Vehicular Communications 17 (2019) 1–9

Contents lists available at ScienceDirect

Vehicular Communications

www.elsevier.com/locate/vehcom

Adaptive optimization of QoS constraint transmission capacity of VANET

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ARTICLE INFO

Article history:
Received 29 September 2018
Received in revised form 23 February 2019
Accepted 21 March 2019
Available online 27 March 2019

Keywords:
Vehicle-to-vehicle communication
Security and privacy
ITS
Transmission capacity
PSO

ABSTRACT

Safety applications would be one of the most important on-board implementations in Vehicular Ad-hoc Network (VANET). Broadcasting the Basic Safety Message (BSM) periodically could help drivers increase their awareness range for preventing casualties of traffic accidents or reducing the number of traffic accidents. Usually, the safety applications have more stringent performance requirements (e.g. time delay and reliability) than other kinds of applications. However, because the vehicle density and speed are both changed frequently, the optimal network transmission parameters should not remain the same. So, setting constant transmission parameters in all conditions may cause problems, such as channel congestion, packet collisions and so on, which could degrade Quality of Service (QoS) of safety applications. For the purpose of maximizing the transmission capacity and keeping the application-level QoS of safety applications meeting their requirements, this paper proposes an optimization scheme with standard Particle Swarm Optimization (PSO) to adjust transmission parameters dynamically. The experimental results show that the optimized transmission parameters can get better results on transmission capacity and awareness probability compared with the transmission parameters which are used in real testbeds.

1. Introduction

Vehicular Ad-hoc Network (VANET) is one of the key components in Intelligent Transportation System (ITS). Vehicles can communicate with each other directly via the VANET without central control infrastructure. Dedicated Short Range Communication (DSRC) radio technology, being standardized as IEEE 802.11p [1], is projected to support low-latency wireless data communications between vehicles and from vehicles to roadside units. With the VANET capability, safety messages of vehicles, such as position, velocity, and direction can be broadcasted by vehicles to their adjacent vehicles periodically to reduce the frequency and severity of traffic accidents [2], which is called basic (beacon) safety message (BSM) or Cooperative Awareness Messages (CAMs) [3].

VANET could support multiple safety applications using one-hop or multi-hop broadcasting to disseminate safety-related messages, e.g., Cooperative Collision Warning (CCW) [4], Slow vehicle Indication (SVI) [5], and Rear-end Chain Collision Warning (RCW) [6], etc. As they are safety-related, it is important to guarantee the low latency and high reliability of the BSM transmission to ensure different Quality of Service (QoS) for different applications.

Many investigations on QoS of BSM dissemination over MAC-level have been done and several important reliability metrics are proposed and evaluated by analytical models or empirical models, for example, Packet Reception Probability (*PRP*), Packet Reception Ratio (*PRR*) and Packet Delivery Ratio (*PDR*), etc. [7–10]. However, these MAC-level indices couldn't characterize the reliability of some safety applications [11] that have combined stringent delay limits and reliability requirements. So, some studies have given application-level (APP-level) reliability metrics for safety applications. Bai et al. [12] characterized the reliability of safety applications using application latency and T-Window Reliability (*TWR*), where *TWR* is defined as the probability of successfully receiving at least one packet out of multiple packets from a broadcast vehicle within a given time T_a (referred to as application tolerance window). In [11], the author extended *TWR* and proposed the concept of Awareness Probability, which is depicted as the probability of successfully receiving at least n packets within the time window T_a. The above measurements are expressed as a function of *PRP* and affected by network transmission parameters, hidden

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https://doi.org/10.1016/j.vehcom.2019.03.005
2214-2096/

terminals, channel fading, and other issues. The transmission capacity denotes the capability that the DSRC communication system could provide to the end users [13], and [14,15] gave the definition of transmission capacity, theoretically analyzed the upper bound as well as the lower bound of the DSRC. The decreasing transmission capacity could definitely affect the reliability of the application awareness, hence, the reliability and the transmission capacity should be combined to analyze the DSRC system. To the best of our knowledge, there have been no works to analyze the composite metric of reliability and the transmission capacity at the same time.

However, since the vehicle density and driving speed are both highly dynamically changed under various vehicular environments [16,17], fixed transmission parameters may not be able to always meet the requirements of the safety applications and might cause issues, such as channel congestion, data packet collisions, and communication signal attenuation and fading. Therefore, the motivation of this paper is trying to adjust transmission parameters dynamically according to the local network conditions to ensure the APP-level QoS of safety applications while guaranteeing the maximization of the transmission capacity.

Lots of works are trying improving the QoS of VANET by adapting network and MAC-layer parameters. Van Eenennaam et al. [18] proposed a scheme by tunning the beaconing frequency adaptively to improve the cooperative awareness in a scalable manner. S. Rezaei [19] first studied the adaptation of beacon generation rate in order to compromise between information accuracy and bandwidth consumption. And then they proposed a scheme to adapt beacon rate according to the VANET traffic behavior. However, in their study, reliability metrics were not included. In [20], Kayhan Zrar Ghafoor proposed an intelligent Adaptive Beaconing Rate (ABR) approach based on fuzzy logic to control the frequency of beaconing by taking traffic characteristics into consideration. The proposed ABR considers the percentage of vehicles traveling in the same direction, and status of vehicles as inputs of the fuzzy decision-making system, in order to tune the beaconing rate according to the vehicular traffic characteristics. However, this work just adjusted the beaconing rate to balance the traffic load and the cooperative awareness between vehicles, without considering the communication as well as the application QoS metrics.

Nguyen et al. [21] proposed a broadcast frame adjustment algorithm, that could support broadcast services on the control channel by adjusting the broadcast frame length efficiently. Rani and Tarannum [17] proposed an Adaptive Medium Access Control (AMAC) scheduler for prioritized multi-channel DSRC based Vehicle-to-Vehicle communication in IEEE 802.11p MAC protocol, and the results showed that AMAC performs better than existing Non-Cooperative Cognitive Multiple Access in terms of collision, successful packet transmission and throughput efficiency. Patel et al. [22] proposed an adaptive transmission power scheme based on transmission range and vehicle density to improve the Average Connected Coverage of VANET, and then they proposed a new adaptive transmission Range and clear channel assessment (CCA) power scheme to enhance the Average Connected Coverage of VANET [23].

Although some of those works [18–20,24,25] took various factors into consideration, only beacon generation rate was adjusted. Other works also contributed to adapting other parameters, such as contention window [26], transmission power [22,23], frame length [21] and so on. But with one transmission parameter adjusted, it might not utilize most of the channel capacity of the VANET. Moreover, the APP-level QoS of safety applications and transmission capacity were not included at the same time in these works. With that in mind, an optimization scheme to adjust transmission parameters dynamically is proposed in terms of these two factors, which is also the innovation of this paper.

As for optimization, heuristic-based methods are relatively more popular in VANET that involves complex real-world problems. A survey [27] showed that the majority of researchers are using heuristics based population for resolving the routing problem in both MANET and VANET. The exploitation and exploration are the two main parts of the heuristic algorithms, and different algorithms have different implementations and weights of these two strategies. With the simple and clear formula, the Particle Swarm Optimization (PSO) algorithm could identify these two parts clearly. And as a tradeoff between performance and explicit, PSO has become one of the most popular algorithms among Swarm Intelligence (SI) algorithms [28]. Some works further pointed out that the PSO algorithms perform excellently for some particular optimization problems [29]. e.g., PSO and DPSO are the best algorithms for maximizing the area coverage in Wireless Sensor Networks [30], and the experiments showed that PSO algorithms have better performance in both computational time and solution quality than other existing ones. Multi-objective PSO algorithms [31–33] were proposed to solve the cost-based or unreliable data based feature selection problems. Moreover, the comparative study showed that these proposed algorithms could produce highly competitive solution sets with respect to convergence, diversity, and distribution. Also, a modified particle swarm optimization [34] was proposed as a cooperative strategy for a multi-robot system, so that the odor source could be located rapidly and accurately.

In this paper, the combination of transmission parameters of VANET are adjusted dynamically to let the APP-level reliability meets the requirements of safety applications, and at the same time, the transmission capacity would be approached to maximizing the utilization of the VANET. To this end, the system reliability is assessed to confirm its availability in the first step of the optimization model. Then, for the reasons given above, a standard PSO algorithm is used to adjust the beacon generation rate simultaneously along with other transmission parameters, such as data rate and contention windows, to approach the transmission capacity.

As illustrated in our experiments, the results obtained by the conventional PSO based algorithm can fully meet the requirements of safety applications, which means the selected PSO algorithm is sufficient to the optimization task in this paper. For more complex optimization problem extended from this paper in the future, other excellent modified version of PSO could be used in the subsequent works, such as adaptive bare-bones PSO [35], quantum-behaved PSO [36], and so on.

The main contributions of this paper are two folds:

- An optimization scheme is proposed to adjust transmission parameters according to the VANET conditions, in order to keep the reliability meeting the requirements of safety applications in a highly dynamically changed vehicular environment.
- Because of the real-time requirements of VANET optimization, it is important to choose an algorithm with small complexity and fast convergence. An appropriate PSO algorithm and its hyperparameters are found and tested in this paper.

This paper adopts many mathematical symbols, so in addition to giving definitions of the symbols in the context, a summary of these symbols is given in Table 1 to make this paper more readable.

The rest of this paper is organized as follows. Section 2 gives a brief introduction of the Awareness probability analytical model. An optimization-based framework of our model and its implementation are presented in Section 3. Then in Section 4, the numerical results are demonstrated and discussed. And the paper is concluded in Section 5.

Table 1
Summary of symbols.

Symbols	Descriptions
O	transmitter, node who transmits data
U	receiver, node who receives data
x	distance between node O and node U
R	transmission range
λ	beacon generation rate, each vehicle generates packets following Poisson point process
β	node density, vehicles randomly placed on a straight line according to a Poisson point process with node density β (vehicles/m)
C_N	number of cars, $C_N = \beta * 1000$ m
P_0	the probability of at least one packet ready to transmit at the MAC layer in each vehicle
W	802.11 CSMA back-off window size
T	time period to suspend a back-off timer
R_d	system transmission data rate
$E[L_p]$	average packet length
L_H	length of packet header
δ	propagation delay
$DIFS$	the time period for a DCF (distributed coordination function) inter-frame space
σ	slot time duration
$\overline{n}_\Sigma$	the average number of nodes transmitting in the concurrent slot in the area $[-(R-x), R]$
TR_y	reception threshold, a packet can be received if the signal is stronger than TR_y
m	shape parameter of *Nakagami* distribution
ω	average power strength received at node U
P_A	awareness probability, the probability of at least n packets received successfully every second at node U
T_a	application tolerance window
N_{ROI}	the number of nodes in the region of interest
ξ	P_A threshold of APP-level QoS requirement
n	minimal packets required by applications in every second
w	inertia weight of PSO algorithm
c_1	local acceleration coefficient of PSO
c_2	global acceleration coefficient of PSO
T_n	the time complexity to computing P_A in specific model
n_p	the number of particles in PSO algorithm
n_{1st}	the max number of iterations in the first step of proposed scheme
n_{2nd}	the max number of iterations in the second step of proposed scheme
$\boldsymbol{X}$	position of a PSO particle
$\boldsymbol{X}_{i,pbest}$	the best historical location of particle i of PSO
$\boldsymbol{X}_{gbeat}$	the best historical location of global solution of PSO
$\boldsymbol{V}$	velocity of a PSO particle

2. Awareness probability analytical model

Deriving Packet Reception Probability (*PRP*) from the transmission parameters of VANET is the first step in assessing the system reliability and approaching the transmission capacity of the VANET. And it can be done in three ways: a) analytic model in [9]; b) SIR model in [37]; c) empirical model in [38]. In this paper, we use the model proposed in [9], which takes IEEE 802.11 MAC, 1-D highway geometry and non-saturated message arrival interval into account. As for the channel fading, there are various models proposed for analyzing the impact of wireless communication channels [39], such as log-distance path loss [40], Weibull distribution [41], Gaussian distribution [42]. Among these models, actual measurements indicated that the *Nakagami* distribution fits the amplitude envelope of signal transmitting on DSRC channel better to VANET [43,44]. So, the *Nakagami* fading channel with path loss is also taken into consideration. We briefly introduce this analytic model in this section to keep the paper self-contained. There are five assumptions made in [9] shown as follows:

1. The model is based on a one-dimensional broadcast VANET scenario, which consists of a collection of mobile vehicles randomly placed on a straight line according to a Poisson point process with node density β (in vehicles per meter);

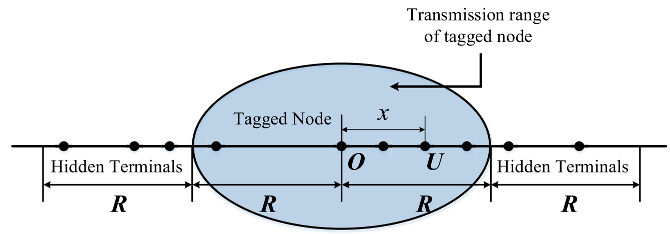


Fig. 1. One-dimensional VANET model.

2. All vehicles in the VANET have identical transmission range, receiving range, and carrier sensing range, which is denoted as R;
3. At each vehicle, packet arrivals follow Poisson point process with rate λ (in packets per second), according to [45]. And the queue length of packets at each vehicle is unlimited;
4. *Nakagami* fading model is assumed for analyzing the impact of channel fading [38];
5. Impacts of vehicle mobility on the reliability are neglected.

The transmission scenario considered in [9] is shown in Fig. 1. Set the origin at the position of tagged transmitting node O, U is one of the receivers and has a certain distance $x \in (0, R)$ to O, R is the transmission range. There are three factors need to be considered when deriving the *PRP*, which are hidden terminal problem, concurrent transmission collisions, and packet errors caused by fading with path loss.

2.1. Impact of hidden terminals

Two necessary conditions must be satisfied to avoid the impact of hidden terminals. First, event H_1 represents none of the hidden terminal vehicles are in the transmitting state when the tagged node starts its transmission. Second, event H_2 represents none of the hidden terminal vehicles start transmitting during the tagged node broadcasting a packet.

Considering that event H_1 is the complement of the event of existing at least one hidden terminal in the transmitting state, the probability of H_1 can be described as:

$$P_{H_1}(x) = 1 - \frac{1}{2} x\beta\lambda T (1 + e^{\frac{-2\beta R P_0}{W+1}}) \tag{1}$$

where P_0 is the probability that there is at least one packet ready to transmit at the MAC layer in each vehicle, which could be iteratively calculated [9], W represents the 802.11 CSMA back-off window size, and T is a time period to suspend a back-off timer when a node with packets detects an ongoing transmission, which is expressed as:

$$T = (L_H + E[L_P])/R_d + DIFS + \delta \tag{2}$$

where R_d is system transmission data rate, $E[L_P]$ represents an average packet length, L_H is the length of packet header, δ is the propagation delay and *DIFS* is the time period for a DCF (distributed coordination function) inter-frame space.

Event H_2 occurs if none of the hidden terminal generated packet during the transmission excluding *DIFS* from the tagged vehicle. Given that H_1 is true, the probability that none of a packet is generated by any hidden vehicle during the transmission of the tagged node could be expressed as:

$$P_{H_2}(x) = \frac{(\beta x)^0}{0!} e^{-\beta x \lambda \frac{L_H + E[L_P]}{R_d}} = e^{-\beta x \lambda \frac{L_H + E[L_P]}{R_d}} \tag{3}$$

2.2. Impact of concurrent transmission collisions

Another condition to cause the collision is that other nodes within the transmission range of the tagged node transmit packets concurrently with the tagged vehicle. Given Poisson node distribution, the probability that none of the nodes within the reception range of U start transmission at the same time with U is:

$$P_{conc}(x) = \frac{(\overline{n}_\Sigma)^0}{0!} e^{-\overline{n}_\Sigma} = e^{-\overline{n}_\Sigma} \tag{4}$$

where $\overline{n}_\Sigma$ is the average number of nodes transmitting in the concurrent slot in the area $[-(R-x), R]$.

2.3. Impact of channel fading with path loss

Considering the *Nakagami* distribution, the probability that a packet is successfully received in the absence of interferes can be equal to the probability that the packet's signal is stronger than the reception threshold TR_y given in *Friis* model [38],

$$\begin{aligned} P_F(y > TR_y) &= 1 - F_{cd}(TR_y, m, \omega) \\ &= 1 - \frac{m^m}{\Gamma(m)\omega^m} \int_0^{TR_y} z^{m-1} e^{-(m/\omega)z} dz \end{aligned} \tag{5}$$

where m denotes fading parameter, ω is the average power strength received at node U, then we could obtain the expected probability of successfully receiving a message at distance x:

$$P_F(x) = 1 - \frac{(x^2 m)^m}{\Gamma(m)} \int_0^{1/R^2} z^{m-1} e^{-x^2 m z} dz \tag{6}$$

Taking the four factors mentioned above into account, the Packet Reception Probability, which is the probability of the node U successfully receives the broadcast message from the tagged node O, can be expressed as:

$$PRP(x) = P_{H_1}(x) P_{H_2}(x) P_{conc}(x) P_F(x) \tag{7}$$

After the *PRP* is derived, the awareness probability $P_A(x, n, T_a)$ [11], an APP-level reliability metrics, can be calculated as follows:

$$P_A(x, n, T_a) = \sum_{k=n}^{\lfloor \lambda T_a \rfloor} \binom{\lfloor \lambda T_a \rfloor}{k} PRP(x)^k (1 - PRP(x))^{\lfloor \lambda T_a \rfloor - k} \tag{8}$$

where T_a is referred to as application tolerance window.

3. Optimization model of QoS constraint transmission capacity

3.1. Framework of adaptive optimization model

The purpose of this article is to dynamically adjust network parameters, making the network meets the QoS requirements of safety applications and at the same time approximating the transmission capacity as much as possible, to maximize the utilization of the VANET under specific conditions.

The QoS constraint transmission capacity [46] is defined as the number of nodes (N_{ROI}) in the region of interest (*ROI*) of the tagged node times the maximum beacon generation rate (λ) at which each source node transmits in a VANET with optimized vehicular communication settings for a specific safety application within its region of interest d_{ROI} such that the awareness of its one-hop surrounding vehicles can be achieved with the required QoS. According to the definition mentioned above, the transmission capacity (*TC*) can be formulated as:

Table 2
The QoS requirements of typical safety applications.

Safety applications	CCW	SVI	RCW
Distance x	400 m	100 m	50 m
Tolerance time T_a	1 s	1 s	1 s
Minimal packets required n	1	3	5
Awareness probability P_A	99.0%	99.9%	99.9%

$$TC = \max(N_{ROI}\lambda) \tag{9}$$

In a particular time slot, it is less likely that the number of nodes N_{ROI} could get changed, so to approximate the transmission capacity, the beacon generation rate should be set as large as possible. To this end, there are two main steps of the adaptive optimization model: assessing the system reliability and optimizing the communication settings.

For a network in a specific state, the first step is to assess whether the entire network is likely to meet the safety application requirements, that is $\max P_A \geq \xi$ [11], where ξ is the threshold of APP-level QoS requirement, and P_A can be derived from the model introduced in Section 2 and optimized by adjusting the DSRC network parameters. If $\max P_A < \xi$, which means the capacity of the network is not enough to sustain the safety application, then other methods need to be adopted, for example, borrow the spectrum resources from other channels in the same system or from other networks, such as LTE cellular network, TV network, WiMAX and so on, which are beyond the scope of this article.

And if there is at least one set of the parameters that allows P_A to meet the QoS requirement of the specific safety application, then the model could go into the second step, which would further improve the performance of VENET to approximate the *TC* under the requirement of QoS. Then the channel utilization of the VANET could be maximized, and the reliability of safety-related applications could be guaranteed.

Because there is a large solution space due to various combinations of parameters, using the heuristic algorithm would be a good idea to reduce the search range in the solution space and improve the optimization convergence speed for real-time adjustment.

3.2. First step: assessing the system reliability

Each safety application has its own specific QoS requirement for awareness probability P_A, for example, Table 2 shows the most stringent QoS requirements of three typical safety applications [5, 47].

The combination of transmission parameters (such as beacon generation rate λ, 802.11 CSMA back-off window size W, data bit rate R_d) could be regarded as a point in a high dimensional solution space. Given a specific safety application (e.g. CCW) and the local transportation environment, several points could be set randomly in the solution space to find out if there is at least one point that can meet the APP-level QoS requirement of the safety application.

At each iteration, the solution space of P_A is randomly searched and the threshold of safety application reliability ξ is compared with the current global maximum P_A, marked as $P_{A\max}$. If a suitable $P_{A\max}$ is found, i.e. $P_{A\max} \geq \xi$, it means the current communication system is able to meet the reliability requirement of the safety application. Then the assessment process could be stopped and the transmission capacity of the VANET will be optimized in the second step. Otherwise, if the termination condition is reached but fails to find a $P_{A\max}$ that meets the QoS requirement, it indicates the system cannot meet the QoS requirement of the safety application. In this case, other measures should be taken. The detailed implementation is presented by pseudo code in Algorithm 1.

Algorithm 1 Assessing the awareness probability of VANET.

Input: $n, T_a, \xi, \beta, x, E[L_p], L_H, \delta, DIFS$.
Output: the evaluation result: True or False.

for each round of iteration **do**
  for each point $\boldsymbol{X}$ **do**
    $\boldsymbol{X} = rand(\lambda, W, R_d)$
    Calculate fitness value $P_A(\boldsymbol{X})$
  end for
  Choose the point with the biggest P_A of all particles as $P_{A\max}$
  if $P_{A\max} \geq \xi$ **then**
    return True
  end if
  if Iteration termination condition achieved **then**
    return False
  end if
end for

3.3. Second step: optimizing the communication settings

After a positive result is given by the first step, the communication settings can be further optimized to approximate the transmission capacity with the constraint of QoS requirement of specific safety application. The heuristic algorithm can be used to maximize the beacon generation rate λ in a candidate solution set, whose elements can make the VANET system meet the P_A threshold. The optimization goal and constraint can be formulated as follows:

$$\begin{aligned} &\lambda_{\max} = \arg\max_{\lambda} TC(N_{ROI}, \lambda) \\ &\text{subject to } P_A(\lambda, W, R_d) \geq \xi \end{aligned} \tag{10}$$

where ξ is the safety application reliability requirement, which may be specified from different safety applications [48].

3.3.1. Particle Swarm Optimization (PSO)

As shown in Eq. (10), couples of parameters need to be adjusted when searching a P_A that can meet the requirements ($P_A \geq \xi$) of safety applications and at the same time maximizing the transmission capacity by optimizing the beacon generation rate λ. Some of the parameters, such as 802.11 CSMA back-off window size W and beacon generation rate λ, might have a large range of values, so the number of combination of the transmission parameters might be enormous or even infinite. Thus, the enumeration is not an optional method to search the global optimum. Hence one of the swarm intelligence algorithms, Particle Swarm Optimization (PSO) [49], could be used to optimize the transmission parameters.

The PSO imitates the behavior of birds feeding, the main idea of this algorithm is that the birds flock gradually move towards the bird who has the shortest distance to food. That is, the algorithm searches the solution space in the direction of the current optimal solution in an iterative manner to obtain the globally optimal solution to the problem. In the optimization process, each solution in the solution space can be regarded as a foraging bird, called particle, and the global optimal solution is the food.

Each particle i has two properties, position $\boldsymbol{X}_i$ and velocity $\boldsymbol{V}_i$, which are used to optimize the particles position. The position $\boldsymbol{X}_i = (X_{i1}, X_{i2}, \cdots, X_{in})$ is a multi-dimensional vector and its elements $\boldsymbol{X}_i[n]$ could be the parameters to be adjusted, in this paper $\boldsymbol{X}_i[1] = \lambda$, $\boldsymbol{X}_i[2] = W$, and $\boldsymbol{X}_i[3] = R_d$. And the basis for adjustment is the best historical location of each particle ($\boldsymbol{X}_{i,pbest}$) and the best historical location of global solution ($\boldsymbol{X}_{gbest}$). The process of adjustment can be presented as follows:

$$\begin{aligned} \boldsymbol{V}_i = & w * \boldsymbol{V}_i + c_1 * rand() * (\boldsymbol{X}_{i,pbest} - \boldsymbol{X}_i) \\ & + c_2 * rand() * (\boldsymbol{X}_{gbest} - \boldsymbol{X}_i) \end{aligned} \tag{11}$$

$$\boldsymbol{X}_i = \boldsymbol{X}_i + \boldsymbol{V}_i \tag{12}$$

where w is the weight of inertia, representing the impact of the last velocity. c_1 and c_2 are the learning factor used to control the influence from particle itself and other particles.

3.3.2. Transmission capacity approximation

Having clarified that the network can meet the QoS requirements of safety applications, the transmission capacity can be further optimized to improve the utilization of the VANET. As described in Section 3.1, $TC = \max\{N_{ROI}\lambda\}$, where N_{ROI} is the number of nodes in the region of interest, and λ is the beacon generation rate. However, within a certain period of time, the number of nodes N_{ROI} is relatively stable and cannot be actively adjusted, the only way to approximate the transmission capacity is to obtain the maximum λ, that is $\lambda_{\max} = \arg\max_{\lambda} TC(N_{ROI}, \lambda)$. After P_A of each particle is calculated, among the particles who meet the constraints ($P_A \geq \xi$), the particle with the current maximum λ will be picked as the goal of next iteration. The specific optimization steps are described as follows:

1. Initialize the transmission parameters of VANET, such as n, T_a, ξ, $DIFS$ and so on;
2. Initialize the parameters of PSO algorithm and particles: w, c_1, c_2 and randomly initialize each parameter of particle position vector according to the particle swarm size n_p and set the initial value of the global optimum beacon generation rate;
3. Calculate the awareness probability P_A with the model proposed in Section 2;
4. Forming a satisfying set with particles who meet the requirement $P_A > \xi$;
5. Update $\boldsymbol{X}_{pbest}$ of each particle and $\boldsymbol{X}_{gbest}$ in terms of λ;
6. Update speed and position of each particle with Eq. (11) and Eq. (12);
7. Repeat step 3 to step 6 until the program reached the preset termination condition;
8. Output the current globally optimal value, that is, the optimal solution to the optimization problem, and end the algorithm.

The pseudo-code of the above beacon generation rate optimization process is shown in Algorithm 2.

3.4. Time complexity of the optimization model

To ensure that the parameters can be adjusted in real time, it is important to reduce the time complexity of the optimization model, which will be derived in this subsection.

There are various models to derive the *PRP* as a function of the transmission parameters of VANET, hence the time complexity for calculating the awareness probability could be different. Let the time cost of this process be T_n, which is independent of data volume and would varies with different analytical models and the accuracy of the numerical algorithm, take the model employed in this paper as an example, the mean and standard deviation of runtime over 10 experiments are 41.86 ms and 2.93 ms, respectively. Besides, let the number of particles be $n_p \in [10, 100]$, the max number of first and second step iterations be $n_{1st} \in [10, 100]$ and $n_{2nd} \in [10, 100]$, respectively.

So, in each iteration of the first step, there are three substeps, which are initialization, calculating P_A for each particle and finding out whether the particle which meets the requirement of safety application exists. The time complexity of these three processes are $O(n_p)$, $O(n_p)T_n$ and $O(n_p)$, respectively. At a certain accuracy of the numerical algorithm, T_n would approach constant, then the total time complexity of the first step would be:

$$(O(n_p) + O(n_p)T_n + O(n_p))O(n_{1st}) = O(n_p n_{1st}) \tag{13}$$

Algorithm 2 Optimizing process of beacon generation rate.

Input: $n, T_a, \xi, \beta, x, E[L_p], L_H, \delta, DIFS, w, c_1, c_2$.
Output: $\boldsymbol{X}$ with the biggest λ, where $P_A(\boldsymbol{X}) \geq \xi$.

for each particle $\boldsymbol{X}$ **do**
  $\boldsymbol{X} = rand(\lambda, W, R_d)$
  $\boldsymbol{X}_{pbest}$ = None
end for
$\boldsymbol{X}_{gbest}$ = None
for each round of iteration **do**
  for each particle $\boldsymbol{X}$ **do**
    Calculate awareness probability P_A
    if $\boldsymbol{X}_{pbest} == None$ and $P_A \geq \xi$ **then**
      $\boldsymbol{X}_{pbest}$ = $\boldsymbol{X}$
    end if
  end for
  for each $\boldsymbol{X}$ in $\{particles | P_A \geq \xi\}$ **do**
    if $\boldsymbol{X}_{gbest} == None$ **then**
      $\boldsymbol{X}_{gbest}$ = $\boldsymbol{X}$
    end if
    if λ from $\boldsymbol{X}$ is greater than the λ from $\boldsymbol{X}_{gbest}$ **then**
      $\boldsymbol{X}_{gbest} = \boldsymbol{X}$
    end if
    if λ from $\boldsymbol{X}$ is greater than the λ from $\boldsymbol{X}_{pbest}$ **then**
      $\boldsymbol{X}_{pbest} = \boldsymbol{X}$
    end if
  end for
  for each particle $\boldsymbol{X}$ **do**
    update velocity in Eq. (11)
    update position in Eq. (12)
  end for
end for

Table 3
Program environment configurations.

Module	Model
Mainboard	LENOVO Provence-5R3
OS	Windows 10 64-bit
CPU	Intel(R) Core(TM) i5-7300HQ CPU @ 2.50GHz
Memory	Samsung DDR4 2400MHz 8G*2
Primary hard drive	NVMe SAMSUNG MZVLW128

The second step of the optimization model consists of initialization and a PSO algorithm. And the PSO mainly includes calculating P_A, updating the global and local optimum position and updating the position of each particle. So, the time complexity of the second step would be:

$$O(n_p) + (O(n_p)T_n + 2O(n_p) + O(n_p))O(n_{2nd}) = O(n_p n_{2nd}) \quad (14)$$

It can be seen from the above analysis results that the optimization algorithm only adds the linear time of particle number n_p and iteration times n_{1st}, n_{2nd} on the original analytical model. So, from this point of view, the optimization model is able to meet the requirement of timeliness.

4. Experiments

4.1. The experimental setting

Algorithm 1 and Algorithm 2 are implemented with Python 3.6 in this paper. And the experiment platform is shown in Table 3.

Transmission parameters used in real testbeds [50,51] are set as a control group of the experiments. The range of transmission parameters, which are optimized in experiments, are shown in Table 4 with the control group. In addition, the randomly combined transmission parameters employed in [9,51] would be compared with the optimized parameters in experiments.

As suggested in [52,53], the hyperparameters of PSO employed in the experiments are also shown in Table 4. Three transmission parameters (λ, R_d, W) are adjusted in the optimization process, and we call each combination of those parameters as a particle of PSO. The particles move among the solution space according to the optimization goals.

Table 4
Parameters of transmission, circumstance and PSO.

Parameters	Control group	Range
λ (packets/s)	10	$10 \sim 40$
W (µs)	15	$15 \sim 1024$
R_d (Mbps)	24	$3 \sim 54$
C_N (/km)	400	$20 \sim 400$
$DIFS$ (µs)	64	–
σ (µs)	16	–
R (m)	500	–
x (m)	400	–
$E[L_P]$ (bytes)	200	–
L_H (bits)	400	–
w	0.792	$0.4 \sim 0.9$
c_1	1.49445	$0.5 \sim 2.5$
c_2	1.49445	$0.5 \sim 2.5$
n_p	50	$10 \sim 100$

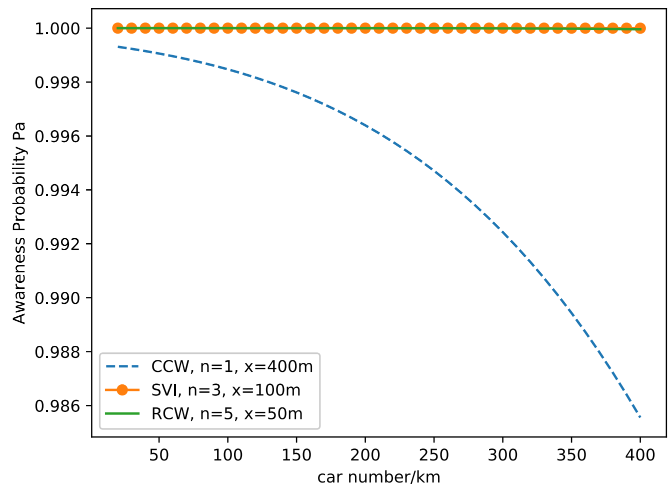


Fig. 2. The awareness probability with fixed parameters in a strict scenario.

4.2. Experimental results and discussions

4.2.1. Necessity of dynamic adjustment

The awareness probabilities of three typical safety applications with fixed transmission parameters (see Table 4) are shown in Fig. 2. It can be seen that with the density of vehicles increasing, it is possible that the values of P_A may not meet the requirements of some of the safety applications. For example, as shown in Fig. 2, it can not meet the requirement of CCW when the density is higher than 350 per kilometer. The results are due to the fact that the longer propagation distance and the higher vehicle density on the road, the receiver will be more likely affected by the hidden terminal problem and channel fading.

With the requirement of CCW application (Table 2) and the fixed parameters (Table 4), the awareness probabilities with different λ are shown in Fig. 3. As demonstrated in Section 2, the awareness probability P_A could be affected by several factors including those not being discussed in this paper, such as average packet length $E[L_p]$ and slot time duration σ. And the results also prove it clearly that simply increasing λ is not a good choice to approximating transmission capacity (defined in Eq. (8)) under the requirements of APP-level QoS ($\xi = 99.0\%$).

Fig. 2 and Fig. 3 illustrate that due to the rapid changes in the circumstance of VANET, it is necessary to adjust multiple parameters simultaneously to ensure that the QoSs could meet the respective requirements of the safety applications.

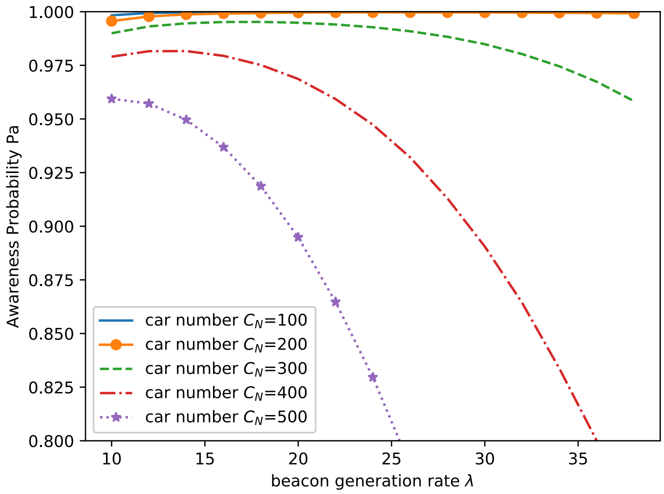


Fig. 3. The awareness probability with different λ.

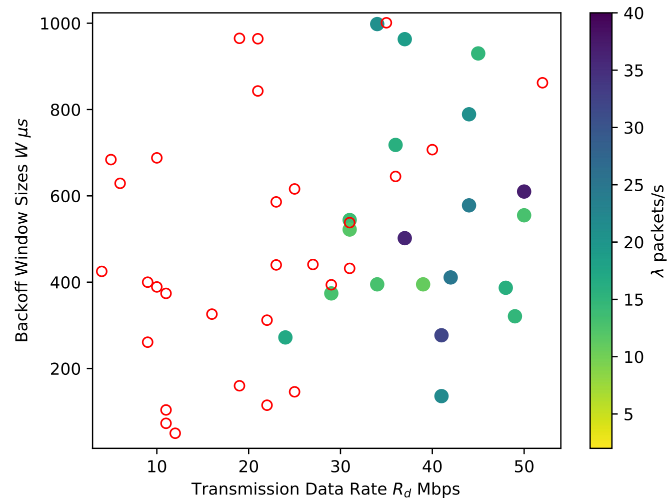
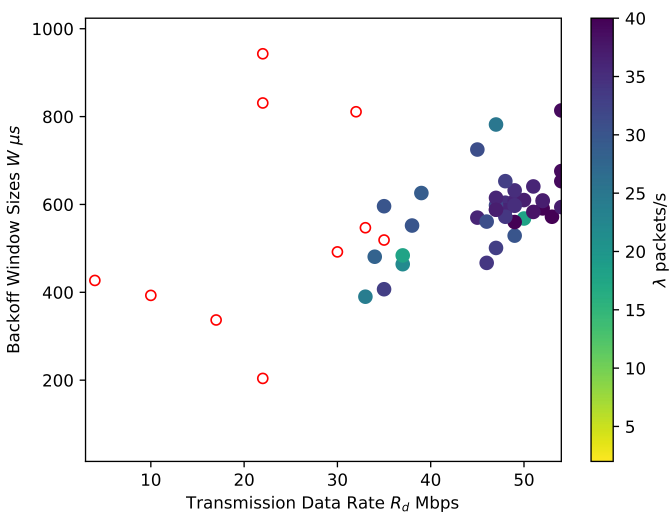
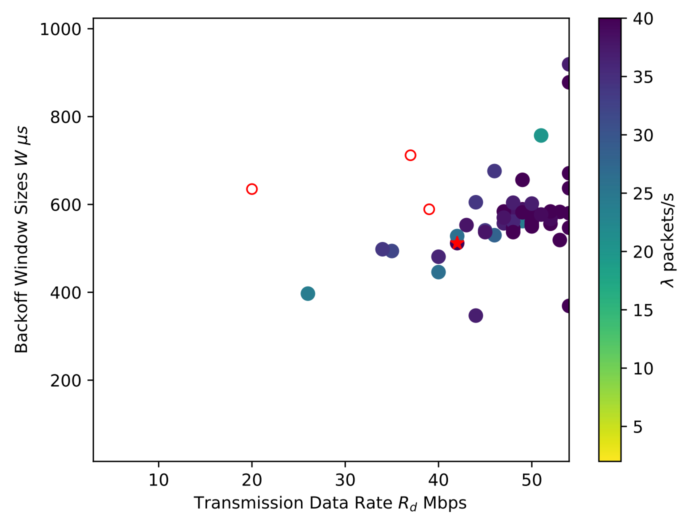


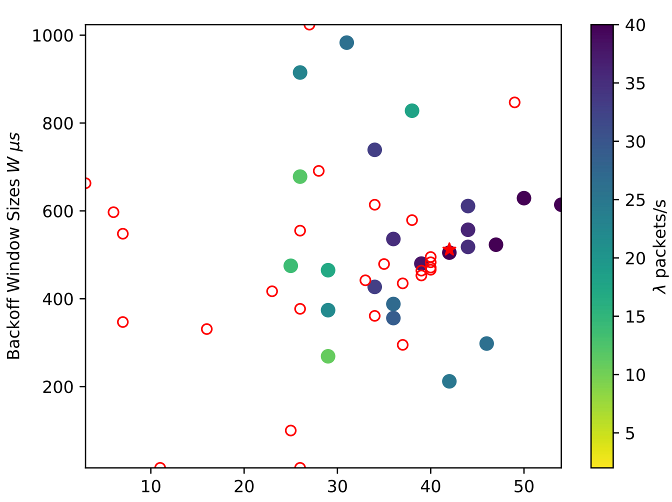
Fig. 4. Position vectors of particles whose P_A satisfied the threshold.



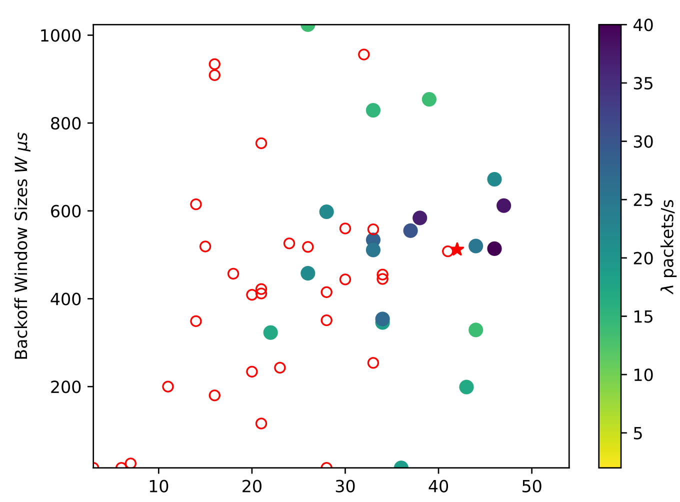
(a) The results of the 2nd iteration



(b) The results of the 3rd iteration



(c) The results of the 4th iteration



(d) The results of the 5th iteration

Fig. 5. The iterative results of the optimization process.

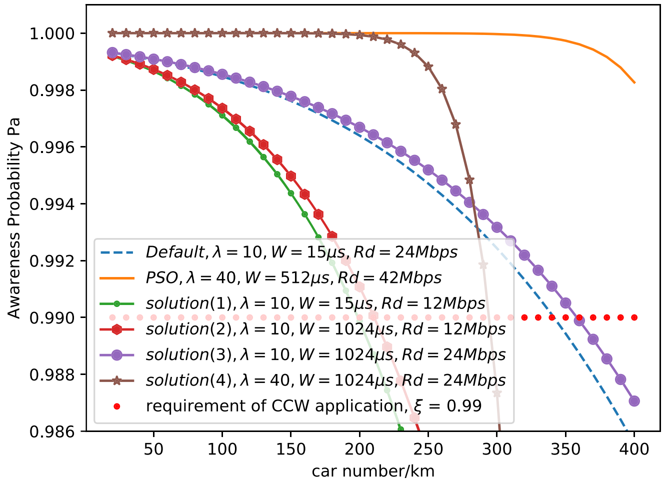


Fig. 6. Comparison of P_As with different set of communication parameters.

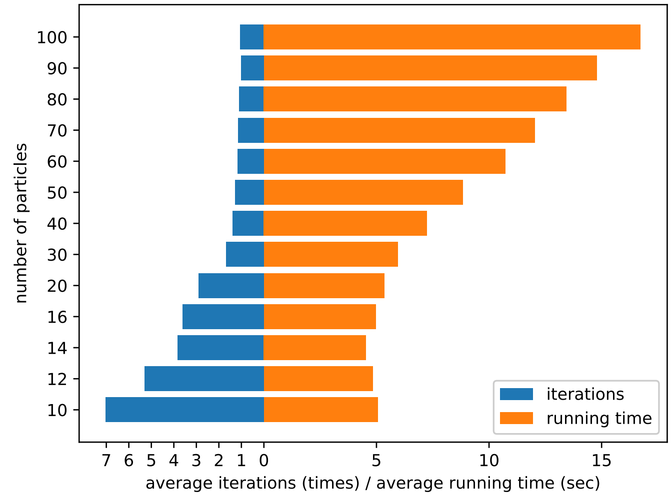


Fig. 7. Runtime of algorithm with different particle numbers of PSO algorithm.

4.2.2. Evaluating VANET systems

As illustrated in Figs. 2 and 3, the QoS might fail to meet the requirements of applications in particular VANET circumstance (e.g., CCW application with 400 cars per kilometer). To improve the QoS in this situation, the optimization model would evaluate the VANET first to see if it is possible to meet the requirements.

Take CCW as an example, 50 particles are set among the solution space randomly. As shown in Fig. 4, the solid circles represent the P_A derived from the particles satisfying the requirement of CCW, and the darker the color, the larger λ value is. Meanwhile, the red ring shows the particle whose P_A is smaller than the threshold ξ.

After confirming VANET has the possibility to meet the requirements of applications through adjusting transmission parameters in the particular circumstance, the optimization model would go into the second step to approximating the transmission capacity.

4.2.3. Approximating transmission capacity

During the second step, all of the particles move towards the particle who meets the threshold ξ and at the same time has the largest λ. Fig. 5 illustrates the iteration results of the optimization model with the parameters set in Table 4. It shows after a few of iterations, the particle with largest λ (the red star) that meets the requirements could be found, after that, the algorithm is trying to search a better solution until the termination condition is reached.

The effects of different solutions for CCW application are compared in Fig. 6, the dashed blue line is the effect of control group setting in Table 4, the solid orange line is the reliability derived from the optimized parameters in this paper, the red dotted line indicates the QoS requirement of CCW application, and the other four employ the parameters randomly combined in [9,51]. The results demonstrate that with the appropriate parameters, which are selected by the optimization scheme, the QoS of the safety application could be improved obviously given a certain VANET environment.

4.2.4. Execution time of algorithm

The runtime of the proposed optimization scheme is tested in this subsection. From Eq. (13) and (14) we can see that the runtime is related to the awareness probability computing model, the number of particles and maximum iterations. While the specific P_A computing model [9] has been employed in this paper, the runtime would be mainly affected by the other two factors.

With the number of particles varies from 10 to 100, the average runtime and the average iterations are calculated respectively with 100 times experiments. The results are shown in Fig. 7, the left side of the figure illustrates the average iterations in each experiment, and the average runtime of each kind of experiment is shown in the right. The average iterations decrease continuously as the particle number increases. While the shortest average running time is found in 14 particles. This is because the fewer particles number, the smaller solution search space will be and the less time would be taken in each iteration. The searching ability of the algorithm and the computing speed finally reach a balance at 14 particles.

5. Conclusion

Aiming at the problem that the fixed transmission parameters may not meet the QoS requirements of the safety application in the highly dynamic network environment of vehicular ad-hoc network, this paper proposes an optimization scheme to adjust the transmission parameters dynamically according to the network conditions to meet the reliability requirements of safety applications.

Therefore, firstly, the paper evaluates whether the current communication system could meet the corresponding safety application reliability requirements. Then, in order to approximate the transmission capacity on the premise of meeting the reliability of the safety applications requirements, a standard particle swarm optimization algorithm is used to adjust the corresponding transmission parameters and optimize the beacon generation rate λ. The broadcast reliability of safety applications with the optimized parameters is compared with the fixed transmission parameters. It shows that optimizing transmission parameters dynamically in terms of VANET circumstances could get better results of awareness probability and transmission capacity. The further experiment shows the number of particles could also greatly affect the runtime of the algorithm, and 14 particles are suggested when optimizing VANET transmission parameters in a standard PSO algorithm.

However, if the current communication system is not able to sustain the safety application with the required QoS, which is evaluated in the first step of this model, extra spectrum resources need to be borrowed from other channel in the same system or other networks such as LTE cellular network, TV network, WiMAX, etc, and it will be our further study in the future.

Acknowledgements

We thank anonymous reviewers for their invaluable comments and suggestions on improving this work. This work is supported by National Natural Science Foundation of China (NSFC) (grant No. 61572150), and Central Fund of Dalian University of Technology.

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