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Algorithm for Creating Optimized Green Corridor for Emergency Vehicles with Minimum Possible Disturbance in Traffic

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Abstract: Green corridor is a dynamic real-time lane created in order to increase the speed at which an emergency vehicle can travel in traffic. Its purpose is to reduce the travel time of emergency vehicles. The paper submitted examines ways to optimize the travel time for emergency vehicles and for other drivers on the roads. The paper takes into account the fact that all vehicles accelerate and decelerate at different speeds and the fact that there might be several traffic guided lights and non-guided lights on the roads. There are other factors considered, such as the speed and safety, in order to create a sustainable solution that can be implemented at scale. SUMO simulation libraries are used to create an environment as close to reality as possible. The trade-off between the number of variables selected and the approximation of a real situation has been carefully selected so that the solution is also feasible in real-life situations.

Keywords: SUMO, Dijkstra's algorithm, Krauss' Model, emergency services

1. Introduction

Transportation system has spread itself to many areas from security [1], reliability, efficiency and many more [2]. Emergency vehicle (EV) route optimization is one such area. Emergency services [3] and health services are essential to save a person's life. Equally important is the fact that such services have to be made available to people on time [4]. Here, transportation plays a very important role. The main focus of this paper is thus how to make these emergency services available in shortest time possible.

The aim is to reduce the time needed for an emergency vehicle to reach a desired location and then get back to a hospital in the shortest possible time [5]. This could be ensured by allocating whole road to emergency vehicles. However, it might cause huge traffic congestion for other vehicles which may or may not be on the emergency list. Therefore, a better option is to efficiently use the road between EV and rest of the traffic [6].

The paper deals with rerouting at two different levels. The first level is the level of the road as such, where an efficient method is needed to create new virtual lanes so that emergency vehicles can travel at faster speeds. At the same time, such vehicles will have special privileges, such as being allowed to travel at higher speed, they take riskier shortcuts or can even overtake from the opposite side [7-8]. The second level consists of optimizing signal lights in order to create a visible green corridor where traffic is not heavy at the point from which the emergency vehicle is moving [9].

2. Structure

The main problem can be divided into several smaller problems that need to be individually addressed in order to create an optimal solution. Many aspects are considered before making an informed decision on selecting the optimal route, such as: Which route is the shortest? Which route is with the least traffic? What traffic lights the EV might encounter? The paper deals with the above-mentioned problems on selecting a route that can be optimally, efficiently and reliably [10] used even for larger networks where the quotient of unpredictability might be higher than in this network.

3. Model & Modelling Technique

Before modeling a solution [11] for the problem stated above, the model is simulated to test the solution on it. The simulation of the network can be seen in several stages, e.g.:

- Simulating a method to imitate car-following model (Krauss Model) [12].
- Simulation of behavior vehicles at junctions or intersections (SUMO's Road Intersection Model) [13].
- Simulating behavior of individual vehicles at microscopic level (ability to break, accelerate, reaction time etc.)

Simulation of traffic lights and the behavior of vehicles at these traffic lights (Standard TLS programs & Adaptive TLS program based on DQN) [14].

3.1 Car-following Model (Krauss Model)

First of all, it shall be noted that the model should work on the basis of discrete time steps, not continuous time steps because the simulation of the problem is done on a computer that understands only discrete time steps.

To build the traffic flow [15], the first step is to model the interactions between the vehicles [16]. To create this model, a model of two vehicles (one in the lead position x_l with velocity v_l and one as a follower, in the position x_f with velocity v_f is taken into consideration. If the vehicle length is l, the gap g between the vehicles is given by the equation below:

$$g = x_i - x_f - l \tag{1}$$

Assuming that the vehicles do not collide in the system, g>0 which implies that

$$\frac{dg}{dt} \geq \frac{g_{des} - g}{\tau_{des}} \tag{2}$$

The required relaxation time τ_{des} and the desired gap g_{des} may be functions of the gap between the vehicles and their speed.

The above safety condition can also be stated as follows:

$$v_l - v_f \geq \frac{v_l \tau - g}{\frac{\underline{v}}{b(\underline{v})} + \tau} \tag{3}$$

Provided that the gap $g_{des} = v_l \quad \tau$ and required relaxation time $\tau_{des} = \tau_b + \tau$, where $\tau_b = \underline{v} \div b(\underline{v})$ is determined by the typical decelerations b that a driver is willing to use.

These equations can be further specified for discrete time systems as follows:

$$\begin{gathered} v_{safe}(t) = v_l(t) + (g(t) - g_{des}(t)) / \tau_b + \tau \\ v_{des}(t) = \min[v_{max}\, v(t) + a(v)\Delta t, v_{safe}(t)] \\ v(t + \Delta t) = \max[0\,, v_{des}(t) - \eta] \\ x(t + \Delta t) = x(t) + v\Delta t \end{gathered} \tag{4}$$

3.2 Simulating Vehicle Behavior at Junctions or Intersections (SUMO's Road Intersection Model)

Based on the previous model, the safe distance at any intersection for a vehicle to cross can be expressed as:

$$\frac{v_l 2}{d_l} > \frac{v_f 2}{d_f} \tag{5}$$

the lane on which the lead vehicle drives is marked A and the lane on which the follower vehicle drives is marked B:

$$\begin{gathered} d_L := pos(C_{AB}) - pos(L) \\ d_F := pos(C_{BA}) - pos(F) \end{gathered} \tag{6}$$

Based on this, the virtual gap g between both vehicles is defined as

$$g := d_F - d_L - length(L) - minGap(F) \tag{7}$$

The model provides full vehicle dynamics at the intersection.

3.3 Simulation of Traffic Lights with Different TLS Programs

In standard TLS programs, a 4-way intersection has a simultaneous 90 seconds green signals at each end. These are the most commonly used traffic signals at places where adaptive signaling techniques have not been developed.

Adaptive signaling techniques require data from every lane to be fed into a centralized system which then determines the optimal signal timing for each road section to better relieve traffic. One of the best methods to achieve this is the proposed DQN-based method, which uses deep reinforcement [17] learning [18] models to predict traffic levels and timing for signals. Since these systems are self-learning, they are gradually improving in at optimizing traffic over time.

The model uses the concept of a machine learning model that learns by getting points for correct and incorrect answers to a problem statement. Over time, the algorithm changes its parameters to minimize [19] wrong answers to a problem, thus becoming more and more accurate over time. Q-learning and Deep Q-learning equations are used to train the system. These modules are not paid much detailed attention to because they affect the overall traffic condition in the area, equally affecting both emergency and normal vehicles. These systems can be implemented beyond the solution presented in this paper and thus improve the overall traffic condition.

4. Mathematical Model of the Solution

The solution presented in this paper provides:

- The shortest route.
- The fastest route.

It shall be noted that the fastest route might not always be the shortest one due to traffic conditions. There might always rerouting necessary in the predetermined route due to unexpected traffic or other obstacles.

To ensure the minimum disturbance of the traffic, other vehicles cannot be stopped for longer periods of time.

4.1 Assumptions

- Vehicles must obey the traffic rules.
- Not all intersections will have a traffic light
- The maximum allowed speed of emergency vehicles is 1.5 times of the max allowed speed provided that doing so is “safe” (the distance between vehicles as calculated above is considered safe).
- Emergency vehicles do not need to follow the traffic rules in the case of emergency.

4.2 The Model

From the problem and the situation presented above, it follows that the priority of the above system is to reduce the time that an emergency vehicle needs to reach its destination in the case of emergency.

The basic algorithm for the shortest route used in this paper is dijkstra's algorithm. The dijikstra's algorithm is used to find the shortest route between two nodes. The shortest route, however, may not be the fastest route. This algorithm is thus slightly modified. The time taken to travel the distance is the weight of edges between the nodes. Therefore, the shortest route becomes the fastest route.

In this model, the weights are defined as "time" rather than "distance", so the resulting model will determine the optimal route in terms of time. The above model is applied after reaching each intersection, which will ensure that the route for the emergency vehicle is selected dynamically as the traffic conditions change over time.

The detection of an emergency vehicle by a traffic signal can be done by using specialized microphones that can identify the siren of an ambulance or other such emergency vehicles and clear the lanes for incoming vehicles. The second part of the algorithm is related to TLS programs, since the ambulance will be going through traffic signals; therefore, a general rule will be used, i.e. if the route is safe the ambulance can go through the red light. Since the road is already optimized for the fastest route i.e. the route that has the best (traffic to distance quotient), the ambulance going through such sections will cause minimal problems to the normal flow of traffic. The method mentioned above uses route optimization with respect to time in order to ensure that the route selected has the least volume of traffic, and since the route is already optimized, there is no need to create additional specialized traffic signs. The above solution was tested using a simulation with 500 vehicles as explained below.

5. Simulation

SUMO (Simulation of Urban MObility) was used for simulating the above conditions. The simulation consists of three parts: map (grid of roads), routes (several vehicles with different random routes) and traffic lights.

The simulation was started by random selection of 500 vehicles for a period of 1500 time units with random trips and the time taken to complete this trip was measured. This was done twice.

5.1 Simulation - I (Average Speed vs Time Loss)

In the first run, all the vehicles including ambulances had to stop at signals; the ambulances were not optimized to find faster lanes. The ambulances could still travel at the speed 1.5 times higher than the maximum allowed speed provided that the conditions were favorable to do so. This was done in order to test the effect on ambulance's speed on time optimization.

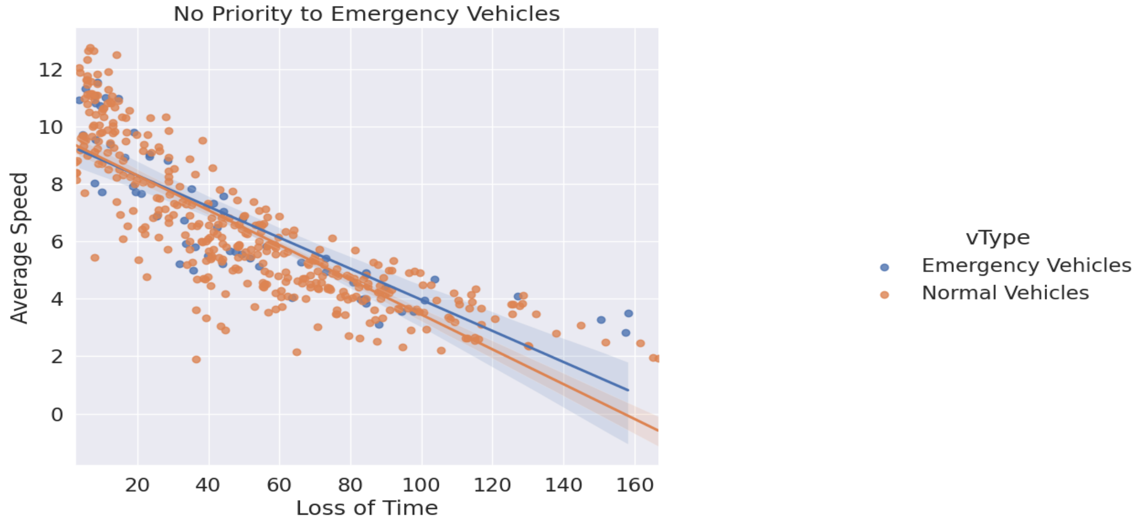

Fig. 1 A scatter plot of the number of all 500 vehicles over 1500 units of time with the emergency vehicles having no extra privileges except for higher speed. Source: authors

5.1.1 Corresponding Output

The graph above shows the average speed of each vehicle vs the total loss of time of the vehicle. The time loss is the time that the vehicle loses due to traffic or other factors in the simulation.

As seen in the figure 1 above, the regression line [20] of normal vehicles shows a slightly more absolute slope compared to emergency vehicles. This is basically due to the fact that emergency vehicles can travel faster than other vehicles, which enables them reaching the destination in record time. Overall, it is quite clear from the graph that the average speed of vehicles decreases with the higher time loss of the vehicles.

5.2 Simulation II (Average Speed vs Time Loss)

During this simulation, emergency vehicles were given special privileges, including the possibility to go through the red light and route optimization.

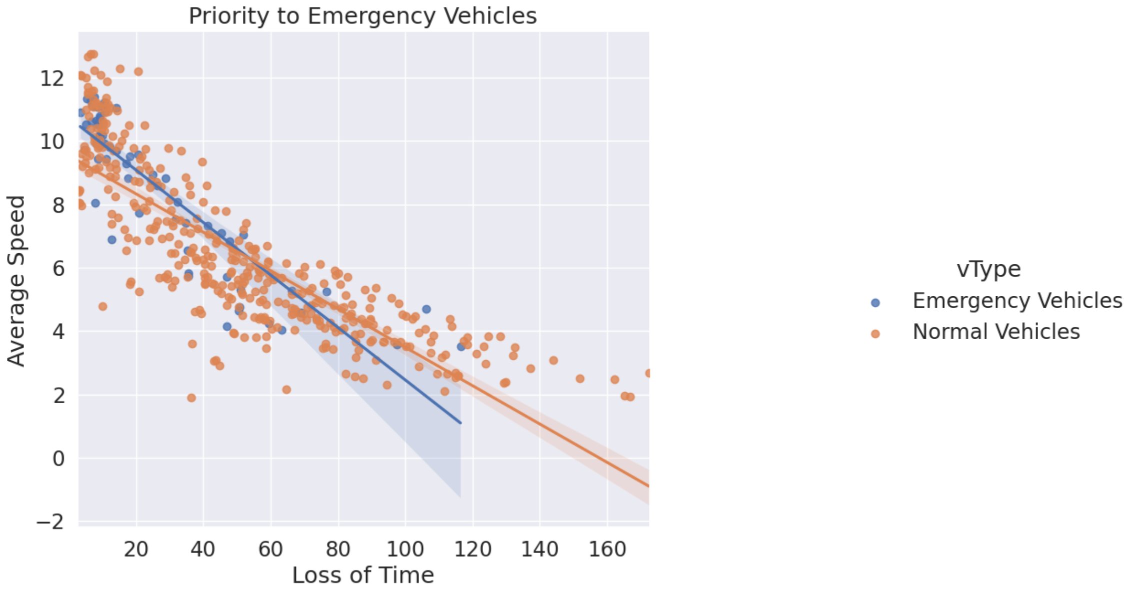

Fig. 2 A scatter plot of all 500 vehicles over 1,500 time units with the emergency vehicles having extra privileges including going through red lights and route optimization w.r.t to time. Source: authors

5.2.1 Corresponding Output

In the second simulation, it follows from the figure that the emergency vehicles are performing better than normal vehicles when it comes to reducing the time loss. Most of the emergency vehicles show very low time loss, which is reflected in the graph in a very steep negative regression slope. This indicates that the above-mentioned method of route optimization actually works.

5.3 Simulation I (Effect of Traffic on Vehicles When There is no Special Priority)

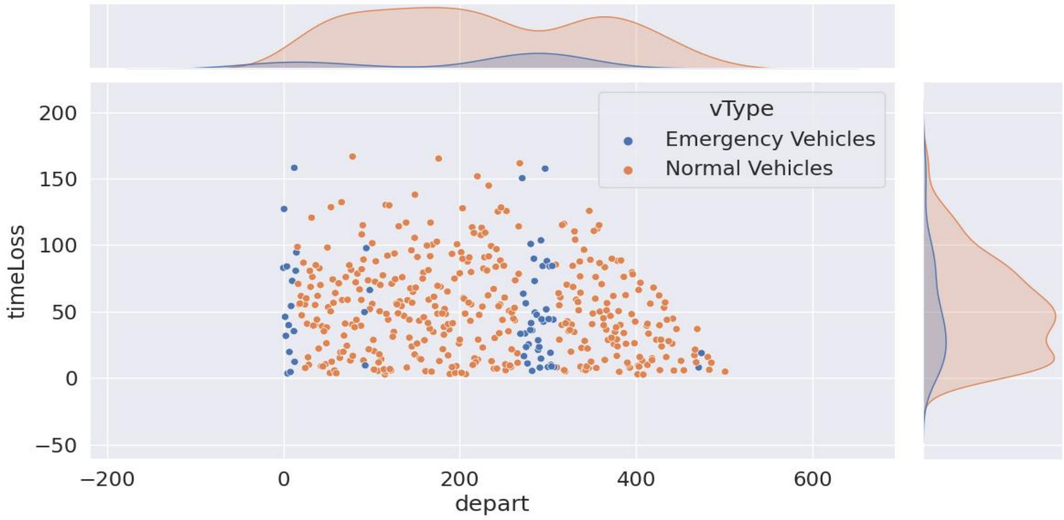

Fig. 3 A bivariate graph of time loss vs time of randomly selected vehicles in the traffic grid when all vehicles have equal rights. Source: authors

The graph above describes the effect of traffic on vehicles at different speeds. The two graphs above and below look similar at first glance but there is a striking difference between them. At any given data point on the x-axis, the number of scattered points in the y-direction shows the traffic at that point in time. The horizontal graph above the main graph shows the increase in traffic over time as the number of vehicles increases.

The graph adjacent to the y-axis shows the cumulative time loss of vehicles at a certain point of time in the trip.

5.3.1 Corresponding Output

The graph above shows the amount of time taken by various vehicles at different times in the map. It shall be noted that the distribution of both emergency vehicles and normal vehicles w.r.t the y-axis is approximately the same, which means that the traffic had similar effect on both normal and emergency vehicles despite the higher speed of emergency vehicles.

5.4 Simulation II (Effect of Traffic on Vehicle Priority)

The graph below looks similar in the x-direction, but there is a visible difference in the y-axis of the graph. The data points for emergency and normal vehicles are no more equally distributed. It can be clearly seen that the points are denser in the lower y-axis compared to the upper y-axis.

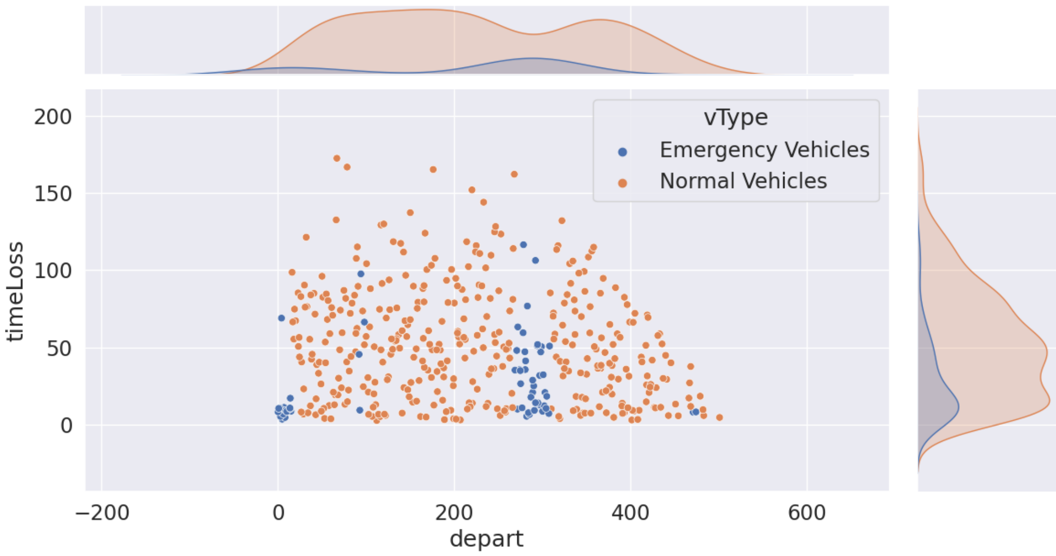

Fig. 4 A bivariate graph of time loss vs time of other vehicles in the traffic grid with emergency vehicles having special privileges. Source: authors

5.4.1 Corresponding Output

This can be due to the fact that vehicles at exactly the same time as in the previous case show much lower time loss compared to the previous situation, which can be clearly seen in the form of a sharp spike in the lower section of the y-axis in the graph adjacent to the y-axis of the main graph. It can be concluded from the above result that simply optimizing the route and providing special access to emergency vehicles can significantly increase the efficiency of such systems without deteriorating the traffic condition.

5.5 Discussion

The selection of the optimal for emergency vehicles is discussed but the effect of such route selection on other vehicles in the same system has not been confirmed yet. This has been measured in terms of driver impatience, i.e. even a slight increase in driving time compared to a normal scenario will cause difficulties for normal vehicles that need to be optimized by the research.

For the calculation, the following method was used. The cumulative waiting time of both emergency and normal vehicles is calculated and normalized by dividing by the number of such vehicles. This provides the average waiting time of a vehicle in the above two simulations calculated by the following code:

```
avg_duration_emergency_in_emergency = (file_emergency.query('vType == "Emergency Vehicles"')['duration'].sum())/file_emergency.query('vType == "Emergency Vehicles"').shape[0]
avg_duration_no_emergency_in_emergency = (file_emergency.query('vType == "Normal Vehicles"')['duration'].sum())/file_emergency.query('vType == "Normal Vehicles"').shape[0]
```

When there were no special privileges:

- Average duration of a journey for a normal vehicle: 89.86031746031745
- Average duration of a journey for an emergency vehicle: 88.85245901639344

The difference between emergency and normal vehicle’s travel time is 1.00785844392 time units.

When there were special privileges given to emergency vehicles:

- Average duration of a journey for a normal vehicle: 89.62645502645502
- Average duration of a journey for an emergency vehicle: 66.98360655737703

The difference between emergency and normal vehicle’s travel time is 22.6428484691 time units while the difference between the travel time of normal vehicles in both the simulations is less than 1 time unit. This confirms that the simulation works as expected and reduces the travel time of emergency vehicles without affecting the travel time of other vehicles.

6. Conclusion

This paper presents work in the field of adaptive traffic systems for creating modern green corridor and also proposes a novel method to create such corridors effectively in locations with limited computational power. Since such systems need to be interconnected, the solution is designed while considering that any solution should work like an interconnectable module that can be connected in future to other such modules to create a larger network of adaptive traffic lights and traffic congestion control systems. The system can be optimized to provide results that are more than 25% optimized to a random network with no privileges. This shows that the proposed solution can be implemented for larger systems with relatively lower levels of required computation. The current solution tests the effectiveness of a system with only one lane on each side, due to which overtaking vehicles and sharp turns create excessive traffic on the roads. A future version of this solution may be focused on testing the effectiveness of such systems in a real-life scenario with several multiple lanes and turn lanes. This will require testing the system to its limits to get better insight into the user behavior in case of congestion. Moreover, the system currently considers a standard probability distribution for rule-breaking vehicles, but in real life, the probability distribution of rule- breaking and hence accidents are closely related to patience and traffic levels. Further research should consider these features.

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