI)[16] to carry out the performance evaluations of MNTR. SUMO is the most popular open source microscopic simulator of urban road traffic. It is a discrete-event simulator which is quite suitable for us to solve the predefined problem (see Section II) based on discrete time-dependent road traffic network. TraCI is a part of SUMO release package which allows users to manipulate and control the simulation process while it runs. Specifically, we use TraCI to implement most of the key features in MNTR in Python to dynamically retrieve traffic information and allocate routes for vehicles.

B. Grid Map v.s. Realistic Map

The evaluation of MNTR is carried out in both grid and realistic map.

Owing to the lack of accessibility of realistic city maps and traffic demands data, we use a set of grid maps to perform our experiments for the first stage (i.e. finding suitable weight values allocation and MNTR levels). In addition, the grid map can help us to investigate MNTR performance by mitigating the unexpected impact of varying road network topologies.

There are 7 grid maps with various scales in our evaluation, 3×2, 4×3, 5×4, 6×5, 7×6, 8×7 and 9×8. For instance, 6×5 means this grid map has 5 junctions in the horizontal axis and 4 junctions in the vertical axis. Apart from the number of junctions, they share all the rest of settings. For example, all road segments in our grid map set have equal length of 150 meters and each of them comprises of two lanes with opposite directions. We uniformly generated traffic demand for all the grid map scenarios for a 30 minute duration. We also enabled traffic lights but kept their phase change settings as default: i.e. static, which means every traffic light has the same phase duration regardless of the changes in traffic conditions.

The realistic map we have chosen is a sub-scenario of TAPASCologne 0.17.0. TAPASCologne is an open project providing large-scale dataset with the highest realism for urban vehicular simulation based on SUMO. It uses realistic map of Cologne extracted from OpenStreetMap[17] and generates traffic demand from 6:00am to 8:00am using Travel and Activity PAtterns Simulation (TAPAS) methodology and Gawrons dynamic user assignment algorithm. Because the size of original TAPASCologne is so huge (1129.71km^2) which makes it inefficient to run on a computer, we used its sub scenario which is an 18.15 km^2 large area located on the left-hand side of the river in Cologne city center. Besides, we kept the original traffic demand from 6:00am to 6:30am in this sub-map.

For both scenarios, grid map and city center of Cologne, the whole simulation keeps running until all the vehicles finish their trips.

C. Evaluation metrics

We have chosen the following two metrics to assess the performance of MNTR.

1) Average Trip Time: average trip time is the most significant indicator of urban traffic congestion. It is calculated using Eq. (1). We mainly focus on this metric as its reduction leads to lower fuel consumption, economic growth and better living experience for citizens.

2) System Stability: to encourage more individual drivers to start considering the impact that their re-routing decisions may have on other drivers trips, we need to explore the relationship between average travel time variation and the global traffic load changes. This metric also shows whether MNTR can maximize the utility of the existing road infrastructure or not. We measure the stability of the road traffic system in terms of traffic load $TL_{E_i}^{t_j}$ we discussed previously. Here, $TL_{E_i}^{t_j}$ refers to the traffic load (occupancy) of road E_i at time interval t_j. We first compute how different is the traffic load variation among all roads at a specific time interval, which is the standard deviation SD_{t_j} for all $TL_{E_i}^{t_j}$ at t_j,

$$SD_{t_j} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(TL_{E_i}^{t_j} - \frac{1}{N}\sum_{i=1}^{N}TL_{E_i}^{t_j})^2} \tag{5}$$

Then we get a set of standard deviations for all equal length time intervals ($\{t_1, t_2, \cdots, t_j, \cdots, t_J\}$ where $t_{j+1} - t_j = 30s$):

$$\{SD_{t_1}, SD_{t_2}, \cdots, SD_{t_j}, \cdots, SD_{t_J}\} \tag{6}$$

The larger the variation of those standard deviations are, the worse the system stability we get.

D. Scenarios

We compare five scenarios to highlight the efficiency of MNTR and the importance of altruism re-routing under both grid and realistic maps.

- Original (**ORG**): the scenario with original traffic demand but without any roads closed due to en route events and any extra routing strategies applied.
- En route event (**ERE**): the ORG scenario with one lane in the center of the map (shown in Fig.5) closed for 20 minutes (from 5th min to 25th min) to simulate the occurrence of an en route event.
- Constant Rerouting (**ConRe**): the ERE scenario with all vehicles updating their complete routes every predefined time interval (grid map: 1s /city center: 90s) throughout the whole simulation using on-broad rerouting system.
- Moderate Rerouting (**ModRe**): during the road closure time period in ERE scenario, all vehicles that have the closed road included in their unfinished routes, reroute once according to their current traffic.
- **MNTR**: during the road closure time period in ERE scenario, our proposed MNTR is enabled for congestion avoidance.

V. Evaluation Results and Analysis

In the first stage, we explore the optimal allocation of the weight values, w_{TL}, w_{GC}, w_T used for utility function calculation in Eq. (4). We use 11 possible allocations as candidates, in which w_{GC} and w_T are always equally important (i.e. have the same value) because they are the indicators which highlight the individual benefit, while the indicator of global benefit, w_{TL}, is decreased by 0.1 from 1.0 to 0.0. We apply Level-1 MNTR with all 11 weight value allocations to all 7 grid maps to alleviate the congestion caused by the en route event. The test results are recorded in the average trip time. Finally, we find that the allocation ($w_{TL} = 0.7 w_{GC} = 0.15 w_T = 0.15$) has the best average

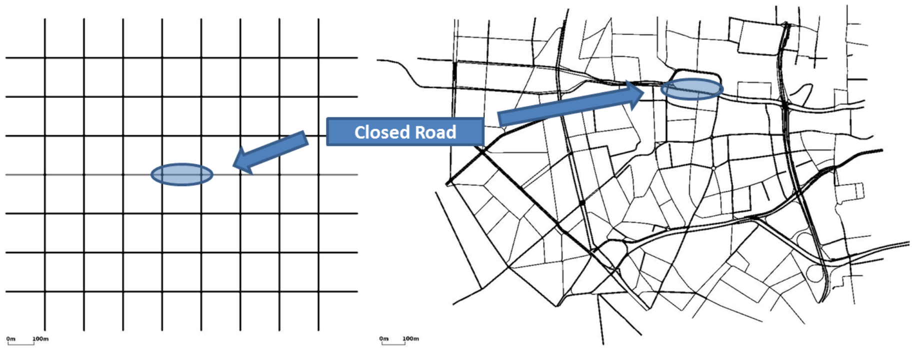

Fig. 5. Locations of the closed road: grid map (left, 8×7), realistic map (right, city center of Cologne)

performance compared to other allocations under all grid maps. It also reveals the fact that if the global benefit is given the higher weight value in each re-routing decision, more significant reduction of trip time can be achieved for a larger number of vehicles.

As discussed in Section III, MNTR has several level options. The higher level the user chooses, the more traffic lights around the closed road will be activated to perform MNTR. We apply MNTR to the three large grid maps (6×5, 7×6, 8×7) from Level-0 to Level-4. Compared to Level-0 MNTR, the average trip time reduction (expressed in percentage) achieved by MNTR in all other higher levels are shown in Fig.6.

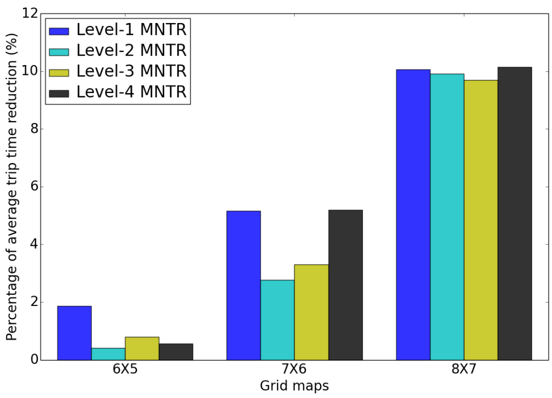

Fig. 6. Performance improvement of MNTR under higher levels vs. Level-0 MNTR performance: metric used is Average Trip Time

We can learn from this figure that the upgrade from Level-0 to Level-1 only brings an average reduction of trip time equals to 5.69% (i.e. average improvement achieved under the three grid maps). Considering the communication cost between TMC and traffic lights and the extra energy consumption that this may incur, Level-1 MNTR with only five traffic lights enabled can be the most efficient choice to provide good performance while keeping the operational cost of MNTR as low as possible.

For the overall performance comparison on both grid and realistic maps under 5 scenarios, we apply Level-1 MNTR with the following weights allocation $w_{TL} = 0.7$, $w_{GC} = 0.15$ and $w_T = 0.15$. The obtained results for the average trip time and the system stability (according to standard deviation values obtained in Eq. (6)) are plotted in Fig.7 and Fig.8, respectively.

From these two figures, we can see that MNTR outperforms all other re-routing strategies (i.e. ConRe and ModRe) in terms of both average trip time and system stability. In grid map, Level-1 MNTR can achieve up to 51.50% average trip time reduction. Even in the city center of Cologne which has 11 times more areas (i.e. less negative impact when one road only is closed) and 3 times more vehicles (i.e. nearly 4 times less traffic density), Level-1 MNTR can still decrease the average trip time by 11.90%. For system stability, Level-1 MNTR outperforms significantly the other re-routing strategies and provides nearly the same system stability level as the original scenario (ORG) in which no en route event occurs. In addition, for the comparison between ConRe and ModRe, surprisingly, if each vehicle keeps updating its route under current traffic conditions using on-board navigation system every fixed time interval, it performs even more worse (77.9% in grid map, 18.35% in realistic map) than doing nothing with ERE. This discovery shows the devastating impact of the excessive using of selfish re-routing and the importance of applying the smart altruism re-routing strategy.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, we have proposed a Multi-Agent based re-routing strategy dubbed "MNTR" to avoid the unpredictable traffic congestion due to random en route events such as accidents. Our strategy diverts each affected vehicle, due to this en route event, to its optimal next turn using a novel smart solution. The obtained evaluation results under various scenarios highlight that MNTR can achieve a reduction of average trip time up to 51.50% in grid map and 11.90% in realistic map. Moreover, it can ensure nearly the same system stability level as the scenario where no en route event occurs on the road. Furthermore, our evaluation results also reveal the devastating impact of overusing selfish re-routing and highlight the benefit of smart altruism re-routing used in MNTR. In future work, we plan to use machine learning algorithms (e.g. gradient descent) to find more accurate optimal weight allocation under different benchmarks (i.e. various city maps and traffic densities). Besides, we also

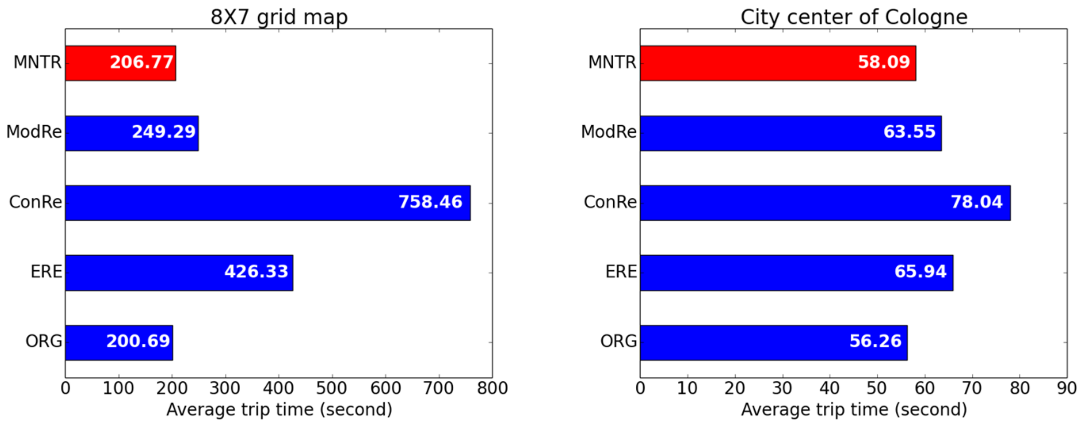

Fig. 7. Comparison of average trip time achieved by the different re-routing strategies

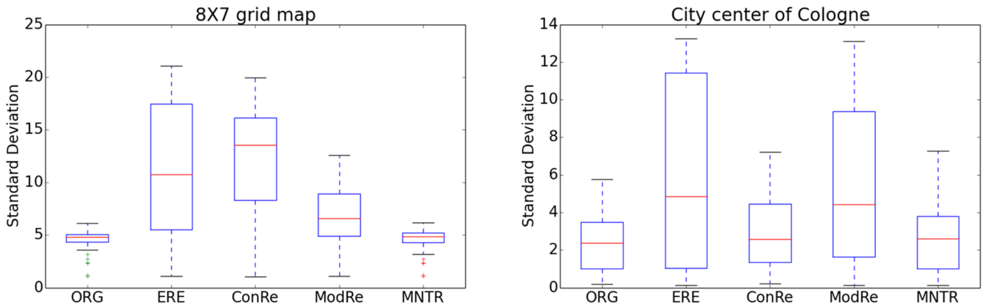

Fig. 8. Comparison of system stability achieved by the different re-routing strategies

plan to extend MNTR by optimizing traffic light phases by leveraging Vehicle to Vehicle (V2V) communication technology.

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