

Research Article

A Mobility-Aware Link Enhancement Mechanism for Vehicular Ad Hoc Networks

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With the growth up of internet in mobile commerce, researchers have reproduced various mobile applications that vary from entertainment and commercial services to diagnostic and safety tools. Mobility management has widely been recognized as one of the most challenging problems for seamless access to wireless networks. In this paper, a novel link enhancement mechanism is proposed to deal with mobility management problem in vehicular ad hoc networks. Two machine learning techniques, namely, particle swarm optimization and fuzzy logic systems, are incorporated into the proposed schemes to enhance the accuracy of prediction of link break and congestion occurrence. The experimental results verify the effectiveness and feasibility of the proposed schemes.

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1. INTRODUCTION

With the growth up of internet in mobile commerce (m-commerce), service subscribers, providers, content developers, and researchers have reproduced various mobile applications, including context-aware services, mobile financial services, massively multiplayer online games, and mobile auctions. Most of these applications can be accessed via personal digital assistants or mobile phones. However, it is impractical or dangerous to use handhelds during car driving due to the limited abilities of handhelds.

In recent years, enabling new m-commerce applications for drivers or passengers in motor vehicles becomes possible owing to the explosive growth in wireless local area network (WLAN) devices and wireless networking technologies. These applications are varied from entertainments and commercial services to diagnostic and safety tools. However, there are several challenges need to be tackled before vehicular *m*-commerce are realized.

Wireless mobile ad hoc networks (MANETs) technology promises delivery of network access area without the need of infrastructure, which is required by other technologies. There have been several researches [1, 2] on the construction

of ad hoc network among vehicles in the early stage of development of MANETs. Recently, the usage of MANETs as a base technology in intervehicle communication (IVS) has gained popularity due to its potential applications, such as providing support for intelligent transportation systems (ITSs) and expediting internet access in highways.

It is well known that the major challenge for designing routing protocols in MANETs is to find a path from the source to the destination without any preconfigured information or regularly varying link situations. The position-based routing becomes a suitable candidate for vehicular ad hoc networks (VANETs) because this kind of routing protocol depends on geographic position information only and the information can be easily obtained by navigation systems, such as GPS [3, 4].

Mobility management [5, 6] has been widely recognized as one of the most challenging problems for seamless access to wireless networks [7]. Most researches involved discussions of some node mobility models that exhibit the dominating effect of mobility on MANET performance [8–10]. It is necessary to generate synthetic movement patterns in these analytical models since real-life traces are difficult to obtain. Many literature works show that the performance

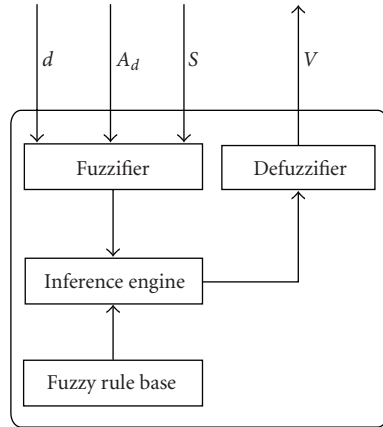


FIGURE 1: The fuzzy speed prediction module.

of a MANET heavily depends on the appropriate choice of a mobility model. There are two main aspects that need to be considered in mobility management; one is location management and the other is connection management. In this work, we mainly focus on connection management.

Most studies on mobility of MANET protocols [11, 12] focus on node mobility in various environments in which a mobile node might randomly change its speed and direction. Moreover, vehicle movements are often expressed by extending these models and are typically related to road traffic condition and are restricted to one dimension. Thus, several traffic models [13–15] that represented vehicles as randomly moving particles do not fit for realistic traffic pattern. In this work, we proposed an alternative link construction mechanism based on the prediction of possible link break and congestion. A fuzzy congestion detector and a fuzzy link break predictor are proposed to determine whether alternate route construction process should be activated. Particle swarm optimization (PSO) technique is used to adjust the parameters of the membership functions employed in the fuzzy logic systems in order to deal with the volatile characteristics of the VANET. A series of experiments were conducted to compare the proposed scheme with other representative ad hoc routing protocols in the literature, including the well-known AODV routing protocol and a recently presented state-of-the-art ad hoc routing protocol in the literature, congestion-adaptive routing protocol (CRP) [16]. In CRP, the number of packets currently buffered in interface is defined as network load and the congestion is classified into different statuses. If congestion is detected at a node, a bypass route is used to ease the congestion. The experimental results showed that the proposed work achieves better performance than other representative schemes in the literatures in terms of several performance metrics such as packet delivery ratio, end-to-end delay, and control overhead.

The remainder of this paper is organized as follows. Section 2 presents the proposed link enhancement mechanisms. The simulation results are given in Section 3. Conclusion is made in Section 4.

2. PSO-TUNED FUZZY LINK CONNECTIVITY ENHANCEMENT MECHANISM

In the VANETs, the robust connectivity can be established by offering alternative routing paths whenever the broken link event or the congestion event occurs on the routing path. In this work, a link failure avoidance module and a congestion detection module, which are mainly composed of fuzzy logic systems, are used to predict possible link event and congestion occurring at each node. Meanwhile, we adopt particle swarm optimization technique to adjust the parameters of the membership functions employed in the proposed fuzzy logic systems.

2.1. Constructing alternate route based on link break indicator

In order to prevent link break caused by mobility, we use mobility pattern, including the distance between two consecutive vehicles, driver's age, and the current speed of the vehicle as the inputs to the fuzzy speed prediction module to estimate the vehicle's speed during the next time period. Notably, the distance between two consecutive vehicles is chosen as one of the parameters because it can be used as the essential indicator of whether two vehicles are able to communicate with each other. When two vehicles move apart by a distance greater than the communication range, their link is assumed to be broken. The driver's age is adopted as the second parameter here because it was observed that the driver's age has direct impact on his/her driving behavior [17–19]. Older participants were found to make more mistakes than younger participants in both real and simulated driving tasks [17], and older drivers require closer distances to correctly perceive the orientation of the letter on the nighttime highway sign [18]. In addition, older participants tend to overestimate speed at lower velocities, underestimate speed at higher velocities, and make less accurate time-to-contact estimates than younger drivers [19]. Last but not least, the current speed of a moving vehicle is used as the third parameter because it was adopted to determine whether a link between two vehicles keeps connected and was helpful to provide reliable connections among vehicles in a VANET routing protocol [20]. Other factors, such as "wearing glasses" and "weather", are not considered in this work because no evidence has yet shown that they can influence the driving behavior, to the best of our knowledge.

Once a vehicle's speed and those of its neighbors during the next time period are estimated, we can easily determine whether the vehicle is within the communication range of its neighbors by computing the distances between the vehicle and its neighbors during the next time period. In case the vehicle's position is expected to be out of the communication of its neighbors during the next time period, the vehicle can initiate a backup route construction process to prevent link failure caused by mobility of vehicles via piggybacking link break warning message to its neighbors.

2.1.1. Fuzzy speed prediction module

The fuzzy logic techniques have been used to solve several resource assignment problems efficiently in ATM and wireless networks in the literature [21]. We thus employ fuzzy logic systems to determine the vehicle's speed during the next time period.

Figure 1 shows the architecture of the fuzzy speed prediction module. The basic functions of the components in the module are described as follows.

- (i) *Fuzzifier*. The fuzzifier performs the fuzzification function that converts three inputs into suitable linguistic values which are needed in the inference engine.
- (ii) *Fuzzy rule base*. The fuzzy rule base is composed of a set of linguistic control rules and the attendant control goals.
- (iii) *Inference engine*. The inference engine simulates human decision making based on the fuzzy control rules and the related input linguistic parameters.
- (iv) *Defuzzifier*. The defuzzifier acquires the aggregated linguistic values from the inferred fuzzy control action and generates a non-fuzzy control output, which represents the predicted speed.

Notably, the input to the fuzzifier d represents the distance between the vehicle and its front vehicle, the input A_d denotes the driver's age, and S stands for the current speed of the vehicle. The fuzzy linguistic variables "close", "intermediate", and "far" give different distance measures in the membership function for d . Three linguistic term sets, "young", "middle", and "old", are used for A_d , and "slow", "medium", and "fast" are used for S . The output parameter of the inference engine, V , is defined as the estimated speed of the vehicle during the next time period. The fuzzy linguistic variables for the output of the inference engine, V , are "slow", "medium", and "fast".

Figure 2 illustrates the reasoning procedure. The rule as given in Figure 2 is defined as

IF the distance measure between the vehicle and its front vehicle is "intermediate", **AND** the driver's age is "young", **AND** the current speed of the vehicle is "slow", **THEN** the estimated speed of the vehicle during the next time period is "slow".

The nonfuzzy output of the defuzzifier can then be expressed as the weighted average of each rule's output after the Tsukamoto defuzzification method is applied:

$$V = \frac{\sum_{i=1}^{27} V_i \cdot w_i}{\sum_{i=1}^{27} w_i}, \quad (1)$$

where V_i denotes the output of each rule induced by the firing strength w_i . Notably, w_i represents the degree to which the antecedent part of each fuzzy rule constructed by the connective "AND" as shown in the above example is satisfied.

Once a vehicle's speed and those of its neighbors during the next time period are estimated, we can easily determine whether the vehicle is within the communication range of its

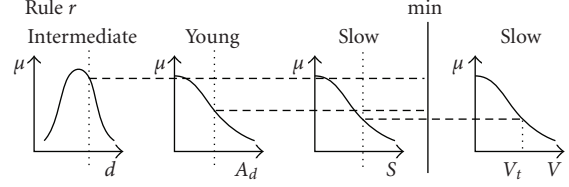


FIGURE 2: The reasoning procedure for Tsukamoto defuzzification method.

neighbors by computing the distances of the vehicle and its neighbors during the next time period as follows:

$$\vec{p}_{\text{next}} = \vec{v}_{\text{self}} \cdot t - \vec{v}_{\text{neighbor}} \cdot t + \vec{p}_{\text{cur}}, \quad (2)$$

where \vec{v}_{self} and $\vec{v}_{\text{neighbor}}$ denote the speed of the vehicle and that of its neighbor vehicle during the next time period, respectively, t represents the length of a single time interval, and \vec{p}_{cur} is the current position of the vehicle.

2.1.2. Complexity analysis of fuzzy speed prediction module

A summary of the standard fuzzy logic algorithm is given in Algorithm 1. Let m and n_i represent the number of the input parameters and the counts of the linguistic variables used for the i th input parameter, respectively. The reasoning procedure for each rule is realized during each iteration of the FOR loop in the algorithm. Notably, trapezoidal membership functions are employed in the algorithm to reduce the computation complexity. As illustrated in Algorithm 1, two additions and one division instructions are required for computing the membership degree of m input parameters in the fuzzifier module, one addition and m multiplication instructions are needed for the inference engine, and two additions and one multiplication instructions are expected in the defuzzifier module. At the last iteration of the FOR loop, one more division instruction is needed to derive the final defuzzified output. Accordingly, the total number of instructions required for the computation of the fuzzy logic algorithm includes $5 \cdot \prod_{i=1}^m n_i$ additions, $(m + 1) \cdot \prod_{i=1}^m n_i$ multiplications, and $1 + \prod_{i=1}^m n_i$ divisions.

2.2. Congestion avoidance mechanism

In case congestion occurs in a node along the routing path, we allow the congested node to piggyback congestion information in the data packets to its neighbors for notifying the occurrence of the congestion. Once the message is received by its downstream neighbor, the downstream node will reinitiate route discovery process to construct a new route to the destination.

2.2.1. Fuzzy congestion detection module

We utilize fuzzy logic systems to determine whether congestion might occur at a node. As shown in Figure 3, there are three parameters for the fuzzy congestion detection module to avoid occurrence of possible node congestion.

```

Input:  $m$  parameters  $(p_1, p_2, p_3, \dots, p_m)$ .
Output: The weighted average of each rule's output after the Tsukamoto defuzzification method,  $V$ 
Initialize  $N = 0, D = 0$ , where  $N$  and  $D$  denote the numerator and the denominator of (1), respectively.
FOR  $j = 1$  to  $\prod_{i=1}^m n_i$ 
  // The reasoning procedure for the  $j$ th rule.
  //  $n_i$ : the number of linguistic variables for the  $i$ th parameter.
  // Fuzzifier
  // Compute the membership degree of  $m$  input parameters in each rule.
  // Trapezoidal-type membership functions are adopted here to simplify the computation.
  FOR  $i = 1$  to  $m$ 
    
$$L_j^i(p_i) = \begin{cases} 0 & p_i \leq a_{j,i} \\ \frac{p_i - a_{j,i}}{b_{j,i} - a_{j,i}} & a_{j,i} \leq p_i < b_{j,i} \\ 1 & b_{j,i} \leq p_i < c_{j,i} \\ \frac{d_{j,i} - p_i}{d_{j,i} - c_{j,i}} & c_{j,i} \leq p_i < d_{j,i} \\ 0 & d_{j,i} \leq p_i \end{cases}$$

    //  $p_i$  is the  $i$ th parameter,  $\forall i \in [1, m]$ .
    //  $a_{j,i}, b_{j,i}, c_{j,i}$ , and  $d_{j,i}$  denote the four intersection points of the two legs and the two bases of the  $i$ th trapezoidal-type membership function used in the  $j$ th rule.
  END FOR
  // Inference Engine
  // Derive the output of the  $j$ th rule,  $V_j$ , induced by the firing strength  $w_j$ .
   $w_j = L_j^1(p_1) \cdot L_j^2(p_2) \cdot \dots \cdot L_j^m(p_m)$ ,
  
$$V_j = \begin{cases} A_j & 0, \\ B_j + w_j \cdot C_j & 0 < w_j < 1, \\ D_j & 1, \end{cases}$$

  //  $w_j$  is the consequence inferred from product inference engine.
  //  $A_j, B_j, C_j$ , and  $D_j$  are the four intersection points of the two legs and the two bases of the trapezoidal-type membership function used for the consequence in the  $j$ th rule.
  // Defuzzifier
  // The non-fuzzy control output  $V$  is generated by the Tsukamoto method.
   $N = V_j \cdot w_j + N$ 
   $D = w_j + D$ 
  IF  $j = \prod_{i=1}^m n_i$  Then
     $V = \frac{N}{D}$ .
  END IF
END FOR

```

ALGORITHM 1: Fuzzy logic algorithm.

The input qL denotes the queue length, $numP$ stands for the hop counts that the packet travels through the vehicles, and S represents the expected number of the vehicles within radio range of the vehicle during the next time period. The defuzzified output is the congestion indicator. Among the three input parameters, the queue length is defined as the number of packets that is currently buffered in its interface queue [22]. When a vehicle does not have enough buffers to accommodate data packets originated from the new route, it is easy for the new route to cause congestion. In [23], the significance of hop counts on the network capacity is analytically demonstrated, and the impact of this parameter on the tradeoff between the throughput and the end-to-end delay in multihop wireless networks is studied in [24]. Hop counts also affect the target

searching cost and latency in most existing ad hoc routing protocols [25]. The use of the third parameter, the expected number of the vehicles within radio range of the vehicle during the next time period, is motivated by the report given in [26]. It was observed that the number of vehicles within radio range sharply increases when vehicles encounter congestion.

Figure 4 illustrates an example of the reasoning procedure for the fuzzy congestion detection module. This example rule can be interpreted by

IF the queue length qL is “middle”, **AND** the hop counts that the packet travels through the vehicles $numP$ is “less”, **AND** the expected number of the vehicles within radio range of the vehicle during the next time period S is “less”, **THEN** the degree of congestion Cg is “low”.

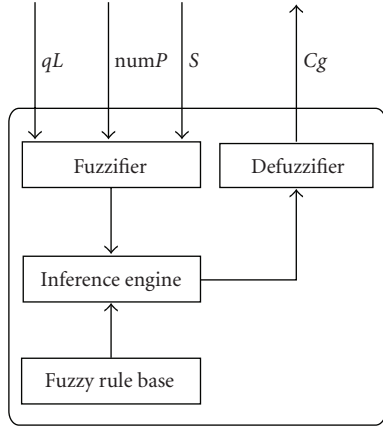


FIGURE 3: The fuzzy congestion detection module.

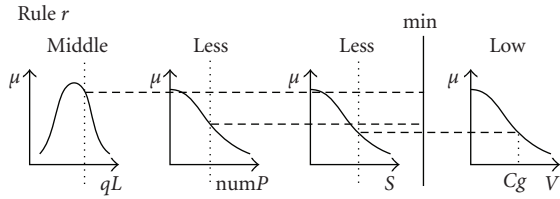


FIGURE 4: The reasoning procedure for Tsukamoto defuzzification method.

2.2.2. Alternate route construction process

Figures 5 and 6 show the construction process of the alternate path that prevents the congestion or link break. Consider a path S-A-B-C-D constructed as illustrated in Figure 5. When there is a possible congestion or link break detected at node B, it sends a congestion/link break warning message to all its neighbors. As node A receives the message, it reinitiates route discovery process with congestion/link break indicator piggybacked in the data packets to find an alternate path to destination D. Thus, new arrived data packets can then be delivered via a new path S-A-E-C-D as shown in Figure 6.

2.3. Particle swarm optimization

Particle swarm optimization (PSO) is a computational intelligence approach to optimization that is based in the behavior of swarming or flocking animals, such as birds or fishes. In PSO, every individual moves from a given point to a new one which is a weighted combination of the individual's best position ever found, and of the group's best position. The PSO algorithm itself is simple and involves adjusting a few parameters. With little modification, it can be applied to a wide range of applications. Because of this, PSO has received growing interest from researchers in various fields.

In this work, we allow each vehicle to execute its individual PSO algorithm in order to adapt to the volatile VANET environment. The motivation of using PSO in the fuzzy speed prediction module and fuzzy congestion detection module is to provide learning and adapting capability in

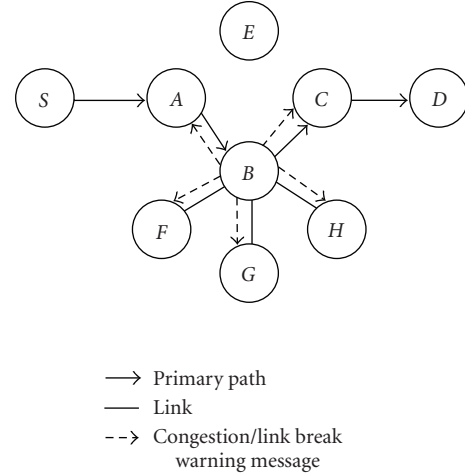


FIGURE 5: Congestion/Link break warning message.

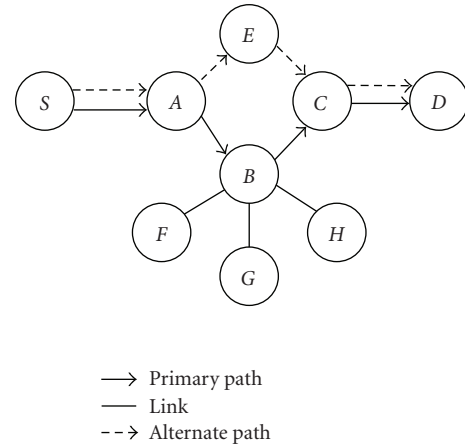


FIGURE 6: Alternate path construction.

the traditional fuzzy modeling approach. The target objects to be tuned include the mean and the variance of each membership function in the fuzzy logic rules. To speed up the learning process, the fuzzy speed prediction module and fuzzy congestion detection module employs the predefined membership functions as the initial premise membership functions in order to avoid starting tuning procedure from scratch. The learning set which contains the training data to train the system is obtained by collecting the data from the two above-mentioned modules when the performance metric, packet delivery ratio, is higher than some predefined threshold for several consecutive time intervals. In addition, the learning process will be reactivated whenever the packet delivery ratio drops below a preset threshold for several consecutive time intervals in order to adapt to the volatile VANET environment. Notably, packet delivery ratio is defined as the percentage of data packets received at the destinations out of the number of data packets generated by the sources [16]. Similar to the approach taken in the AODV, an acknowledgment (ACK) packet is sent back to the

source node when the destination node receives a data packet in order to certify that each packet is successfully delivered to the destination. If the source node does not receive an ACK packet within a short period of time, either because its data packet was damaged or because the returning ACK packet was damaged, the source node rediscovers a path. Through counting the data packets and the ACK packets that pass through, the nodes on the transmission path can accordingly compute the packet delivery ratio that is used as the performance metric for the PSO algorithm.

A standard PSO algorithm maintains a swarm of particles that represent the potential solutions to the problem on hand. In this work, each particle $\vec{P}_i = \vec{x}_{i1} \times \vec{x}_{i2} \times \vec{x}_{i3} \times \vec{x}_{i4} \times \vec{x}_{i5} \times \vec{x}_{i6}$ embeds the relevant information regarding the six decision variables that correspond to the means and variances of the three premise membership functions. These particles fly through hyperspace and have two essential reasoning capabilities, including their memory of their own best positions and the knowledge of the global or their neighborhood's best ones. Members of a swarm communicate good positions to each other and adjust their own positions and velocities based on these good positions.

The PSO algorithm employed in this work can be summarized by the following.

- (1) Initialize the swarm of the particles such that the position $\vec{x}_{ij}(t = 0)$ of each particle is random within the hyperspace.
- (2) Compare the fitness function of each particle, $F(\vec{x}_{ij}(t))$, which is the packet delivery ratio of each individual during the current time period, to its best performance thus far, $pbest_{ij}$: if $F(\vec{x}_{ij}(t)) < pbest_{ij}$, then

$$\begin{aligned} \text{(i)} \quad & pbest_{ij} = F(\vec{x}_{ij}(t)), \\ \text{(ii)} \quad & \vec{x}_{pbest_{ij}} = \vec{x}_{ij}(t). \end{aligned} \quad (3)$$

- (3) Compare $F(\vec{x}_{ij}(t))$ to the global best particle, $gbest_j$: if $F(\vec{x}_{ij}(t)) < gbest_j$, then

$$\begin{aligned} \text{(i)} \quad & gbest_j = F(\vec{x}_{ij}(t)), \\ \text{(ii)} \quad & \vec{x}_{gbest_j} = \vec{x}_{ij}(t). \end{aligned} \quad (4)$$

- (4) Revise the velocity for each particle:

$$\begin{aligned} \vec{v}_{ij}(t) = & \vec{v}_{ij}(t-1) + c_1 \cdot r_1 \cdot (\vec{x}_{pbest_{ij}}(t) - \vec{x}_{ij}(t)) \\ & + c_2 \cdot r_2 \cdot (\vec{x}_{gbest_j}(t) - \vec{x}_{ij}(t)), \end{aligned} \quad (5)$$

where r_1 and r_2 are random numbers between 0 and 1, and c_1 and c_2 are positive acceleration constants, which satisfy $c_1 + c_2 \leq 4$ as suggested in [27].

- (5) Move each particle to a new position:

$$\begin{aligned} \text{(i)} \quad & \vec{x}_{ij}(t) = \vec{x}_{ij}(t-1) + \vec{v}_{ij}(t), \\ \text{(ii)} \quad & t = t + 1. \end{aligned} \quad (6)$$

Repeat steps (2) through (5) until convergence.

TABLE 1: Simulation parameters.

Parameter type	Parameter value
Simulation time	500 sec
Simulation terrain	1000 m \times 1000 m
Number of vehicles	50
Traffic flow	0.1 ~ 0.5 veh/sec
Traffic model	microscopic model
Mobility	10 ~ 30 m/s
Channel bandwidth	2 Mbps
Mac protocol	802.11
Transmission range	33.75 m
CBR data sessions	25

3. SIMULATION RESULTS

We ran a series of simulations to evaluate the performance of the proposed work by using a network simulator written by C++. We chose AODV [28] as the base routing protocol since the AODV is capable for both unicast and multicast routing, and the route discovery is simply on-demand. The compared schemes include the proposed alternate route construction mechanisms embedded with PSO-tuned fuzzy inference system (MAODV-PF), the alternate route construction mechanisms embedded with traditional fuzzy inference system (MAODV-F), the alternate route construction mechanism based on link break indicator alone (MAODV), the pure AODV, and a recently introduced state-of-the-art routing protocol, CRP [16].

3.1. Simulation scenario

The simulation environment is a 1000 \times 1000 square meter, and 50 vehicles are randomly distributed within the network. In order to simulate the road traffic, the traffic flow is simulated with microscopic model [29]. The detailed simulation parameters are listed in Table 1. Notably, CBR/UDP traffic is generated between randomly selected pairs of vehicles and the bandwidth for each channel is 2 Mbps. The CBR data packet size is 512 byte and the packet rate is 4 packets per second. Each vehicle moves along the direction of the pathway, and the speed is randomly changed within a preset range that is related to the driver's age and the distance between the vehicle and its front vehicle. Once it reaches that position, it will change its speed and repeat the process.

3.2. Simulation results and analysis

We first investigate the impact of the vehicle speed on the packet delivery ratio, end-to-end delay, and control overhead. The vehicle speed is varied from 10 m/s to 30 m/s, the traffic flow is fixed at 0.1 veh/sec. As shown in Figure 7, it is observed that CRP and AODV simply drop data packets when the route is disconnected, packet delivery ratios for these two schemes are thus worse than that for the proposed MAODV-PF and MAODV-F schemes. The proposed MAODV-PF and MAODV-F have better packet

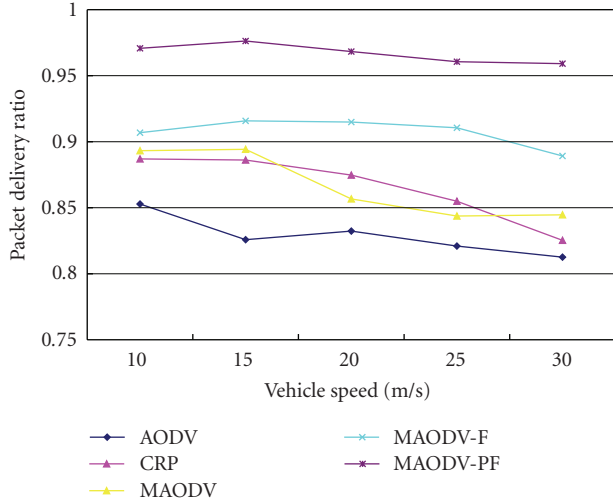


FIGURE 7: Packet delivery ratios for CRP, AODV, MAODV, MAODV-F, and MAODV-PF under different moving speeds.

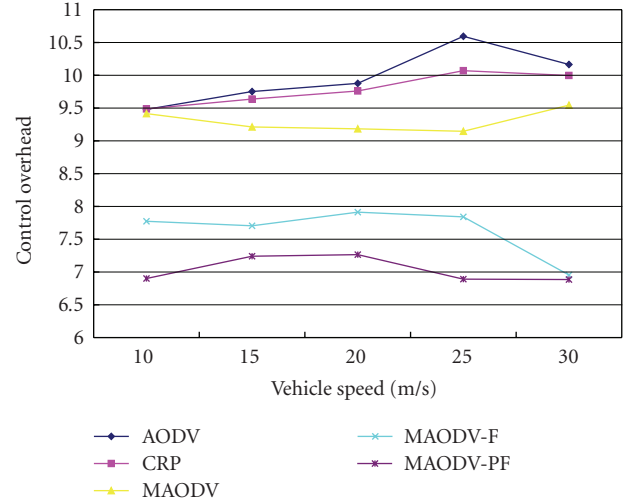


FIGURE 9: Control overhead for CRP, AODV, MAODV, MAODV-F, and MAODV-PF under different moving speeds.

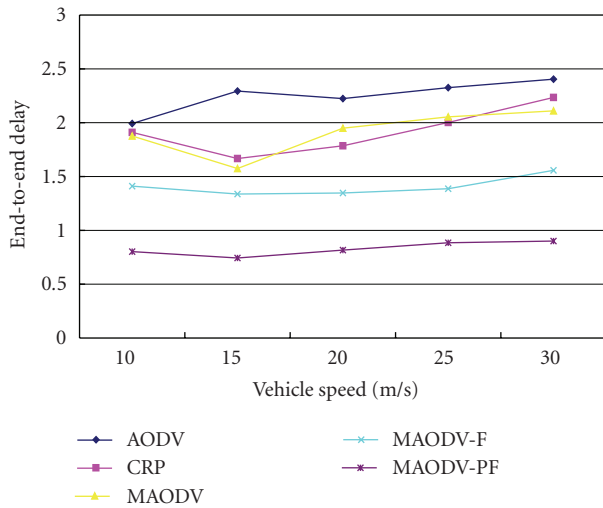


FIGURE 8: End-to-end delays for CRP, AODV, MAODV, MAODV-F, and MAODV-PF under different moving speeds.

delivery ratio since they construct alternate path in case they predict a link break. The one embedded with PSO-tuned fuzzy logic systems, MAODV-PF, achieves better accuracy on the prediction of congestion and link break indicators than MAODV-F and MAODV due to the effective tuning of the parameters used in the fuzzy inference systems.

Figure 8 shows the end-to-end delays for the five schemes under different moving speeds. Notably, the end-to-end delay is defined as the accumulative delay in data packet delivery due to buffering of packets, new route discoveries, queuing delay, MAC-layer retransmission, transmission and propagation delays [16], and other processing delays such as the calculation of the PSO calculation time and fuzzy inference time. The delay is measured for those data packets traveling from the source vehicle to the destination vehicle. The proposed MAODV-PF scheme has the best performance

since it is able to rapidly find an alternative path to reinitiating packet transmission through backup route mechanism. It not only transmits data packets through shorter path but also prevents losing data packet caused by link break. On the contrary, AODV has the longest end-to-end delay owing to spending extra time for new route discovery and queuing delay.

Figure 9 shows the control overhead for the five schemes under different moving speeds. The control overhead is the required number of control packets that completes a data transmission. Apparently, CRP, MAODV, and AODV have much higher control overhead than the MAODV-F and MAODV-PF schemes. It can be inferred that the accurate prediction of link break and congestion occurrence significantly reduces control overhead owing to the avoidance of link failures and congestions. The prediction accuracy comparisons for the CRP, MAODV-F, and MAODV-PF schemes under different moving speeds are given in Table 2. The results exhibit that the PSO-tuned fuzzy inference system can indeed accurately predict link break and congestions. In case a link break or a congestion condition is not detected by the proposed scheme, our scheme will follow the approach taken in AODV to initiate a new route discovery in order to find an alternate route.

Figures 10 and 11 demonstrate the impact of different traffic flows on the network performance. As shown in Figure 10, the proposed MAODV-F and MAODV-PF schemes have better packet delivery ratios than CRP and AODV as expected. We believe the congestion prediction mechanism embedded in the proposed schemes assists the networks in constructing the alternate route to transmit packet through congestion-free path. On the other hand, AODV and MAODV discard more packets because of congestion and thus have poorer packet delivery ratios.

Figure 11 shows the end-to-end delays for the five schemes under different traffic flows. The proposed schemes embedded with congestion avoidance mechanism have

TABLE 2: The prediction accuracy comparison for CRP, MAODV-F, and MAODV-PF under different moving speeds.

Schemes	Vehicle speed				
	10 (m/s)	15 (m/s)	20 (m/s)	25 (m/s)	30 (m/s)
CRP	69.99%	70.92%	69.14%	69.05%	66.00%
MAODV-F	79.44%	78.19%	77.30%	74.57%	72.57%
MAODV-PF	91.48%	89.12%	88.05%	85.75%	84.35%

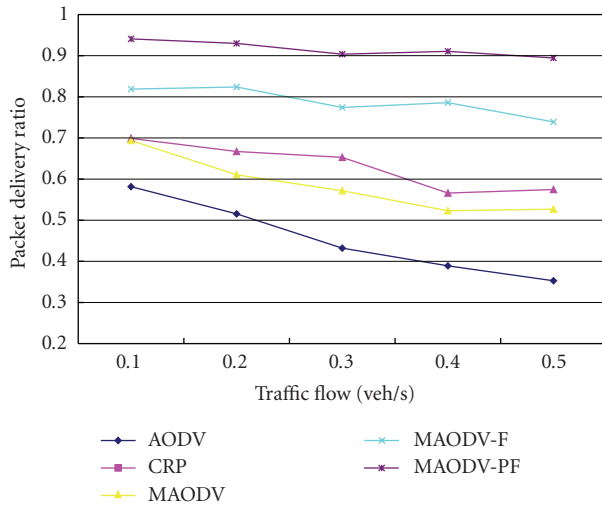


FIGURE 10: Packet delivery ratios for CRP, AODV, MAODV, MAODV-F, and MAODV-PF under different traffic flows.

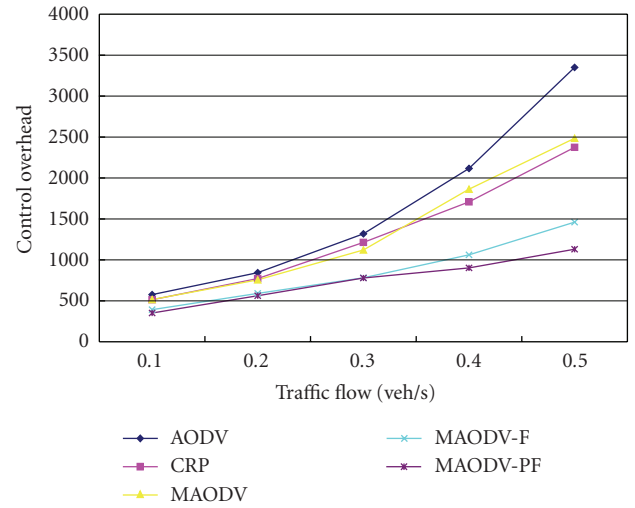


FIGURE 12: Control overhead for CRP, AODV, MAODV, MAODV-F, and MAODV-PF under different traffic flows.

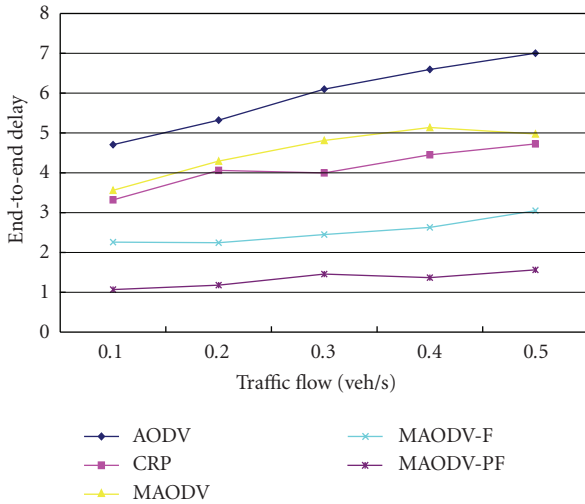


FIGURE 11: End-to-end delays for CRP, AODV, MAODV, MAODV-F, and MAODV-PF under different traffic flows.

short delay time than those without congestion avoidance mechanisms since more packets are transmitted via congested nodes in the latter schemes. The proposed schemes, MAODV-F and MAODV-PF, have better end-to-end delays than CRP and AODV. Evidently, MAODV-F and MAODV-PF conform to real-time applications with the specific

QoS requirement. It is observed that each vehicle spent 17.6 milliseconds in executing its individual PSO algorithm during training process in average, and the time taken by the prediction mechanism is averagely 4.48 milliseconds during each time interval, which is set to one second in this work. Therefore, the complexity overhead introduced by the proposed algorithm applied in the real-time applications. In addition, there are lots of solutions on chips that allow fuzzy inferences to be hardware-computed and high-speed, low-cost fuzzy chips have been introduced recently. The implementation of fuzzy logic by hardware thus becomes feasible nowadays.

The control overhead for the five schemes under different traffic flows is shown in Figure 12. We can see that more control packets are required to keep network topology updated when the traffic flow becomes heavy in the schemes without the aid of the congestion avoidance mechanism. The last but not the least, it can be inferred from Figures 7–12 that the PSO algorithm can effectively adapt the parameters of the membership functions employed in the fuzzy logic systems to the volatile change of network topology in the VANETs.

The prediction accuracy comparisons for the CRP, MAODV-F, and MAODV-PF schemes under different traffic flows are given in Table 3. Again, the results verified that the PSO-tuned fuzzy inference systems built in this work indeed accurately predicted the possible link breaks and congestions.

TABLE 3: The prediction accuracy comparison for CRP, MAODV-F, and MAODV-PF under different traffic flows.

Schemes	Traffic flow				
	0.1 (veh/sec)	0.2 (veh/sec)	0.3 (veh/sec)	0.4 (veh/sec)	0.5 (veh/sec)
CRP	58.38%	54.13%	47.98%	36.74%	27.32%
MAODV-F	61.64%	65.48%	63.84%	64.47%	55.97%
MAODV-PF	86.79%	87.49%	85.00%	86.43%	75.24%

4. CONCLUSION

In this paper, a link enhancement mechanism for VANETs is proposed. Alternate route construction mechanism and congestion avoidance mechanism based on mobility pattern are presented to prevent the link failures caused by vehicle movements and the congestion occurrences. Fuzzy logic systems are used as the core modules in the link enhancement mechanism to generate the link break and congestion indicators that can be piggybacked in the data packets to inform the neighboring vehicles. Meanwhile, particle swarm optimization technique is adopted to dynamically tune the parameters of the membership function employed in the fuzzy systems to adapt to the volatile characteristics of VANETs. The simulation results show that the proposed alternate route construction mechanism based on mobility pattern can improve the performance metrics, including packet delivery ratio, control overhead, and end-to-end delay, owing to the effective prevention of the link breaks and congestion occurrences caused by varied vehicle movements and traffic flows. The feasibility of the proposed link enhancement mechanism is thus verified.

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