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An Intelligent Traffic Light Scheduling Algorithm by using fuzzy logic and gravitational search algorithm and considering emergency vehicles

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Abstract

Traffic lights play an important role in urban transportations, but they also cause delays in streets leading to junctions. Scheduling of traffic light, therefore, puts a considerable effect on urban traffics and routing delays. The proposed routing aims to route the vehicle agent so that the driver arrives at its destination by the fastest path. In this paper, a new intelligent algorithm is proposed for scheduling traffic lights to decrease traffic density and less delay in routing. This algorithm considers traffic flow density and the presence of emergency vehicle agents. The algorithm evaluates the status of the traffic flow by fuzzy logic. The evaluation is done by considering traffic flow speed and density. The output of fuzzy logic is used by Gradational Search Algorithm (GSA). GSA considers the status of the flow, the priority of the traffic flow, and the distance of the emergency vehicle to the traffic light. The simulation results prove that the proposed algorithm has better performance.

Keywords: Traffic light scheduling, Fuzzy logic, Gravitational Search Algorithm (GSA), Multi-agent traffic routing.

1. Introduction

Congestion controls in cities reduce the quality of life, waste time, increase expenses, and cause increasing air and sound pollutions. Therefore, there is a need to develop intelligent transportation

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systems. On the other hand, traffic lights play an important role in handling traffic. Different algorithms have been developed to schedule traffic lights intelligently by flow conditions in the streets. These algorithms try to improve traffic flow.

The classical idea of “routing” often consists of a solution that is generally defined by assigning customers to vehicles and the sequence of the assigned customers is determined for every vehicle. These algorithms are usually modeled based on mathematical graphs. These graphs are composed of vertexes (representing junctions) and edges (representing roads). Edges generally contain costs that often specify distances between customers or the travel times [1]. The vehicle routing problem (VRP) includes searching for the best path. It should set a path for k vehicles so that each vertex is met exactly once, and the total routing cost (like the length of the path) is minimized.

In most cases, this algorithm should determine the routes with a minimum cost for a set of vehicles to provide services to some customers with specific requests. Classical VRPs are usually considered static and deterministic, but in the real world, information is not always completely available, and it may change as time progresses and may be affected by uncertain events such as vehicle break down, crash, changes in traffic congestion, and ongoing customer requests. Thus, these problems in real-world applications could be dynamic (plan can be adapted rapidly at several points to the decision-maker) and stochastic (uncertainty is substantial in the exogenous process). With the combination of these dimensions, four vehicular routing problems can be identified [2], [3].

Furthermore, as the world becomes more complex, our ability to understand it should also increase. Hence, it is important to develop systems that simulate real-world issues and allow us to analyze ”complex systems”. A complex system consists of several components or interacting entities called the agent. An agent is an object or a class with properties and methods [4]. If the system contains many agents, then there will be many interactions and relationships among its agents, making it difficult to predict the behavior of a complex system.

In recent years, the study of complex systems has been unified as a new scientific discipline [5]. To analyze the behavior of complex systems, we first need to understand the behavior of each component interacting in simple ways with its neighbor components [6]. The total behavior of these interacting components is nonlinear. In other words, although each component of a complex system may behave uniformly, its total behavior may lead to unpredictable results in the overall system behavior.

On the other hand, traffic light scheduling algorithms have a considerable impression on traffic density. These algorithms consider the expected arrival time to the signalized intersection or the density of competing for traffic flows [7]. Therefore, a well-chosen schedule of traffic lights contributes to efficient processing of vehicle flows at intersections, which raises the average speed and decreases time spent by cars in traffic jams [8].

Traffic light scheduling algorithms have to evaluate the conditions of traffic flows. Such an evaluation should be done by considering one or more parameters. The results of the evaluations must reflect the current conditions and somewhat should represent conditions of the traffic flow prediction in near future. Scheduling of the traffic lights should be done dynamically and intelligently.

The proposed algorithm aims to increase the speed of flows in streets leading to the junction and also decrease the waiting delay of vehicles at traffic lights. It aims to provide the least possible delay for the emergency vehicle (i.e. ambulances, fire engines, and police scouts) and buses. It schedules traffic lights by using Gravitational Search Algorithm (GSA). It evaluates the conditions of flows by using fuzzy logic.

The remainder of this article is organized as follows: Section 2 discusses related works, Section 3 describes the system model and the summary of the proposed algorithm, Section 4 is the Simulation and results, and finally, Section 4 presents the conclusion.

2. Related work

Multi-agent models offer an alternative definition of classical traffic flow models and develop more general and effective frameworks to model the driver's behavior [9]. MAS models have received more attention in traffic management, signal control, and route guidance. This method has special benefits: greater flexibility, faster response, robustness, resource sharing, and better compatibility in aggregating pre-existing and independent systems.

Markov and Gray's models predict traffic volume [10]. Genetic algorithms are also used to predict traffic volume. In [11] and [12], a comparison has been made to determine the optimal method to predict the short-term traffic volume between the three methods. The source [13] offers model time windows provided by customers, which are considered fuzzy random variables. Group intelligence patterns, especially ant colony, have been widely used to solve complex problems. Ant colony algorithms utilize the behavior of ants and the use of pheromone for routing, and there are various tasks in this field [14], [15], [16].

An intelligent algorithm is introduced in [17]. This algorithm considers the real-time traffic characteristics of each traffic flow that intends to cross the road intersection of interest, whilst scheduling the time phases of each traffic light. The introduced algorithm aims at increasing the traffic fluency by decreasing the waiting time of traveling vehicles at the signalized road intersections. Moreover, it aims to increase the number of vehicles crossing the road intersection per second.

In [18] an algorithm that exploits WSN is introduced. Sensor nodes are deployed in lanes that sample the number of vehicles that pass the sensor nodes. This number is used to schedule traffic lights. The sensor nodes are organized in hierarchical order. Each sensor reports to its upper-level sensor. The traffic light scheduling is done by the sensor nodes at the third level.

Jihene Rezgui and et. al. in [19] proposed three different algorithms to schedule traffic lights. These algorithms are developed by using a heuristic method that considers the density of flows as well as the waiting time of the vehicles. These algorithms are named STLSD, SDLSDT, and SDLSDE. STLSD considers the density of flows for scheduling. SDLSDT considers density and the wait time of the vehicles for scheduling. SDLSDE improves SDLSDT by taking into account emergency vehicles. Different configurations of a genetic algorithm to find an effective traffic light schedule which is based on a genetic algorithm by the process of natural selection is discussed in [8].

In [20] a new traffic light scheduling is proposed which uses GPS information. This algorithm assumes that a good proportion of people use Map services like Google Maps in their commute and they follow the route direction by these services. This algorithm uses the users' data.

Meisam Razavi and et. al. proposed an algorithm by combining IoT, image, and video processing techniques in [21]. It considers density and the number of passing vehicles. This algorithm has two approaches. The first approach uses an image of the traffic conditions to determine the density of each flow. The second approach uses live video to count the number of vehicles in streets leading to junctions.

A hybrid cellular swarm optimization method is proposed to optimize the scheduling of urban traffic lights [22]. Particle swarm optimization plays an important role in this proposed framework. This framework exploits two models: PSM and POM. PSM conserves the scheduling settings and carries out transition rules to achieve comprehensive scheduling and POM devotes to optimizing the phase timing schedule.

3. Proposed Algorithm

In any intersection, usually, there are four incoming traffic flows and eight outgoing traffic flows. This algorithm assigns an integer number between 1 and 8 to each outgoing flows and evaluates the incoming traffic flows by considering the speed and density of the flow and distance of the emergency vehicle to the traffic light. Three types of emergency vehicles are considered, ambulance, fire engine, and police scouts, and also busses. A priority is an integer between 1 and 5 to each flow.

Vehicles send their speed, position, and their type (i.e. ambulance, fire engine, police scout, bus, and ordinary) to the traffic lights as they enter the street leading to the junction through VANET communication. Traffic lights will accumulate this information and calculate the average speed of flows by Eq. 1 and distance by Eq. 2. The results of this calculation are given to the fuzzy engine, which evaluates the flow status.

$$\bar{\nu} = \frac{\Sigma_{i=0}^{n} \bar{\nu}_i}{n}$$

$(1) Calculation\ of\ flow\ speed$

$$d_i = \sqrt[2]{(x_1 - x_{TL})^2 + (y_1 - y_{TL})^2}$$

$(2) Distance\ between\ vehicle\ and\ traffic\ light$

3.1. Fuzzy interference engine

The fuzzy engine aims to evaluate the status of each incoming flow to a junction. The evaluations are done by two parameters speed and density of the flow. The outcome of this test is the ratio of vehicles that can pass the traffic light in the green interval. If the outcome is zero, no vehicle can pass the junction and if the outcome is one, all vehicles can pass the junction. The fuzzy system is shown in fig .1.

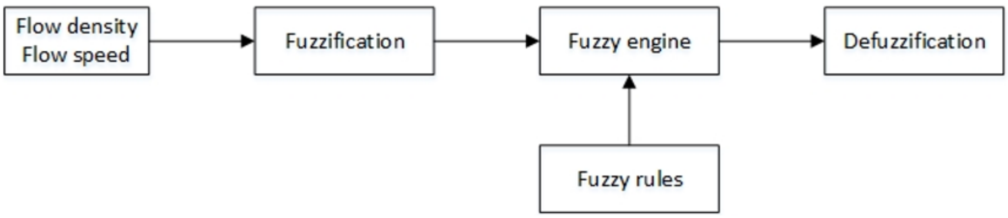
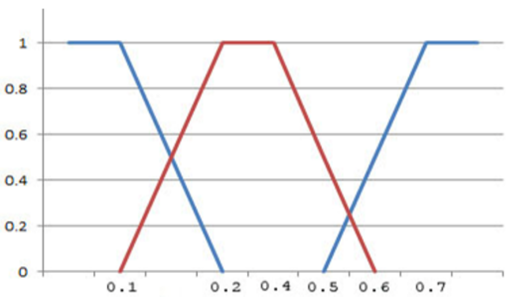


Figure 1: Block diagram of the fuzzy system

The membership function of the density of a traffic flow is shown in fig 2. Low, mid, and high are fuzzy linguistic variables for density.



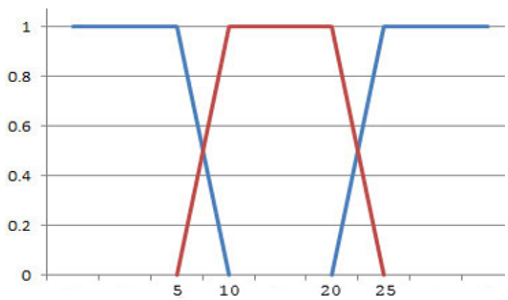


Figure 2: The density of a traffic flow

Figure 3: Flow speed

The membership function of the flow speed is shown in fig 3. Slow, mid, and fast are fuzzy linguistic variables for flow speed. Fuzzy if-then-rules are shown in table 1.

Table 1: Fuzzy rules

	Density	Flow speed	Time
Rule 1	light	fast	low
Rule 2	mid	fast	low
Rule 3	heavy	fast	mid
Rule 4	light	mid	low
Rule 5	mid	mid	mid
Rule 6	heavy	mid	high
Rule 7	light	slow	mid
Rule 8	mid	slow	high
Rule 9	heavy	slow	high

3.2. Scheduling traffic light

Scheduling is done based on passing ratio, the priority of the flow, and distance of the emergency vehicle to the junction. Total green intervals in each junction fall into $[min, max]$. It means that the i total green interval could be 3 minutes and the $i + 1$ total green interval be 2.5 minutes. This allows the emergency vehicle which is close to the traffic light pass immediately and another flow gets the green light.

Scheduling is done by the gravitational search algorithm. The initial population is produced by algorithm 1. The members of the initial population are created randomly. This population for each traffic light may differ and is optimized gradually. Each member has four flows and an eligibility value which is determined 4. Where st_i is the status value of the flow, p_i is the priority of the flow, d_i is the distance of the emergency vehicle to a traffic light, and α_i is the green interval assigned to the flow.

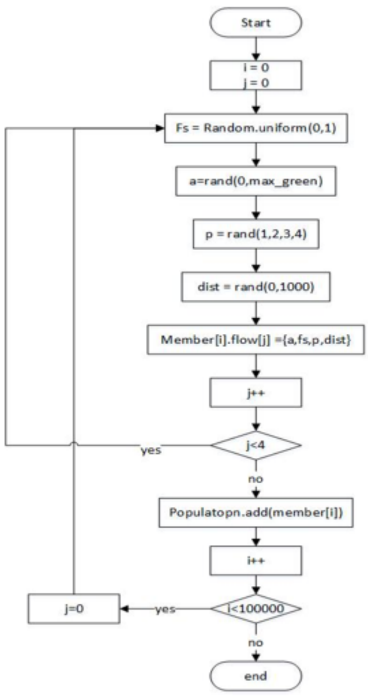


Figure 4: Initial population production

$$e = \frac{\alpha_1 \times p_1 \times d_1}{st_1} + \frac{\alpha_2 \times p_2 \times d_2}{st_2} + \frac{\alpha_3 \times p_3 \times d_3}{st_3} + \frac{\alpha_4 \times p_4 \times d_4}{st_4} \qquad min \leqq \alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 \leqq max$$

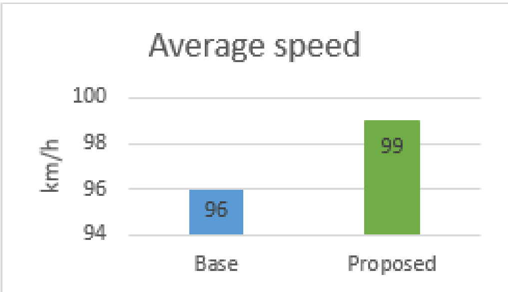
$$(4). Eligibility\ of\ members$$

4. Simulation and results

To evaluate the proposed algorithm, three different scenarios are run. The difference between these scenarios is the number of vehicles. There are 144 intersections in the scenarios. In the meantime, the proposed algorithm of [22] is considered as the base algorithm, as Wenbin Hu and et. al. proposed an algorithm that has considerable results. Conditions of the simulation are shown in table 1.

4.1. The average speed of vehicles

This parameter is considered to evaluate the fluency of flows on intersections. This parameter is calculated by averaging the average speeds of all vehicles that traveled to their destination. As seen in fig 4, fig 5, and fig 6, the proposed algorithm has better performance. The proposed algorithm has evaluated the performance.



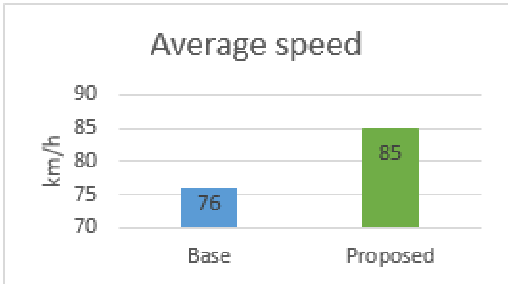


Figure 5: Average speed by 2500 vehicle

Figure 6: Average speed by 5000 vehicle

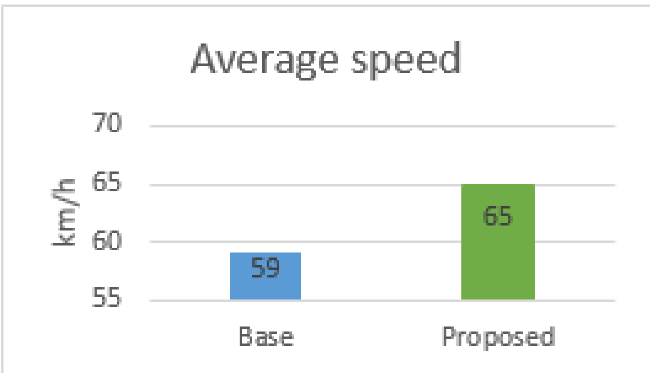
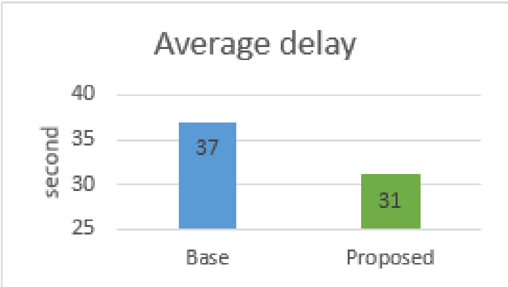


Figure 7: Average speed by 10000 vehicle

4.2. Average delay

This parameter shows the average delay of vehicles in intersections. The Delay interval of vehicles in the control area of traffic lights is recorded and is averaged at the end of the simulation. The simulation results show that the proposed algorithm had less delay, according to fig 7, fig 8, and fig 9.



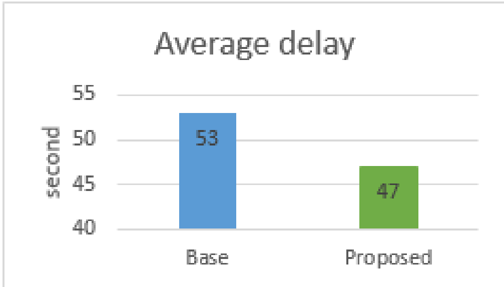


Figure 8: Average delay by 2500 vehicle

Figure 9: Average delay by 5000 vehicle

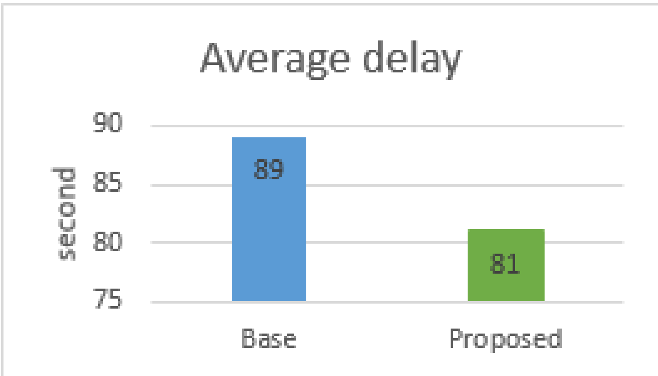


Figure 10: Average delay by 10000 vehicle

5. Conclusion

This paper provides an intelligent solution to control and manage the crossroad traffic using the fuzzy logic and gravitational search algorithm. Scheduling of green and red traffic lights is determined based on the density and speed of the flows passing through the main streets leading to the junctions. The proposed algorithm has provided less delay for vehicles. It also has considered emergency vehicles and busses. It performed more efficiently than the base algorithm.

In future studies, the proposed algorithm will be tested for different penetration rates, and its behavior will be investigated in the case that all vehicles are not equipped with vehicular transceivers.

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