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Research Article

# Routing Optimization in Vehicular Social Networks Using Firefly Algorithm

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**Abstract**

Vehicular communications have been considered to be an enabler for numerous vehicle safety and information applications.Vehicle Social Networks (VSNs) are a type of ad-hoc networks which allows wireless communication between two adjacent vehicles. Routing and communicating with adjacent nodes are one of the problems in VSNs. A literature review indicated that the time limit to transmit data and route is a problem due to the geographical distance and speed of the vehicles. The present paper aims to provide an innovative near-optimal solution with minimal delay for the routing problem in these networks, using the optimization algorithm of firefly applicable in dynamic and geographically extensive environments. Vehicles and their movements are considered to be fireflies and their absorption, respectively. The two factors of mean distance and the possibility of two vehicles reaching each other were examined for car absorption and routing. In addition, the number of vehicles in each area, measured by the different density of vehicles in both urban and suburban areas, is another directly effective factor in the routing accuracy. Finally, the proposed method is simulated in the 5G networks and the results indicated the improvement of the proposed method compared with the dynamic group division algorithm in terms of mean car routing distance, urban, and suburban area separation, light changes, light absorption coefficient variations, random number between zero and one changes, and random initial vehicle mobility changes up to 14.68, 13.63, 2.65, 20.08, 18.39, 17.57, and 18.45, respectively.

*Keywords* : Vehicle Social Networks (VSNs); Routing; 5G; Vehicular ad-hoc network (VANET).

## 1 Introduction

VEhicle Social Networking is an emerging communication field inspired by the concepts of the two different disciplines, namely vehicular ad-hoc networks (VANET) and mobile social networks (MSNs) [5]. In VANET cars communicate with roadside devices known as vehicle-to-infrastructure (V2I) communication. In addition, vehicles can communicate with each other via

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no infrastructure, which is known as vehicle-to-vehicle (V2V) communication. In general, the communication time of each communication loop is limited due to the high mobility of network interconnections. How to share mobile nodes with radio sources to ensure the service quality is one of the important not completely solved issues with vehicular ad-hoc networks. In the draft of the Society of Electrical and Electronics Engineers, standard 802 set forth in the Wireless Network Access Protocol introduces V2V as the only standard for hardware address in communication. Since this standard is designed for low mobility networks, it cannot fully control high mobility networks. The present paper aims to provide an efficient method for routing in vehicle social networks based on the emission speed improvement.

The remainder of the present paper is as follows. Section 2 presents with the literature review. Section 3 introduces femtocell networks. Section 4 briefly introduces the firefly optimization algorithm. The proposed method is described in Section 5. Finally, the simulation results and conclusions are provided in Section 6 and 7, respectively.

## 2 Literature Review

In [2], an algorithm called CFD, as a data transfer mechanism based on the reliability and validity of nodes for sending data to the VSN in which the average and weak nodes were strengthened to increase their cooperation level with other nodes, and increase the reliability level of the other nodes by sending them more messages. They used real-world experimental results and mobile studies. Finally, the data extracted from the algorithm were compared with those of other algorithms proving the proposed algorithm to be less delayed which can significantly increase data collection in VSNs, while its implementation is comparatively costly.

In 2017, [5] proposed a new interest-based scheme for VSNs using a social energy metric in order to determine the capabilities of mobile nodes to send messages to others. They categorized communities based on node interests, and provided precise solutions for calculating social energy including inter- and intra-community energy, and performed extensive simulations showing the efficiency of their proposed scheme [5].

In [15], social vehicles were examined. Failure to trace social vehicles prevents research into the social characteristics of vehicles in the VSN. Thus, they proposed a different generation of social vehicles based on the mobile data model and applied social areas. Their approach mainly consists of network demand, and description and simulation of social vehicle routes with SUMO demand. In addition, it can be used to construct a traffic scenario to simulating VSNs. In their proposed approach, vehicles choose a route based on simulation tools, which may lead to traffic on some roads. They modeled Beijing traffic whose results were almost consistent with real-time traffic conditions published by the Beijing Traffic Management Office, indicating that their approach is more accurate and efficient than the previous ones [15].

In 2018, [14] conducted a study on categories, applications, services and route data privacy. They first introduced the concepts of route data and categorized the route data into explicit and implicit routing data based on the data formats. Afterwards, they provided a systematic review of the various route data application, claiming that many issues persist in route data applications such as data scarcity and the efficiency of processing and query for big route data. However, developing data technologies and routing data mining methods can solve these problems to some extent in future. In addition, they provided a comprehensive view of route data services completely explored from the government and commercial organizations perspective, and discussed the significant challenges in analyzing route data. Based on the results of developing data technology and routing data mining techniques, their proposed approach can solve these problems to some extent in future [14].

In another study, [17] highlighted the importance of data transfer in VSN for smart cities and mentioned the anomalies in this field. However, VSNs can be considered as integrated social networks instead of IOVs to improve the life quality of citizens, highly complex VSN study methods are conceivable along with the necessity of analyzing many issues. They believe VSNs will attract widespread attention in future research [17].

In [4], the structure of evolutionary associations in complex networks was studied to identify the dependencies between structures and performance of a particular community. Nowadays, the majority of association recognition algorithms rely solely on optimization criteria such as modular which may not be suitable for showing the structure in complex networks. The process of identifying the association as a multi-objective optimization problem (MOP) was proposed to examine the association structures in complex networks. A multifunctional optimization algorithm was suggested based on the advanced firefly algorithm in order to overcome the limitations of the association recognition in order to obtain a set of dominant solutions. A new tuning parameter based on the irregular mechanism and the newest possible self-adaptive mutation strategies were used in their proposed algorithm to improve the algorithm efficiency. The experimental results on synthetic hybrid networks and complex real-world networks indicated that the multifunctional association recognition algorithm is useful to detect overlapping associative structures [4].

In addition, [8] investigated the applications of the FA algorithm in various areas of optimization problems. Optimization is the process of determining the best solution to create something as effective as minimizing or maximizing the parameters in challenges and problems. Several optimization problems such as rupture, irregularity, multi-objectivity and so on have been inspired by firefly behavior. FA is often used to solve optimization problems in computer sciences and engineering, some of which are optimized or combined with other fans for a better performance. In addition, the results showed that the FA technique performed better than other meta-heuristic algorithms in most cases, and that the hybrid FA algorithm yielded better results than the FA algorithm alone [8].

The two protocols of LABEL and BUBBLE RAP were presented in [9, 10], which are community-based routing protocols. LABEL simply sends messages merely to the members of the target community. However, BUBBLE RAP is more complex and is known for its social coverage, utilizing the central community nodes to build conscious social coverage, which effectively enhances routing performance. The disadvantage is that the cost of constructing and maintaining conscious social coverage is high [9, 10].

Further, [7] examined the ant colonies optimization and proposed SMACO. An ant-colony optimization model based on SMACO simulation results can reduce packet loss and response time in solving network routing problems [7].

## 3 5G Femtocell Networks

The system model consists of 5G femtocell networks. Todays, wireless networks are struggling with the particular problem of the increasing data being shared and consumed by users and different electronic devices compared to the past, which will reduce the bandwidth for users and the service speed, leading to an increase in disconnections [4].

Using femtocell networks is considered as one of the available solutions for this problem. The most efficient routing is required for the utmost efficiency of the network. Thus, the car-motion-based femtocell network is tested with the 5G network architecture, which operates in the high bandwidth range of 30 to 300 GHz, known as the millimeter wave spectrum. Millimeter waves can transmit data packets at a really high speed. Small cells are the portable miniature stations requiring the minimum energy for the optimal performance. In the case of femtocell networks, suppose every wireless channel is a street, and all of the streets of the city are congested without entering more cars. However, building new streets may solve this problem. The femtocell network always adapts itself to the fastest vehicle, which can be a car, train, or bus 1. Cars can adjust their communications with other cars as well as with the base station via the femtocell network. This technology increases the throughput and reduces the delay rate in the system response time. Femtocell networks can continuously serve wireless networks to solve the problem of ad-hoc vehicle and mobile vehicle including lack of central node and slow speed change [4].

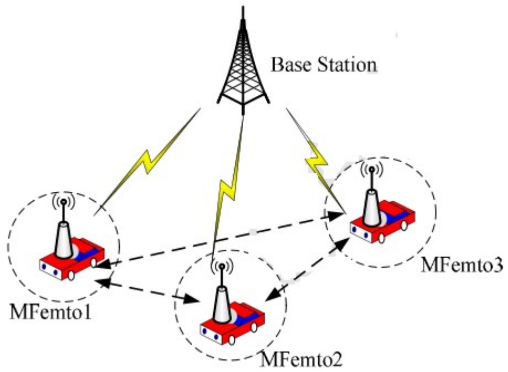


**Figure 1:** Motion-based femtocell network [4]

# 4 Firefly Optimization Algorithm

Firefly algorithm is considered as one of the meta-heuristic optimization algorithms widely used in solving the problems of engineering, economics, and so on. The basis of this algorithm is the firefly light emitting behavior. The amount of the light received by other fireflies depends on the distance with the source, intensity of the light, and power of light absorption. Firefly characteristics can be summarized in the three following sections.

1 . All fireflies are of the same kind, and their sex has no role in their absorption ability, meaning each firefly has the ability to absorb all the other fireflies through its own light. In the present paper, all of the cars regardless of their speed and other quantitative and qualitative features will move towards the others provided that they find the correct route by the other cars, as mentioned in the proposed algorithm.

2 . The attractiveness of each firefly for the others is directly related to the brightness and indirectly related to the distance, which means that the less attractive fireflies move towards the more attractive ones. However, in case of the absence of more attractive fireflies nearby, the firefly is bound to move randomly. In the present paper, any car that is able to be guided correctly with a predetermined probability of reaching the target with a slight distance from its neighboring car will move to that car in order to obtain a proper routing eventually.

3 . The brightness or intensity of the fireflies is selected based on the criterion by which the optimization is performed, referred to in the proposed algorithm in Section 4 [12].

# 5 The Proposed Algorithm

In this section, an algorithm is proposed based on the firefly algorithm to optimize the distance between cars for the purpose of an accurate routing. The $KDT$ algorithm is introduced, where $K$ indicates the average of the number of vehicles, $D$ shows the average distance between cars, and $T$ is considered as the average time zones of a vehicle moving continuously. The data are transmitted between close nodes and each node receives the relevant data for transmission from its neighbor. On the other hand, the data transmission should be in such a way that the dim firefly (the car with lower position and power) moves towards the shinier one (the car with higher position and power). Thus, Equation (5.1) is considered as the criterion for the firefly/ car absorption.

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha\epsilon_i. \tag{5.1}$$

Random processes proved that the number of vehicles entering the segmentation area has Poisson distribution, upon which the probability that the number of vehicles entering the area over time $t$ equals $k$ is as follows:

$$P\{N(t = k\} = \frac{(\lambda t)^k}{k!}e^{-\lambda t}.$$
$$k = K_{t_0}, K_{t_1}, \cdots, K_{t_i}, \cdots, K_{t_n} \tag{5.2}$$

In Equation (5.1), $N(t)$ is the number of cars entering the segment in time $t$, The Poisson constant is $\lambda$ , and in effect is equal to the average number of cars that entre the segment in a given time unit. In addition, $P\{N(t) = k\}$ is the probability that the number of cars entering the area over time $t$ equals $k$.

Averaging on the Poisson distribution, the average number of vehicles entering the study area can be described as follows:

$$E\{N(t)\} = \lambda t. \tag{5.3}$$

$E\{\cdot\}$ in Equation (5.3) is the mathematical hope calculator of the function. Suppose cars $u_k$ and $u_m$ are in the area at the time interval of $t_i$ and the number of cars in the area is $K_i$. Consequently, the distance $d_{mk}$ between cars $u_k$ and $u_m$ is defined as in Equation (5.4)

$$d_{mk} = \sqrt{(x_m - x_k)^2 + (y_m - y_k)^2}. \tag{5.4}$$

where $(x_m, y_m)$ shows the position of the vehicle $u_m$ and $(x_k, y_k)$ indicates the position of the vehicle $u_k$. Suppose $P_{mk}$ equals to the probability that the car $u_m$ is routed to the car $u_k$. Thus, $d_{t_i}$ is introduced as distance deviation in the time interval $t_i$. First, the distance between the cars i.e.$d_{mk}$ is calculated and multiplied with the accurate routing probability i.e. $P_{mk}$ . Then, the same process is repeated for all the cars in time $t_i$ in the region which are $K_{t_i}$. Finally, the result is averaged.

$$d_{t_i} = \frac{1}{K_{t_i}^2} \sum_{m=1}^{K_{t_i}} \sum_{k=1}^{K_{t_i}} d_{mk} P_{mk}. \tag{5.5}$$

Regarding the best routing, variables $\bar{K}$ and $\bar{D}$ over time period $\bar{T}$ should be maximized in order to obtain the proposed algorithm. In order to apply the Equation (5.1) the values $\beta_0$, $\gamma$ and $\alpha$ are replaced with the values 1, 5 and 1, respectively. Then,$\epsilon_i$ is considered as a uniform distribution between zero and one, variable at each stage of $t_i$ change.

In addition, we consider the time periods ranging from 10 to 100 seconds. In order to compare the results with those of the proposed algorithm, we take 10 samples of time intervals in the form of 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 seconds for the time period $t_i$ and drawing the routed distance between cars.

Further, we replace the distribution function $P_{mk}$ for all the $m$ and $k$ with a uniform and maximum distribution of $\omega$ the results of which for different $\omega$ are examined. Furthermore, Monte Carlo simulations are considered to be 10000.

Based on the reference paper, the present results are examined in both urban and intercity situations and their difference is in the density of cars per square meter. Thus, in the proposed algorithm, we display the variables with $u$ index for urban and $su$ for suburban areas.

### 5.1 Algorithm Steps

Step 1: Separate the vectors $K_u$ and $K_{su}$ into two zones with different vehicle density and calculate them randomly in two different intervals.

Step 2: Put Poisson's constants $\lambda_u$ and $\lambda_{su}$ equal to the mean of the vectors $K_u$ and $K_{su}$.

Step 3:Calculate $P_u\{N(t_u) = k_u\}$ and $P_{su}\{N(t_{su}) = k_{su}\}$ for all the intervals of $K_u$ and $K_{su}$ in the specified time period $t_i$, based on Equation 5.2.

Step 4: Consider $t$ from $E\{N(t)\} = \lambda t$ equal to the set size i.e. the number of total time intervals and obtain $N_u$ and $N_{su}$ regarding $\lambda_u$ and $\lambda_{su}$ from Step 2.

Step 5: Calculate the length and width coordinates of the cars in a 3000 square meter area with a uniform distribution for the number of $N$ calculated in Step 4.

Step 6: Calculate the distance between two cars using Equation 5.4.

Step 7: Calculate the shift of car/ firefly $i$ to the more attractive car/ firefly $j$ from Equation 5.1.

Step 8: Find the attractiveness of the fireflies according to the values of $\beta_0, \gamma, \alpha$ and $\epsilon_i$.

Step 9: Replace the length and width of the firefly with those of the more attractive one.

Step 10: Calculate the probability function $P_{mk}$ for all the cars for one probability distribution function.

Step 11: In case there are still fireflies in this timeframe whose attraction has not been calculated go back to Step 6 and repeat the process for all the cars/ fireflies. Otherwise, go to Step 12.

Step 12: Calculate $d_{t_i}$ from Equation 5.5.

Step 13: Calculate the sum of all the elements of $\sum_{m=1}^{K_{t_i}} \sum_{k=1}^{K_{t_i}} d_{mk} P_{mk}$ and substitute the result in Equation 5.5.

Step 14: In case the car density is not zero in the time interval, there are still cars in the interval whose distance is not calculated. Go back to Step 12 and add the new $d_{t_i}$ to the previously calculated $d_{t_i}$. Otherwise, go to Step 15.

Step 15: Repeat Step 14 for all the cars.

Step 16: Go back to Step 3 and repeat the process for all $t_i$s.

Step 17: Go back to Step 1 and select the new density for $K_u$ and $K_{su}$ regarding the movement of fireflies.

Step 18: Repeat Step 15 using the Monte Carlo simulator 10000 times and average.
Step 19: Compare the results with those of the reference paper.

## 6 Simulation Results

Figure 2 displays the routing and distance results of vehicles over time in both the proposed algorithm and dynamic group division algorithm proposed in the reference paper. Results are presented for an average of five cars per any time interval, regardless of the urban or suburban density of the vehicles in the area.

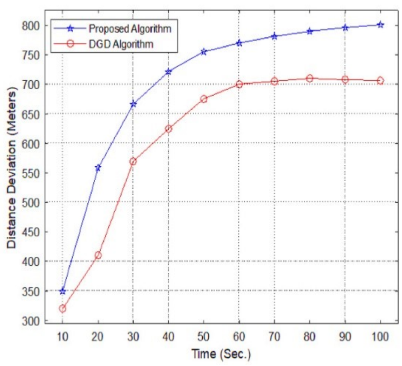


**Figure 2:** The comparison between the routed distance of the cars in the segmented areas in the proposed and reference algorithm.

results indicated the improvement of the proposed method compared with the dynamic group division algorithm in terms of mean car routing distance up to 14.68 .

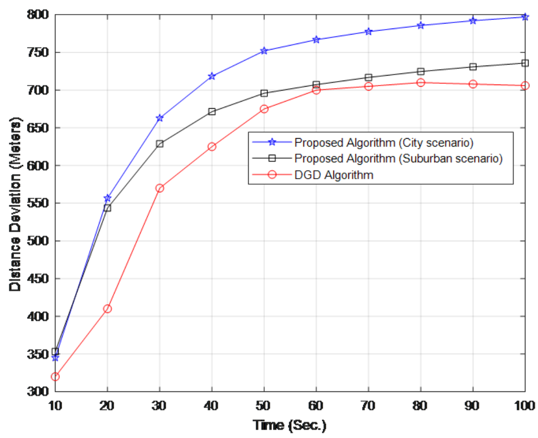


**Figure 3:** The comparison of the routed distance of the cars in the segmented areas regarding the urban and intercity areas.

results indicated the improvement of the proposed method compared with the dynamic group division algorithm in urban up to 13.36 and suburban up to 2.65

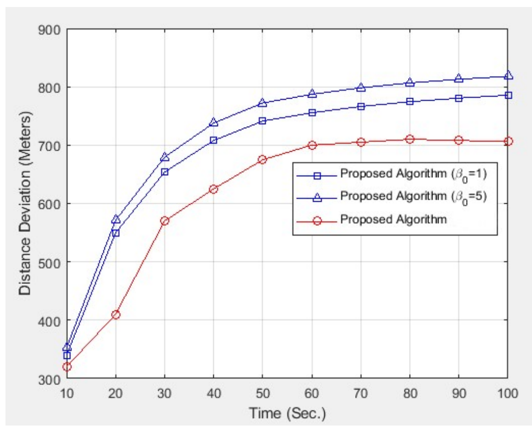


**Figure 4:** The comparison of the routed distance of the cars in the segmented areas regarding $\beta$ changes.

results indicated the improvement of the proposed method compared with the dynamic group division algorithm in light changes up to 20.8.

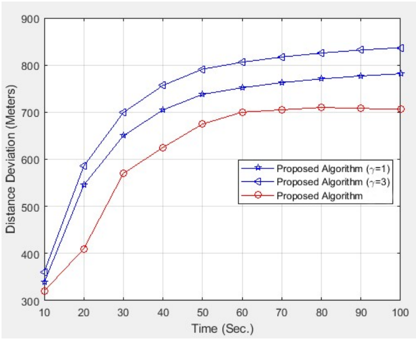


**Figure 5:** The comparison of the routed distance of the cars in the segmented areas regarding $\gamma$ Changes.

results indicated the improvement of the proposed method compared with the dynamic group division algorithm in light absorption coefficient variations up to 18.39.

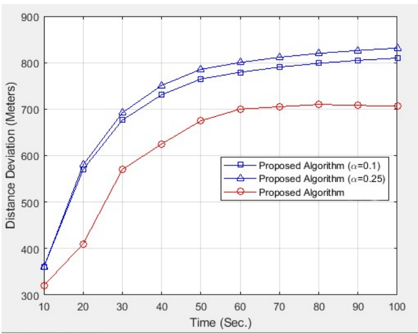


**Figure 6:** The comparison of the routed distance of the cars in the segmented areas regarding $\alpha$ changes.

results indicated the improvement of the proposed method compared with the dynamic group division algorithm in random number between zero and one changes up to 17.57.

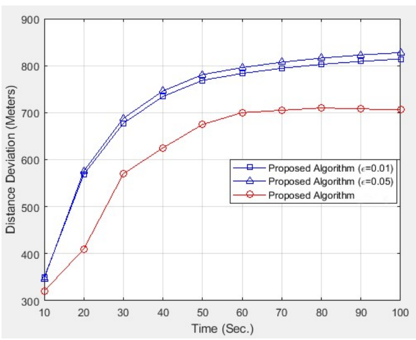


**Figure 7:** The comparison of the routed distance of the cars in the segmented areas regarding $\epsilon_i$ changes.

results indicated the improvement of the proposed method compared with the dynamic group division algorithm in random initial vehicle mobility changes up to 18.45.

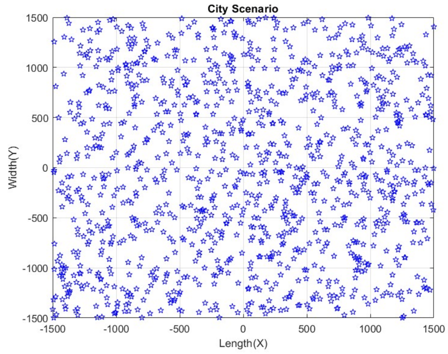


**Figure 8:** The density of the number of the cars i.e. the number of cars per square meter in the 3000 square meter urban area.

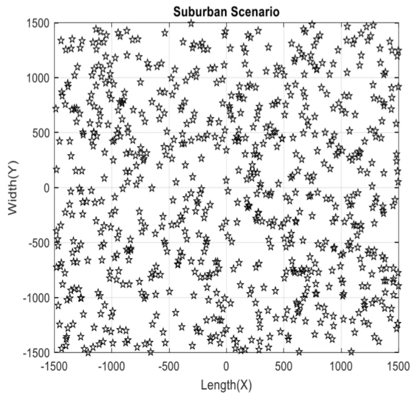


**Figure 9:** The density of the number of the cars i.e. the number of cars per square meter in the 3000 square meter suburban area.

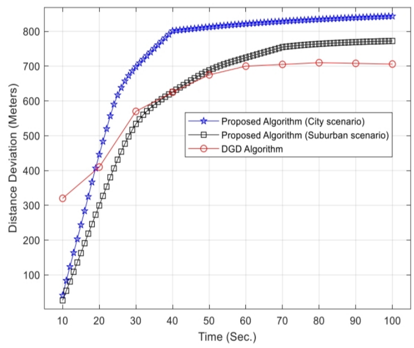


**Figure 10:** The comparison of the routed distance of vehicles in large scale between the proposed algorithm results and the reference paper.

The results showed that the routing improvement of the proposed method compared to the reference algorithm in city and suburban is quite clear. The vehicles used the reference algorithm to route just 700 meters in 100 seconds, while at the same time the vehicles used the proposed algorithm to route 790 meters in suburban areas and 890 meters in urban areas.

## 7 Conclusion

In the present paper, an algorithm for optimizing the routing in social vehicle networks was presented using the firefly algorithm and the two factors of the average distance and likelihood of two cars reaching each other were examined for car absorption and routing. In addition, the number of vehicles in each area with different densities of vehicles in urban and suburban areas was studied. Figures displays the routing and distance results of vehicles over time in both the proposed algorithm and the dynamic group division algorithm proposed in the reference paper. Finally, the proposed method is simulated in 5G networks and the results indicated the improvement of the proposed method compared with the dynamic group division algorithm in terms of mean car routing distance, urban and suburban area separation, light changes, light absorption coefficient variations, random number between zero and one changes, and random initial vehicle mobility changes up to 14.68, 13.63, 2.65, 20.08, 18.39, 17.57, and 18.45, respectively.

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