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Adaptive-ARW: Adaptive Autoregressive Whale Optimization Algorithm for Traffic-Aware Routing in Urban VANET

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Abstract: A traffic-aware routing in VANET is a prime step in transmitting the long data for applications. Researchers' address that the traditionally used routing protocols employed in Mobile Ad Hoc Networks are not suitable for routing in VANET, as VANETs differ from MANETs in the mobility model and environment. The demand to develop a traffic-aware protocol in VANET initiated to propose a routing protocol, termed as Adaptive Autoregressive Whale Optimization algorithm (Adaptive-ARW). The main goal of the proposed algorithm is to select the optimal path for performing routing in VANETs, for which the traffic required to be predicted. For predicting the traffic in the road segment, Exponential Weighed Moving Average (EWMA) is employed that predicts the traffic based on the average vehicle speed and the average traffic density. The minimum values of average speed and vehicles average traffic density to the less traffic density. Using the predicted traffic, the routing paths are generated, and the optimal paths are selected using the proposed algorithm that exhibits adaptive property. The analysis of the proposed algorithm provides the End-to-End delay, distance, average traffic density, and throughput of 2.938, 2.08, 0.0095, and 0.1354, respectively.

Keywords: Exponential Weighed Moving Average (EWMA), End-to-End Delay (EED), Whale Optimization algorithm (WOA), Autoregressive Model, Adaptive property.

I. Introduction

A Vehicular Ad Hoc Networks (VANET) aims at providing safe and comfort communication between the vehicles to manage traffic [1]. VANETs are comprised of OnBoard Units (OBUs) that are provided with vehicles and Road Side Units (RSUs), which are arranged along the roads [2]. OBU and RSU is the interface in communicating between the vehicles for a short distance known as vehicle-vehicle communication, and this communication continues until the vehicles lie in the transmission range of an RSU. After the reception of the messages, they are sent to the RSU, termed as Vehicle-RSU communication (V2R) [3] [4]. VANETs find valuable application in smart cities and the vehicles in VANET are furnished with the wireless communication nodes that ensure network connectivity. The wireless network assists the drivers to apt an optimal way such that the vehicles crashes are eliminated [5]. Above all, the routing protocols is used for communication in the smart city, and it is very essential in terms of the frequently altering routing topology in order to move up with the smart cities [6] [2].

The routing protocols [7] are grouped into two, and they are topology-based and location-based routing protocols. The commonly employed routing protocols in VANET use greedy routing algorithm that redirects the data packets to the destination node [8] [2]. The former routing protocols possess reactive and proactive routing protocols that employ the data to authorize a path. Due to the path discovery, a node in VANET requests the neighboring nodes with a route request (RREQ) packet. The nodes that receive the RREQ randomly broadcast the message until the path is constructed. Position-based routing protocols ensure that the node is aware of the position of the nodes such that rebroadcast is forbidden and the data is forwarded depending on the location of the source and the destination nodes [9]. Location-based protocols are applicable for VANET [10] as they require an accurate network and traffic information that forbids selecting the unfavorable paths [11].

This paper proposes a traffic-aware routing protocol in VANET using an adaptive optimization approach. Initially, the traffic in the VANET is predicted using the EWMA, and the predicted values are employed for determining the optimal path. The optimal path is determined using the adaptive autoregressive WOA that uses three adaptive factors in optimizing the paths. The three adaptive factors, such as iteration-based, fitness-based, and distance-based adaptive parameters, are the major contribution.These parameters adjust the search agents' optimal position depending on the number of iterations, fitness of the current position, and distance between current and best position of the search agent.

The Organization of the paper is: Section 1 introduces the paper, section 2 depicts the literature works of the paper. The proposed work is discussed in section 3, section 4 portrays the results, and finally, section 5 gives the conclusion of the paper.

II. Motivation

A. Literature Review

Yanmin Zhu *et al.* [12] presented an adaptive routing algorithm, termed as RWR that adapted to the dynamic nature of the network and the importance was that it acquires low deliver delay, but the delay in the network is high in certain cases. Chunfeng Liu *et al.* [9] designed a stable routing algorithm, which lowers the frequency of the requests and offered the extension in the path duration. Thereby, minimizing the link-breakage events, end-to-end delay, and improving the packet delivery ratio. The method suffers from computation complexity and message overhead. Chun-Chih Lo and Yau-Hwang Kuo [11] proposed a Traffic-Aware Routing Protocol with Co-operative coverage-Oriented information correction method (TARCO) that develops the deliver path in the VANET using the real-time conditions of traffic. The method was effective in establishing the effective routing path and adjustable to the dynamic paths due to the variations in the road traffic. Moreover, the protocol had minimized the communication overhead but was integrated with assumptions. Dharani Kumari Nooji Venkatramana *et al.* [13] proposed a Software Defined Network (SDN) in VANETs that tolerated the complexity and dynamicity of the network, but the routing overhead depends on the speed of the vehicle.

B. Challenges

✓ The position-based routing is advantageous over the topology-based routing in the way that any node progressing towards the destination forwards the data, but these position-based protocols never take into account the link stability at the time of broadcast. The stability guarantees the performance of delay-throughput for long data transmission [9].

✓ Local-Maximum-Problem is a major challenge in greedy VANET routing protocol, as the forwarding node did not find a node that was closer to the destination node. This is due to the fact that the forwarding vehicle finds difficulty in locating a suitable vehicle in its radio range to the forwarding packet [2].

✓ The route discovery techniques determine the optimal paths, but the process is time-consuming and causes network overhead. Thus, there is a need for the congestion control techniques for discovering the routes in the real-world applications [12].

III. PROPOSED METHOD OF TRAFFIC-AWARE ROUTING USING THE ADAPTIVE AUTOREGRESSIVE WHALE OPTIMIZATION ALGORITHM

The urban network consists of a number of road segments, in which the vehicles pass by, and figure 1 demonstrates the traffic-aware routing using the proposed algorithm. The vehicles move in the two-way lane in all possible directions. VANETs presented for traffic-aware routing is initially subjected to traffic prediction using EWMA that predicts the traffic in the route using average speed of the vehicles and the average traffic density. Then, the optimal path selection is progressed using the proposed algorithm that initially generates k-paths. From the generated k-paths, the optimal paths are selected based on the objective function. The objective function aims at minimum distance, minimum End-to-End Delay, maximum Link-Life time, and minimum packet delay. Importantly, the proposed algorithm exhibits the adaptive nature using three adaptive factors that ensure effective traffic-aware routing in VANET.

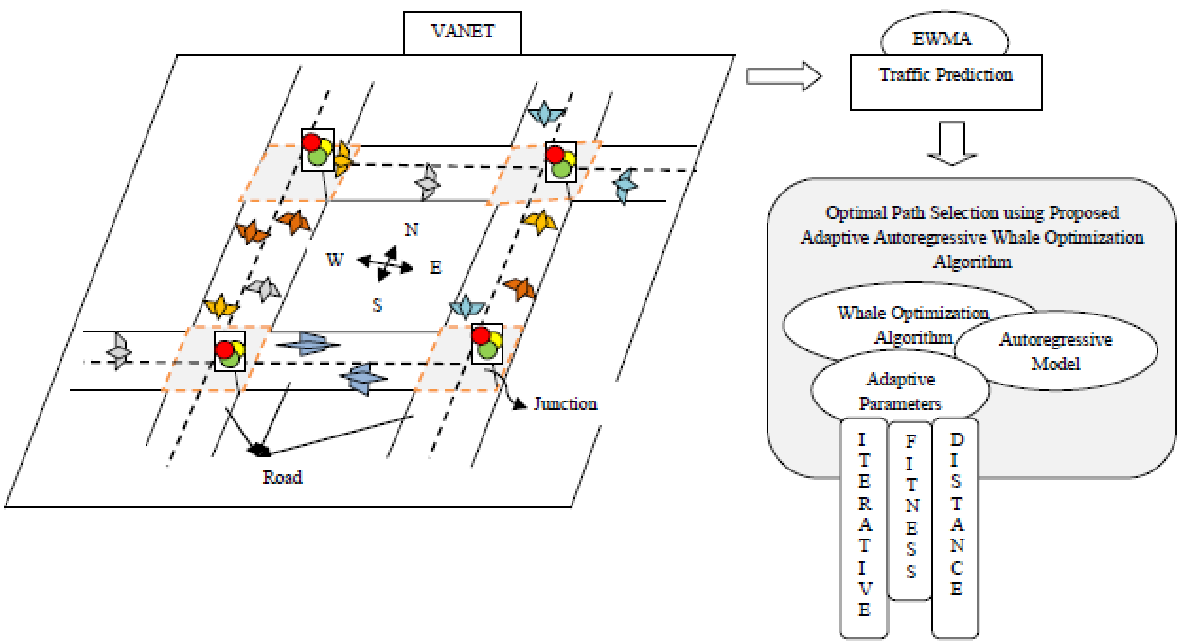


Figure 1. Traffic-aware routing using the proposed algorithm

A. Predicting the traffic for routing using EWMA

The best path selection in VANET is based on the prediction of the traffic existing between the source and destination nodes. The path selection is characterized using the EWMA that determines the low traffic path and the decision-making regarding the low traffic density is based on the previous data, from which the exponentially weighed data is determined. The logic is described as,

$$w(t+1)=\beta\, y(t+1)+(1-\beta)w(t);\ (1\le t\le p) \tag{1}$$

where, p corresponds to the total number of observations and β is a constant ranging in [0, 1]. The observation at a time $(t+1)$ is given as, $y(t+1)$ and the exponential weight at the time t and $(t+1)$ is given as, $w(t)$ and $w(t+1)$.The average speed of the vehicle depends on the traffic density, and if the traffic density is high, the vehicle movement is slow. The average speed is given as,

$$\rho_{\$}a^{r}_{t+1}=\sigma\left[a^{r}_{t}\times T^{r}_{t}\right]+(1-\sigma)*\rho_{\$}a^{r}_{t} \tag{2}$$

where, $\rho_{\$}a^{r}_{t+1}$ refers to the predicted average speed at the time t, T^{r}_{t} denotes the traffic density, a^{r}_{t} corresponds to the average speed of the vehicle moving in a road segment r, σ weighing factor of EWMA for predicting the traffic in the road segment and it is considered as the deep memory of EWMA.

a. Average Speed: The average speed of the vehicle should be high to reduce the travel time to reach the destination, and it is given as,

$$a^{r}_{t}=\frac{1}{H^{r}}\times\sum_{i=1}^{H^{r}}S^{r}_{t}(V_i) \tag{3}$$

where, H^{r} denotes the total number of vehicles moving in the road segment r and $S^{r}_{t}(V_i)$ refers to the speed of the i^{th} vehicle at the time t.

b. Traffic Density: The best path selected should be based on the minimum traffic density such that the delay is minimum when less number of vehicles moving in the road segment at the time t that is modeled as,

$$T^{r}_{t}=\mu\left[\frac{H^{r}\times V^{r}_{i}}{L^{r}}\right]+\delta\left[\frac{D^{r}_{t}}{L^{r}}\right] \tag{4}$$

where, μ and δ are the constants, L^{r} denotes the length of the r^{th} road segment, D^{r}_{t} implies the average distance between the vehicles moving in the r^{th} road segment at the time t. The i^{th} vehicle moving in the r^{th} road segment is denoted as, V^{r}_{i}.

c. Predicted Average Speed: The average speed is predicted based on the expected average speed of the vehicle and the predicted traffic density that is given as,

$$\rho T^{r}_{t+1}=\mu\, T^{r}_{t+1}+(1-\mu)\rho T^{r}_{t} \tag{5}$$

where, the traffic density predicted, average traffic density, and predicted traffic density of the r^{th} road segment at the time t are denoted as, ρT^{r}_{t+1}, T^{r}_{t+1}, and ρT^{r}_{t}, respectively.

d. Expectation Speed: The expectation speed that is based on the expectation function is given as,

$$e^{r}_{t+1}(V_i)=\left[a_t(V_i)+E\rho_{\$}a^{r}_{t+1}\right] \tag{6}$$

where, $a_t(V_i)$ notates the average speed of the i^{th} vehicle and E refers to the expected function that is based on the average speed of the i^{th} vehicle $a_t(V_i)$, and the expectation function is given as,

$$E=\frac{\left|a_t(V_i)-a^{r}_{t}\right|}{\left[\max\left(a_t\left(V_i,a^{r}_{t}\right)\right)\right]} \tag{7}$$

where, a^{r}_{t} refers to the vehicles' average speed in the r^{th} road segment.

B. Adaptive Autoregressive Whale Optimization Algorithm for traffic-aware optimal routing

The optimal path selection is based on the Adaptive-ARWO algorithm that is the algorithm developed by integrating the Autoregressive model and the Whale Optimization Algorithm (WOA) [14] along with the adaptive parameters. The optimal path selection is progressed as Discovering k-paths and selecting the optimal path from the k-paths based on the fitness measure.

a. Discovery of k-paths: The prime step in the optimal path selection is discovering the k-paths existing between the source and destination such that the optimization algorithm aims at selecting the best path based on the four major constraints.

b. Solution Encoding: Solution encoding represents the discovered k paths between the source and the destination.

The routes are the search agents, and they are represented as binary values, and the optimization algorithm determines the optimal path that takes the value 1 indicating that there is less traffic density resulting in the less delay.

c. Objective Function: The objective function is designed based on four constraints, such as End-to-End Delay, Link Life Time, Packet Delay, and distance. The objective function intends to maximize the lifetime of the network and through the expansion of the connectivity throughout the network. The fitness of the optimization is given as,

$$O = \frac{1}{4} \times \left[F_1 + \left(1 - F_2\right) + F_3 + F_4 \right] \tag{8}$$

where, F_1, F_2, F_3, and F_4 denote the objective constraints based on End-to-End Delay, Link Life Time, Packet Delay, and distance. Thus, the best solution is based on less End-to-End Delay, maximum Link Life Time, minimum Packet Delay, and minimum distance. The End-to-End Delay constraint is given as,

$$F_1 = \sum_{\substack{r=1 \\ j=1}}^{H_r} \frac{L^r}{\rho_{\$}\, a_t^r\left(V_i\right)} \tag{9}$$

End-to-End Delay should be in minimum and is the ratio of the r^{th} road segment length to the predicted average speed of the i^{th} vehicle, and the minimum End-to-End Delay indicates that the road traffic in the r^{th} road segment is in minimum. End-to-End Delay acquires values between 0 -1,where '0' is the best value. The Link Life Time is given as,

$$F_2 = \sum_{j=1}^{h} \frac{llt\left(r_j, r_h\right)}{c_{llt}} \tag{10}$$

Equation (10) symbolizes the network life-span, and it should be high. $llt\left(r_j, r_h\right)$ refers to the Link Life Time measure between the j^{th} road segment and its neighborhood, h refers to the neighbouring road segment, and c_{llt} indicates the normalizing factor. The Link Life Time [15] is based on the speed of mobility of the vehicle, its direction, and position. Packet delay evaluates the efficiency of the routing protocol and is given as,

$$F_3 = \frac{H^r}{N} \tag{11}$$

where, H^r denotes the total number of the vehicles traversing in the r^{th} road segment and N indicates the total number of the road segments. The Packet delay should be in minimum, and '0' indicates the best value. Distance is the fourth constraint that is measured between the length of two successive road segments, and this distance is the measure of the Euclidean distance [16]. The fitness based on the distance is given as,

$$F_4 = \sum_{r=1}^{H_r} \frac{g\left(L^r, L^{r+1}\right)}{c_g} \tag{12}$$

where, $g\left(L^r, L^{r+1}\right)$ denotes the distance between the length of the road segments L^r and L^{r+1}, respectively, and is calculated based on the Euclidean distance.

d. Adaptive Autoregressive Whale Optimization Algorithm

The Adaptive Adaptive-ARW algorithm is the hybridization of the Autoregressive model into the position update step of the WOA, and the algorithm is adaptive in nature due to the usage of the adaptive parameters. The proposed algorithm using the WOA [14] and Conditional Autoregressive Value at Risk (CAViaR) model [17] along with the adaptive parameter ensures the determination of the global optimal path. The proposed algorithm is adjustable to the dynamic nature of the network and ensures the accuracy. The proposed adaptive algorithm possesses a greater tendency to avoid the local optimum, exhibits better convergence, and there is a proper balance between the exploration and exploitation phases.

WOA [14] is the population-based meta-heuristic algorithm that is based on the natural behavior of the humpback whales, and the optimization process shares a common feature irrespective of nature. The search process is progressed in two phases: Exploration and Exploitation phase. In the exploration phase, the search process is randomized such that in the exploitation phase sticks to the global optimal solution. WOA establishes a proper balance between the exploration and exploitation phase using the adaptive parameters. The best solution is the prey or the optimal solution. The position update equation in the WOA is modified using the Autoregressive model termed as, Conditional Autoregressive Value at Risk (CAViaR) model [17].

a) Initialization: The population of the whales is initialized in this step, and the number of whales corresponds to the total number of the discovered paths, and the number of the discovered paths equals to k. Moreover, the internal parameters of the optimization, $\vec{P}$ and $\vec{K}$ are initialized, and these parameters are responsible for establishing a proper balance between the exploration and exploitation. The parameters $\vec{P}$ and $\vec{K}$ are the coefficient vectors that are given as,

$$\vec{P} = 2 * \vec{u} * \vec{v} - \vec{u} \tag{13}$$

$$\vec{K} = 2 * \vec{v} \tag{14}$$

where, $\vec{u}$ decreases linearly from 2 to reach 0 during exploration and exploitation such that the parameter $\vec{P}$ remains greater than or equal to 1 in the exploration phase and when $\vec{P}$ goes below '1', symbolizes exploitation, and $\vec{v}$ denotes the random vector that is tuned between 0 and 1 randomly.

b) Fitness Evaluation: The fitness of the population is evaluated based on the objective function given in equation (8) that aims at the maximum value for converging to the global optimal solution.

c) Update the position using the proposed algorithm: The position update using the proposed algorithm uses the CAViaRprinciple in the WOA with the adaptive parameter that is adaptive to the dynamics of the network. The encircling phase is the exploration phase, where the optimal location of the prey is not located. Hence, the position of the whale is updated based on the current best solution, and once the best solution is defined, all the search agents update their positions based on the current best solution. Thus, the position of the search agent is,

$$\vec{x}(t+1) = \overrightarrow{x^*(t)} - \vec{P}.\vec{R} = \left(1 - \vec{P}\vec{K}\right)\overrightarrow{x^*(t)} - \vec{P}.\overrightarrow{x(t)} \tag{15}$$

where, $\vec{R}$ is the measure of distance, $\vec{R} = \left|\vec{K}.\overrightarrow{x^*(t)} - \overrightarrow{x(t)}\right|$ that denotes the absolute value. $\vec{x}(t+1)$ and $x(t)$ are the positions of the search agent at the current and the previous iteration and the current best solution is denoted as, $\overrightarrow{x^*(t)}$. At the same time, the spiral movement is given as,

$$\overrightarrow{x(t+1)} = \vec{R} * e^{mn}.\cos(2\pi n) + \overrightarrow{x^*(t)} = \left|\vec{K}.\overrightarrow{x^*(t)} - \overrightarrow{x(t)}\right| * e^{mn}.\cos(2\pi n) + \overrightarrow{x^*(t)} \tag{16}$$

where, m refers to the shape of the movement of the whale and it varies randomly in [-1, 1]. The autoregressive model is given as,

$$\vec{x}(t) = \lambda_0 + \sum_{t=1}^{b} \lambda_t \vec{x}(t-1) + \sum_{k=1}^{d} \lambda_k f\left(x_{t-k}\right) \tag{17}$$

where, λ_0 is the unknown parameter, and b and d are the constants. The dimension of the parameter $\lambda = b + d = 1$. $\vec{x}(t-1)$ denotes the position of the agent in the $(t-1)$ and $f\left(x_{t-k}\right)$ refers to the fitness of the solution x_{t-k}. When $b = d = 2$, the autoregressive model becomes,

$$\overrightarrow{x(t)} = \lambda_0 + \lambda_1 \overrightarrow{x(t-1)} + \lambda_2 \overrightarrow{x(t-2)} + \lambda_1 \overline{f\, x[(t-1)]} + \lambda_2 \overline{f[x(t-2)]} \tag{18}$$

The above equation indicates that the position of the search agent is based on the position of the agent in the previous two iterations and the parameters, λ_0, λ_1, and λ_2 are the adaptive parameters that vary from iteration to iteration. Substitute the equation (18) in equations (16) and (15) gives,

$$\vec{x}(t+1) = \overrightarrow{x^*(t)}\left[1 - \vec{P}.\vec{K}\right] + \lambda_0 \vec{P} + \lambda_1 \vec{P}\left[\overrightarrow{x(t-1)} + f\left(z_{t-1}\right)\right] + \lambda_2 \vec{P}\left[\overrightarrow{x(t-2)} + f\left(z_{t-2}\right)\right] \tag{19}$$

$$x(t+1) = \overrightarrow{x^*(t)}\left[1 + e^{mn}.\cos(2\pi n)\right] - \begin{bmatrix} \lambda_0 + \lambda_1 \overrightarrow{x(t-1)} + \lambda_2 \overrightarrow{x(t-2)} + \\ \lambda_1 f\left(z_{t-1}\right) + \lambda_2 f\left(z_{t-2}\right) \end{bmatrix} e^{mn}.\cos(2\pi n) \tag{20}$$

Thus, the position update equation of the proposed algorithm becomes,

$$\vec{x}(t+1) = \begin{cases} \overrightarrow{x^*(t)}\left[1 - \vec{P}.\vec{K}\right] + \lambda_0 \vec{P} + \lambda_1 \vec{P}\left[\overrightarrow{x(t-1)} + f\left(z_{t-1}\right)\right] + \lambda_2 \vec{P}\left[\overrightarrow{x(t-2)} + f\left(z_{t-2}\right)\right] \text{; if } X < 0.5 \\ \overrightarrow{x^*(t)}\left[1 + e^{mn}.\cos(2\pi n)\right] - \begin{bmatrix} \lambda_0 + \lambda_1 \overrightarrow{x(t-1)} + \lambda_2 \overrightarrow{x(t-2)} + \\ \lambda_1 f\left(z_{t-1}\right) + \lambda_2 f\left(z_{t-2}\right) \end{bmatrix} e^{mn}.\cos(2\pi n)\text{; if } X \geq 0.5 \end{cases} \tag{21}$$

where, the adaptive parameters, such as λ_0, λ_1, and λ_2 update adaptively based on the iteration number, fitness of the position, and distance measure. The adaptive factor, λ_0 is termed as the iteration-based adaptive factor that depends on the running iteration and the total number of the iterations and it is given as,

$$\lambda_0 = \frac{t}{p} \tag{22}$$

where, t indicates the t^{th} iteration of the optimization process and p implies the maximum number of iterations. The adaptive parameter, λ_1 is termed as the fitness-based adaptive factor, which is the ratio of the fitness of the position of the agent in the current iteration to the best fitness of the solution given as,

$$\lambda_1 = \frac{\mathrm{Fit}\left(\overrightarrow{x(t)}\right)}{\overrightarrow{x_{best}}} \tag{23}$$

where, $\overrightarrow{x_{best}}$ indicates the best position of the search agent. The third adaptive parameter, λ_2 is termed as the distance-based adaptive parameter given as,

$$\lambda_2 = \frac{\partial\left(\overrightarrow{x(t)}, \overrightarrow{x_{best}}\right)}{M} \tag{24}$$

where, M indicates the normalization factor and $\partial\left(\overrightarrow{x(t)}, \overrightarrow{x_{best}}\right)$ denotes the distance between the current position of the search agent and the best position of the search agent. The adaptive parameters enable the adaptive nature of the algorithm in determining the optimal path.

IV. RESULTS AND DISCUSSION

This section discusses the superiority of the proposed method of traffic-aware routing in VANET.

A. Experimental Setup

The experiment is performed in MATLAB that operates in Windows 8 OS, Intel core i-3 processor, and 2 GB memory that possess the simulation area of 100 x 100. Setup 1, Setup2, and setup 3 comprises of 50, 100, and 200 vehicles in VANET with the simulation time of50, 80, and 100 seconds.

B. Evaluation Metrics

The metrics used for analysis include the following:

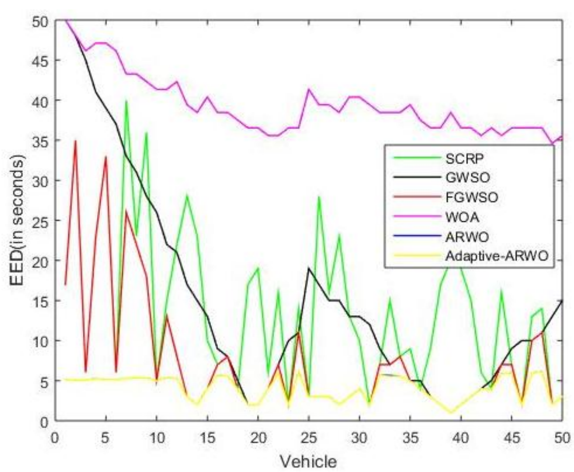
EED is the time taken by the vehicle to reach the destination from the source node. The distance depends on the length of the road segment, the traffic density denotes the number of vehicles in the road at a particular time, and the throughput refers to the number of packets delivered to the destination over simulation time.

C. Comparative Methods

The performance of the proposed method is compared with the Stable CDS-Based Routing Protocol (SCRP) [18], Glow Worm Swarm Optimization (GWSO), Fractional Glow Worm Swarm Optimization (FGWSO), WOA, and Autoregressive+ Whale Optimization (ARWO). GWSO[19], FGWSO, and WOA [14], were applied WOA in the proposed protocol instead of the Adaptive-ARW.

D. Comparative Analysis

a. Analysis using Setup1: Figures 2.a, 2.b, 2.c, and 2.d show the comparative analysis in terms of EED, Distance, average traffic density, and throughput of the proposed method using setup 1. The EED of the methods, SCRP, GWSO, FGWSO, WOA, ARWO, Proposed adaptive-ARWO for 50 vehicles is 2.9412, 14.706, 2.9412, 36.275, 2.9412, and 2.9382, respectively. The EED of the proposed method is less when compared with the other methods. The estimated distance using the proposed algorithm is 2.0823, which is 75.45%, 83.09%, 75.45%, 85.15%, and 0.03% minimum than the distance of the existing methods SCRP, GWSO, FGWSO, WOA, and ARWO. Similarly, the traffic density of the proposed method is less compared with the existing and it acquired a value of 0.0233. The traffic density of the existing SCRP, GWSO, FGWSO, WOA, and ARWO, is0.0294, 0.0344, 0.0263, 0.0252, and 0.0252. The throughput of the proposed method is 0.1354 that is greater than the existing methods SCRP, GWSO, FGWSO, WOA, and ARWO that acquired 0.04, 0, 0.07, 0.06, and 0.05 when the number of vehicles is 50. The throughput of the proposed method is 70.45%, 100%, 48.30%, 55.68%, and 63.07% higher than the existing methods, such as SCRP, GWSO, FGWSO, WOA, and ARWO.



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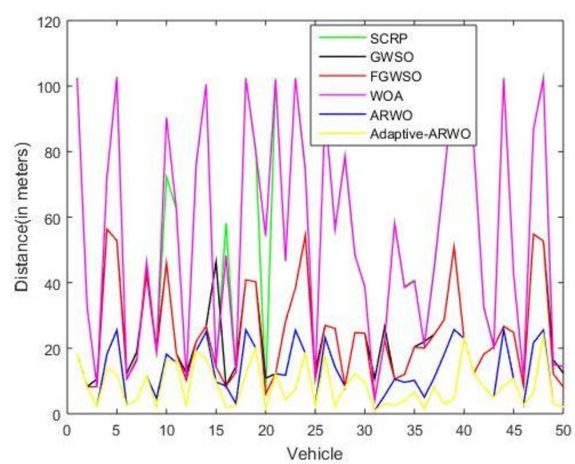

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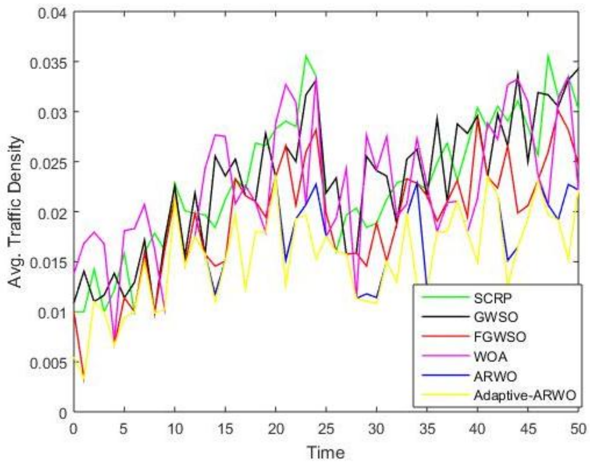

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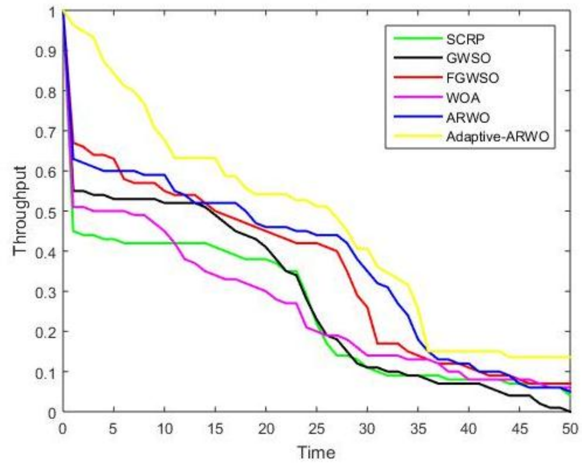
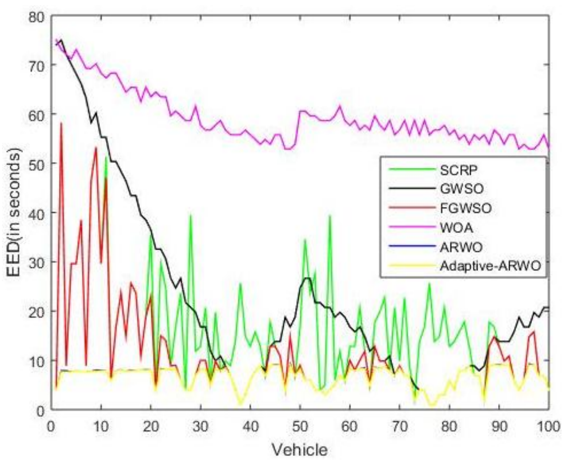


d)

Figure 2. Analysis using setup1 a) EED b) Distance c) Average Traffic density d) Throughput

b. Analysis using Setup2: Figures 3.a, 3.b, 3.c, and 3.dpresent the comparative analysis in terms of EED, Distance, average traffic density, and throughput of the proposed method using setup 2. The EED of the proposed method is 3.8922 for 100 vehicles which is 0.056% minimum than the EED of the SCRP method. The EED of the existing methods GWSO, FGWSO, WOA, ARWO, is 20.455, 3.8961, 55.519, and 3.8961. The EED of the proposed is less when compared with the other methods. The estimated distance using the proposed algorithm is 2.1402, whereas the existing methods SCRP, GWSO, FGWSO, WOA, and ARWO attained the distance value of 8.82, 10.965, 8.6656, 8.4764, and 2.1408. Similarly, the traffic density of the proposed method is less compared with the existing and it acquired a value of 0.015 which is 0.003%, 18.42%, 2.10%, 0.02%, and 0.02% minimum than the traffic density of existing methods SCRP, GWSO, FGWSO, WOA, and ARWO. The throughput of the proposed method is 0.1148 which is 91.28%, 91.28%, 73.86%, 86.93%, and 12.89% higher than the throughput of the existing methods, SCRP, GWSO, FGWSO, WOA, and ARWO when the number of vehicles is 100.



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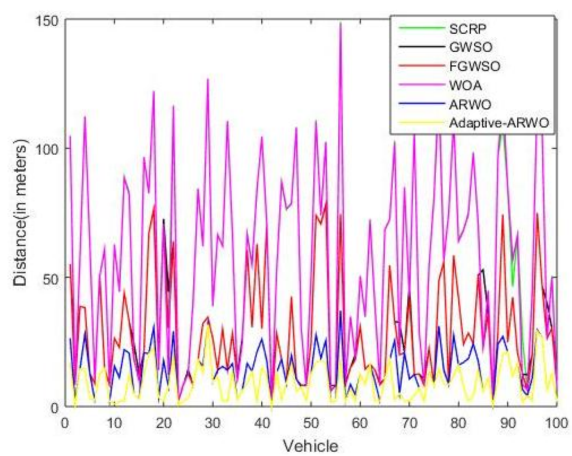

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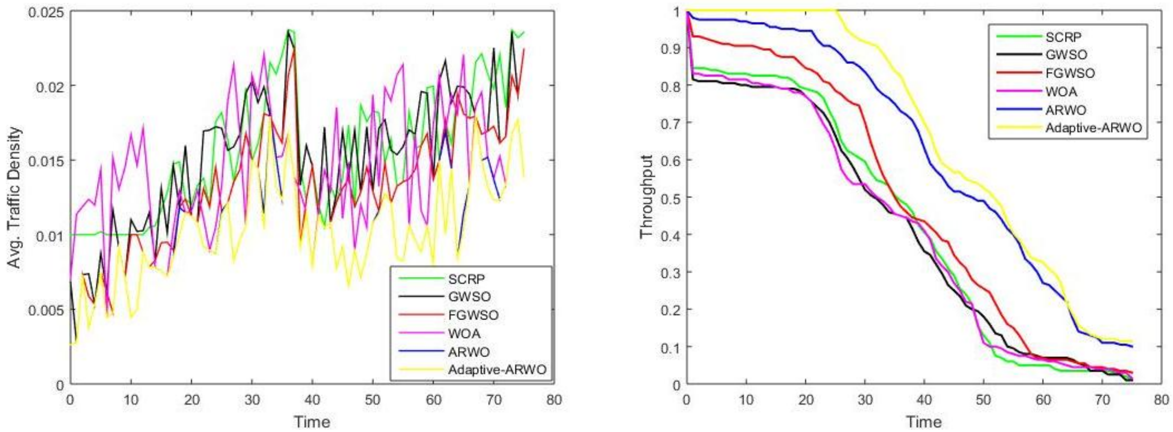
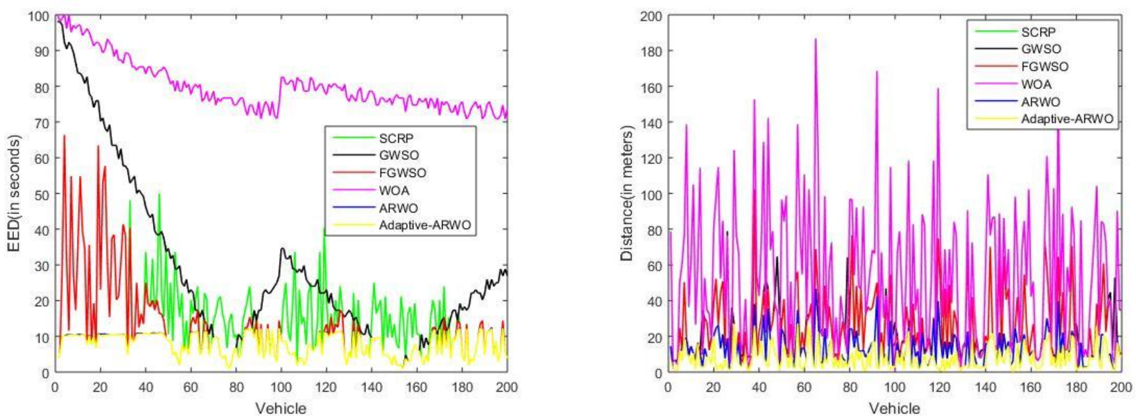


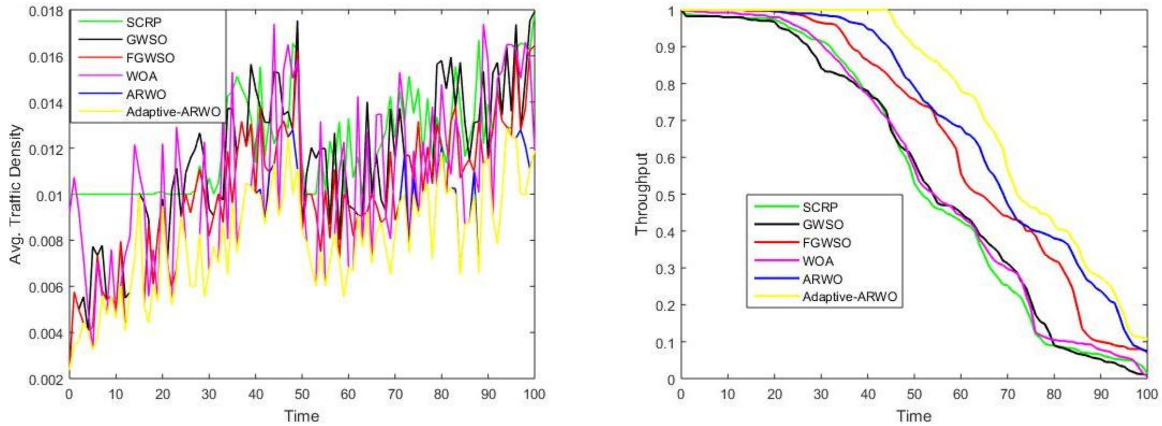
c) d)

Figure 3. Analysis using setup2 a) EED b) Distance c) Average Traffic density d) Throughput

c. Analysis using Setup3: Figures 4.a, 4.b, 4.c, and 4.d depict the comparative analysis in terms of EED, Distance, average traffic density, and throughput of the proposed method using setup 3. The EED of the methods SCRP, GWSO, FGWSO, WOA, ARWO, Proposed adaptive-ARWO for 200 vehicles is 6.666, 27.619, 6.666, 71.429, 6.667, and 6.66. The EED of the proposed is less when compared with the other methods. The estimated distance using the proposed algorithm is 8.5569, whereas the existing methods SCRP, GWSO, FGWSO, WOA, and ARWO attained the distance value of 33.924, 10.33, 10.33, 34.626, and 8.5595. Similarly, the traffic density of the proposed method is less compared with the existing and it acquired a value of 0.0095. The traffic density of the proposed method is 47.8%, 37.5%, 19.49%, and 48.64% lesser than the traffic density of the existing methods SCRP, GWSO, FGWSO, and WOA. The throughput of the proposed method is 0.1077 that is 88.39%, 93.03%, 35%, 95.35%, and 30.36% greater than the existing methods SCRP, GWSO, FGWSO, WOA, and ARWO.



a) b)



c) d)

Figure 4. Analysis using setup3 a) EED b) Distance c) Average Traffic density d) Throughput

V. CONCLUSION

A traffic-aware routing protocol, named as an Adaptive-ARW algorithm, is proposed for traffic aware routing in VANETs. At first, the traffic in the VANET is predicted using the EWMA, and the predicted values are employed for determining the optimal path which is determined by the adaptive autoregressive WOA. The three adaptive factors, such as iteration-based, fitness-based, and distance-based adaptive parameters, are the major contribution of this paper. These parameters adjust the search agents' optimal position depending on the number of iterations, fitness of the current position, and distance between current and best position of the search agent. The performance of the proposed method is analyzed on Setup 1, Setup2, and setup 3 comprises of 50, 100, and 200 vehicles in VANET with the simulation time of 50, 80, and 100 seconds. The proposed routing protocol attains a minimum EED of 2.938, the minimum distance of 2.08, minimum average traffic density of 0.0095, and maximum throughput of 0.1354.

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