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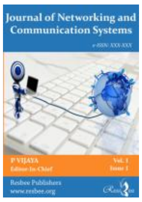

Traffic-Aware Routing in Urban VANET using PSO Model

Deepak Rewadkar
Department Information Technology
Goverment Polytechnic Awasari,India
deepakrewadkar27@gmail.com

Dharmpal Doye
Department Information Technology
Shri Guru Gobind Singhji Institute of Engineering and Technology
Nanded,India

Abstract: This paper intends to propose a Particle Swarm Optimization (PSO) for the Traffic-Aware Routing (TAR) protocol of VANET in urban areas, which could recognize the optimal routes with reduced delay and minimal traffic density. The implemented PSO model explores the optimal path for routing depending on the formulated fitness function. In addition, Exponential Weighted Moving Average (EWMA) is exploited in this context for predicting the speed and traffic density of the vehicle that is considered as the significant aspects in the fitness function of PSO algorithm for finding the optimal TAR. Experimentation of PSO reveals noteworthy enhancement with reduced end to end (e2e) delay and distance when evaluated over the other traditional models. The optimality of the adopted TAR protocol is also confirmed by the execution outcomes.

Keywords: Traffic-Aware Routing, PSO algorithm, e2e delay, Speed, Distance, Density.

1.Introduction

Vehicular Ad Hoc Network (VANET) [1] [2] is a particular category of MANET. Generally, VANET is aimed at providing safety linked information and traffic management. Safety and traffic management involves real time information and directly affect lives of people travelling on the road. Simplicity and security of VANET mechanism ensures greater competence. Safety is realized as prime attribute of VANET system. In VANET each vehicle performing as node acts as a router to switch over data among various nodes in the network. VANETs [3] [4] are modeled to offer vehicle communication. Two kinds of communication are feasible in VANET i.e. roadside to the vehicle and V2V communication. In VANET, there are stable network nodes that are deployed in the structure of roadside units [5] [6]. These kinds of networks are modeled to deal with road traffic, safety purposes, driver control and LBS. In VANETs [7] [8], power utilization and storage capacity are not restricted and the node's position could be portrayed by means of GPS. A self-organized system could be formed by the VANETs [9] [10], but it is not required for a premeditated infrastructure. There is a restricted coverage level for every wireless network of the vehicle, which exists from 100-300 meters and therefore e2e communication is feasible across a huge distance.

To pass on a message to a destination node in VANET [11] [12] [13], it needs messages to deliver through numerous nodes. VANETs [14] could offer cost-effective and scalable solutions for appliances namely, context-aware advertisement, traffic safety, and dynamic route planning by means of wireless communication at short ranges [15] [16]. For functioning appropriately, these appliances necessitate proficient routing protocols. VANETs networks further include the better prospective of extensive usage since it is low-cost, scalable, and offers increased bandwidth when distinguished with cellular communication [17] [34]. On the other hand, it also comprises certain disadvantages associated with the comparatively increased vehicle speed that causes frequent and fast variations in topology.

A proficient traffic-aware routing practices in vehicular [18] [19] [20] surroundings is further meeting up with numerous problems such as, MAC, accessible bandwidth evaluation, increased mobility, exposed and hidden nodes crisis, and speedy handover, movement of node, rapid speed, blockages, and heterogeneous vehicles support [21] [22]. Thus, certain developments have to be incorporated in the traffic-aware routing in VANET systems in the future works using various optimization algorithms [29] [30] [32].

The major contribution of the paper is to enhance the TAR protocol of VANET in urban areas, which could recognize the optimal routes with reduced delay and minimal traffic density. For attaining optimal outcomes, the PSO model [31] is deployed that explores the optimal path for routing depending on the formulated fitness function. In addition, EWMA is used for predicting the speed and traffic density of the vehicle that is considered as the significant aspects for finding the optimal TAR. Moreover, the proposed scheme is compared with the conventional algorithms such as Genetic Algorithm (GA), FireFly Algorithm (FF) [33] and Dragonfly Algorithm (DA) [28] and Crow Search Algorithms (CS) and the results are obtained.

The arrangement of the work is as follows. Section 2 discusses the reviews done on breast cancer detection. Section 3 describes the description of the presented model and section 4 analyses the prediction using the EWMA approach. Moreover, section 5 portrays the results and section 6 concludes the paper.

2. Literature Review

2.1Related Works

In 2018, Khan *et al.* [1] have explored the Traffic-Aware Segment-based Routing (TASR) protocol, which involves two significant aspects. Initial one insists on the calculation of Expected Connectivity Degree (ECD) on various segments, and the second one introduces a novel forwarding technique that performs packet transmission to the destination from the source node. The introduced ECD model considers the densities of vehicles, thus determining the connectivity on every segment. In addition, wide-ranging experiments examine the effectiveness of TASR, thus showing the betterment of the presented model.

In 2016, Darwish, and Abu [2] have developed a Lightweight Intersection-based Traffic-Aware Routing (LITAR) model for VANET in urban networks. Here, the adopted scheme establishes two novel approaches for minimizing the overhead of the network while conserving the accuracy. In addition, the adopted model develops the decisions on routing depending on distance, Road Network Connectivity (RNC) and density. The computation of the implemented model demonstrates noteworthy performance with respect to packet delivery ratio (PDR) and it minimizes the overhead when evaluated over conventional models.

In 2017, Sami et al. [3] have introduced an expansion on VANETs network by assisting two diverse methods of data routing. The initial one includes the delivery of data packets on the ground entirely by means of UVAR-G. The second one includes the transmission of data packets in the air depending on UVAR-S. The implementation outcomes reveal that the hybrid contact between UAVs and vehicles was perfectly appropriate for VANETs when distinguished with the traditional models.

In 2018, Xia *et al.* [4] have designed a Greedy Traffic Light and Queue Aware Routing model (GTLQR) that takes into account of the comparative distance, quality of channel, connectivity and delay to improve the packet loss incurred by vehicle clustering. The adopted model also intends to adjust the traffic loads between vehicles. By carrying out the simulation, the suggested model was found to perform better than other compared models with respect to e2e delay and PDR.

In 2018, Ding *et al.* [5] have presented a scheme that explores the impacts of traffic lights in a street. It further evaluates the connectivity of streets depending on the density and distribution of vehicles at the centre of a street. At last, a street-centric model called traffic-light-aware routing protocol (TLAR) approach was proposed depending on the street connectivity. The experimental outcomes have revealed that the designed model could minimize the e2e delay and enhance the PDR in VANET systems.

3. Description of the Proposed Model

Fig. 1 shows the design of the road network in the urban environment. This urban network includes n count of vehicles, which travel along the road of urban regions. Assume S_i as a vehicle available in the road model, where i lies between $1 \le i \le n$. V indicates the road segment and I denotes the point of intersection, where the traffic lights are fixed. The vehicles travel on the road depending on the pattern of the traffic light. Assume I_1, where the traffic signal seems to be green in east and west directions and it seems to be red in south and north directions. At this moment, the vehicles moving from V_3 and V_1 travels from east to west and west to east directions, and the vehicles available in V_2 and V_6 are requested to wait. The pattern of the traffic light is designed such that the vehicle density should be reduced at the road segments. The road network design is specified by ID, i.e. combination of V and I. $V_t(S_i)$ and $V^{ID}(S_i)$ indicates the vehicle's speed S_i at the time t and V respectively, and its unit is m/s.

Nu_t^{ID} signifies the count of the vehicle at ID at t, S^D denotes the distance occupied by the vehicle and B_t^{ID} signifies the average distance among ID at t. B_t^{ID} and are S^D indicated in meters.

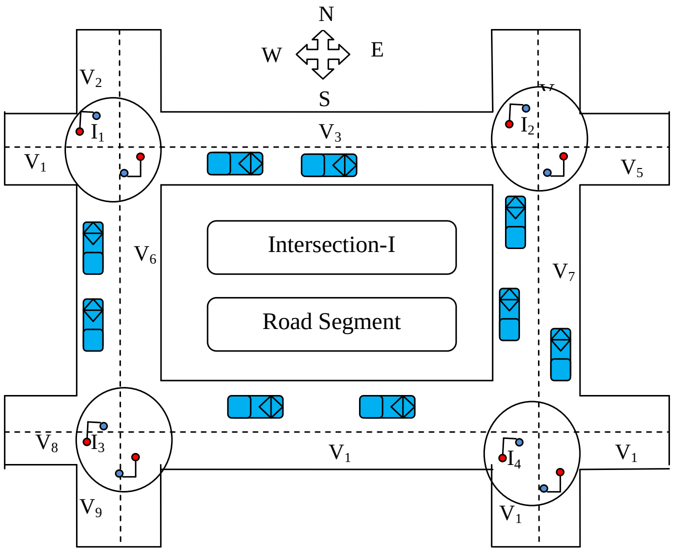

Fig. 1. *Model of road*

3.1Traffic Density

The traffic density of ID (road segment) at t, denoted by Ti_t^{ID} is given by Eq. (1), in which β and α denotes the constant variables and L^{ID} indicates the length of ID in meter.

$$Ti_t^{ID} = \alpha.\left(\frac{Nu_t^{ID} \times S_i^D}{L^{ID}}\right) + \beta.\left(\frac{B_t^{ID}}{L^{ID}}\right) \tag{1}$$

The delay gets increased if the destination path is chosen with more traffic density. The maximum network delay indicates the worst performance of the routing model.

3.2 Average Speed

The average speed of ID denoted by H_t^{ID} is a significant constraint in the TAR. The reduction in an average speed of ID indicates that the specific segment will be soon subjected to congestion. The average speed of ID at t is computed as per Eq. (2), in which n_{ID} denotes the count of vehicles available in ID at t.

$$H_t^{ID} = \frac{1}{n_{ID}} \sum_{i=1}^{n_{ID}} S_t^{ID}(S_i) \tag{2}$$

4.Prediction using EWMA Approach

The traffic density prediction using EWMA model for the selection of an optimal routing path is presented in this section. The EWMA model is established for predicting the average speed and traffic density of vehicles in ID for optimal routing. The optimal route is "a route with road segments containing the less traffic density". EWMA is a technique, which analyses the process in the network and predicts the potential outcomes of the process. The statistics of EWMA is based on the constant factor related to it, i.e. the weighting factor essential for the measurement of sensitive control. The EWMA is given as per Eq. (3), in which A_t denotes the observation at t and ω denotes a parameter in accordance with the memory of EWMA. The average speed of vehicle predicted by means of EWMA is given by Eq. (4), in which D denotes the weighting factor of EWMA.

$$EWMA, A_{t+1} = \omega.A_t + (1-\omega)EWMA(A_t) \tag{3}$$

$$EH_{t+1}^{ID} = D.\left[H_t^{ID} \times Ti_t^{ID}\right] + (1-D)EH_t^{ID} \tag{4}$$

As the deep memory of EWMA model depends on the vehicle speed, the constant parameter is chosen as given by Eq. (5), where ΔTi indicates the time period for sampling and τ signifies the time constant.

$$D = 1 - \exp\left(\frac{\Delta Ti}{\tau}\right) \tag{5}$$

Eq. (6) shows the predicted traffic density of ID that is attained using the EWMA model. The vehicle's expectation speed in ID at the time $t+1$ is specified by Eq. (7), in which the value of f is specified by Eq. (8).

$$ETi_{t+1}^{ID} = D.Ti_t^{ID} + (1-D)ETi_t^{ID} \tag{6}$$

$$E_{t+1}^{ID}(S_i) = \left[H_t(S_i) + f * EH_{t+1}^{ID}\right] \tag{7}$$

$$f = \frac{\left[H_t(S_i) - H_t^{ID}\right]}{\left[Max\left(H_t(S_i), H_t^{ID}\right)\right]} \tag{8}$$

Here, $H_t(S_i)$ and EH_{t+1}^{ID} denotes the speed of the vehicle S_i at a time t and $t+1$ respectively as predicted by the EWMA model.

4.1 K-path Discovery

It is the initial phase of the proposed model. In path discovery, the accessible path among the destination and source of the vehicle in a road network is determined. The path discovery model is depicted by Fig. 2, where V denotes the vehicle available in the road segment V_1. The endpoint of V is V_{12}. There will be paths among the destination and source points by which the vehicle arrives at the destination point. Eq. (9) shows the discovered paths.

$$\begin{gathered} V_1 \to I_1 \to V_3 \to I_2 \to V_7 \to I_4 \to V_{12} \\ V_1 \to I_1 \to V_6 \to I_3 \to V_{10} \to I_4 \to V_{12} \end{gathered} \tag{9}$$

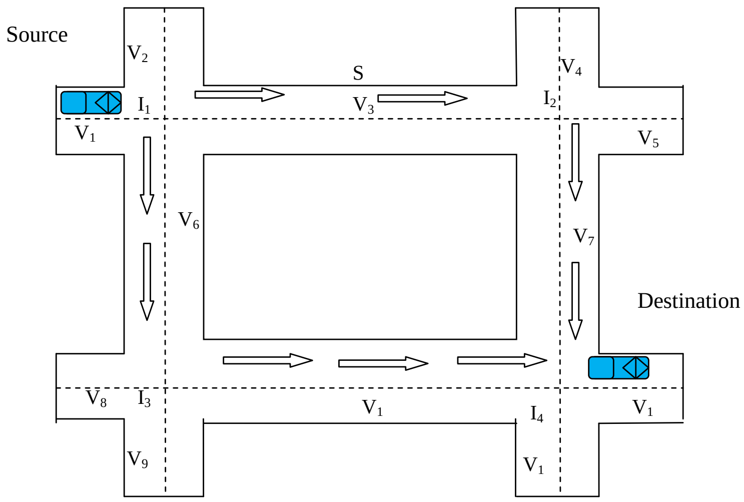

Fig. 2. *Systematic model of Path discovery*

4.2Fitness Function

Eq. (10) demonstrates the fitness function of the presented model, in which L denotes the length and EH denotes the predicted average speed in ID.

$$Fitness = \sum_{\substack{ID=1 \\ t=1}}^{nID} \frac{L_{ID}}{EH_t^{ID}(S_i)} \tag{10}$$

Here, the fitness function is carried out in terms of movement and time consecutively.

4.3 Solution Encoding

In this context, an encoding approach is introduced for optimal path selection depending on the PSO algorithm. The PSO population is equal to the discovered K-paths. Here, based on the average speed of vehicles, fitness evaluation takes place for the search agents. The route with optimal fitness is selected as the desired path. Fig. 3 indicates the solution encoding, where $X = \{1,2,3....K\}$ denotes the initial population of search agents. Every path is iterated using the PSO model and the optimal one is selected as the desired path.

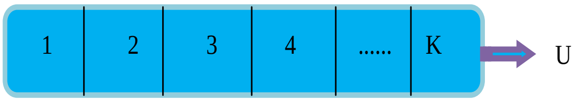

Fig. 3. *Solution Encoding*

4.4 Conventional PSO

PSO [23] was motivated by the behavior of a flock of birds to resolve the optimization crisis. To start with, a random solution is assigned and the optimum solution is explored by updating the subsequent generations. Every particle includes the position vector, the memory vector, and the velocity vector. The position vector is indicated by U_m, the velocity vector is denoted by v_m and the memory vector is signified by U_m^{best}. The solution that is linked with the issue of optimization is offered by the position vector, while the best solution arrives in opposition to the search of one particle that is measured as the memory vector. The particle roams with certain velocity in the dimensional space, wherein the velocity is balanced on the basis of the flying skill of the respective particle, together with its colleagues. Hence, by this function, the particle is able to shift towards the improved region for its search. Consecutively, the updating of the particle is addressed by Eq. (11), in which the updating of the velocity is signified by Eq. (12). Further, r_1 and r_2 indicate the arbitrary variables that are distributed uniformly within an interval of [0,1], c_1 and c_2 symbolizes the accelerating constants, U_g^{best} signifies the best solution that is explored by the whole of the particles and w_m denotes the inertia weight of the particle. The convergence speed of the technique is based on the inertia weight. The pseudo-code of the traditional PSO algorithm is given by Algorithm 1.

$$U_m(iter+1) = U_m(iter) + v_m(iter+1) \tag{11}$$

$$v_m(iter+1) = w_m v_m(iter) + c_1 r_1 (U_m^{best}(iter) - U_m(iter)) + c_2 r_2 (U_g^{best}(iter) \quad U_m(iter)) \tag{12}$$

Algorithm 2: Conventional PSO algorithm [22]

While $iter^{max}$ not met do
For the entire particle in the swarm
    Calculate the fitness value
    If in memory, fitness value < U_m^{best}
    Fitness value = U_m^{best}
End
Choose the most optimal value of fitness of all the particles in a swarm as U_g^{best}
For the entire particle in the swarm
    Compute the velocity using Eq. (12)
    Update the position of the particle using Eq. (11)
End
End While

5.Results and discussion

5.1 Simulation Procedure

The simulation of proposed VANET-TAR was simulated using MATLAB and the corresponding results were obtained. The proposed PSO model was compared with GA [24], FF [25], DA [26] and CS [27] and the results were obtained. The experimentation was done in terms of e2e delay, average distance and traffic density and the outcomes were validated. The experimentation was held for four setups and the results were confirmed.

5.2 Analysis of e2e Delay

The analysis for e2e delay for the proposed model over the traditional models is given by Table 1. From the analysis, the reduced delay is attained by the presented PSO model over the other schemes for all the four setups. On considering set up 1, the proposed PSO model is 85.37% better than GA, 79.95% better than FF, 45.39% better than DA and 85.78% better than CS algorithms. Thus, the betterment of the developed is proved from the results.

Table 1. *Analysis of the E2E Delay for the Proposed Model over Conventional Models*

Methods	Set up 1	Set up 2	Set up 3	Set up 4
PSO	6.6935	8.4176	9.7222	8.4176
CS [27]	12.4355	12.0080	12.8810	12.0080
DA [26]	12.2581	18.1995	23.9802	12.2581
FF [25]	33.3871	49.2766	65.3929	33.3871
GA [24]	45.7581	67.7713	90.2817	50.254

5.3 Analysis of Average Distance

Table 2 demonstrates the average distance of the presented PSO model over other conventional schemes. On observing the outcomes, it could be known that the implemented model provides minimal distance than the other compared models for the four setups.

Table 3. *Analysis of the Average Distance for the Proposed Model over Conventional Models*

Methods	Set up 1	Set up 2	Set up 3	Set up 4
PSO	18.6515	17.7627	17.3962	18.6515
CS [27]	54.8660	53.0092	53.6730	54.8660
DA [26]	27.8668	24.9978	27.4463	24.9978
FF [25]	27.6753	24.9978	26.0122	24.9978
GA [24]	23.1277	22.8261	23.8903	26.254

5.4 Analysis of Average Traffic Density

The results on average traffic density analysis are given by Table 3, from which the betterment of the presented model can be noted. Here, for all the four sets ups, reduced traffic density is attained by the implemented model over the other compared methods.

Table 3. *Analysis of the Average Traffic Density for the proposed model over conventional models*

Methods	Set up 1	Set up 2	Set up 3	Set up 4
PSO	0.0161	0.0114	0.0082	18.6515
CS [27]	0.0233	0.0160	53.6730	0.0121
DA [26]	0.0229	0.0154	27.4463	0.0114
FF [25]	0.0216	0.0152	26.0122	0.0109
GA [24]	0.0205	0.0142	23.8903	0.0107

6. Conclusion

This paper has presented a TAR protocol in VANET at urban areas using PSO that could determine the optimal routes with minimal delay and reduced traffic density. The implemented PSO model explores the optimal path for routing depending on the formulated fitness function. In addition, EWMA was exploited in this context for predicting the speed and traffic density of the vehicle that was considered as the significant aspects in the fitness function of the PSO algorithm for finding the optimal TAR. Experimentation of PSO reveals noteworthy enhancement with reduced e2e delay and distance when evaluated over the other traditional models. The optimality of the adopted TAR protocol was also confirmed by the execution outcomes.

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