IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received April 27, 2018, accepted May 21, 2018, date of publication June 6, 2018, date of current version July 6, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2843175

Be Stable and Fair: Robust Data Scheduling for Vehicular Networks

LIBING WU[1], (Member, IEEE), YOUHUA XIA[1], (Student Member, IEEE), ZHIBO WANG[1], (Member, IEEE), AND HAO WANG[2], (Member, IEEE)

[1]School of Computer Science, Wuhan University, Wuhan 430072, China
[2]State Key Laboratory of Geomechanics and Geotechnical Engineering, Institute of Rock and Soil Mechanics, Chinese Academy of Sciences, Wuhan 430071, China

Corresponding author: Zhibo Wang (zbwang@whu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61472287, Grant 61572370, and Grant 61502352, in part by the Science and Technology Support Program of Hubei Province under Grant 2015CFA068, in part by the Science and Technology Plan Projects of Wuhan City under Grant 2016060101010047, in part by the Natural Science Foundation of Hubei Province under Grant 2017CFB503, in part by the Science and Technology Plan Projects of Shenzhen City under Grant JCYJ20170818112550194, and in part by the Fundamental Research Funds for the Central Universities.

ABSTRACT The stable and fair data transmission of vehicular networks can improve transport efficiency and reduce traffic accident. It is challenging to ensure the stability and fairness of data transmission in dynamic vehicular networks. However, existing works based on opportunistic scheduling cannot support reliable transmission since stability and fairness are difficult to be guaranteed at the same time. In this paper, we propose a stable scheduling scheme for dynamic vehicular networks based on fair allocation of available channel resources. We formulate the problem of stability and fairness as network utility maximization, and propose an algorithm, called SF-NUM, to solve it. SF-NUM uses the stability scheduling method based on back pressure vector for the first time in vehicular networks. In order to achieve the fairness distribution of channel resources of the vehicular networks in the distributed computing way, multiple factors are considered in the SF-NUM algorithm. The experimental results show that the proposed algorithm outperforms other algorithms.

INDEX TERMS Vehicular networks, stable scheduling, fair allocation, data transmission.

I. INTRODUCTION

With the rapid development of wireless communications and increasing number of vehicles, vehicular networks have received popularity in recent years. In order to reduce the occurrence of traffic accidents and improve the efficiency of traveling of the car and the management efficiency of the intersection, many sensors are mounted on the vehicles [1]–[5]. Communication is the most important issue in vehicular networks. A vehicular network consists of Road Side Units (RSU) and vehicles that communicate through Dedicated Short Range Communication (DSRC). Generally speaking, there are two kinds of communication in vehicular networks: Vehicle to RSU (V2R) and Vehicle to Vehicle (V2V) [6]–[9]. However, the vehicular networks are usually dynamic due to high mobility of vehicles. This makes the communication of V2V very unstable and resources allocation unfair. Therefore, it is essential and necessary to ensure stable and fair transmission in vehicular networks.

Due to the instability of data transmission in the vehicular networks and the uneven distribution of channel resources, many traffic accidents will happen. The core goal of vehicular networks is to ensure the reliable communication of vehicles. It's essential to ensure stable data transmission and fair allocation of available channel resources, which however is difficult to be guaranteed. For example, controlling congestion by the way of fair beaconing rate adaption [10], it lacks of consideration of fair allocation of available channel resources. As a consequence, reliable data scheduling is urgently required to solve the problem of link stability and fair allocation of available channel resources quickly and efficiently.

Vehicular networks mainly consist of V2I (Vehicle to Infrastructure) communication and V2V (Vehicle to Vehicle) communication. As shown in Figure 1. Vehicular networks include vehicles, RSU and cloud servers. Vehicles can communicate with other vehicles, RSU and cloud servers. Due to the mobility of vehicles, it is uncertain for the contact opportunity among the communication of vehicular networks. It is unstable for the communication between vehicle and vehicle. It is not fair for the allocation of channel resources due to uneven contact opportunities between vehicle and vehicle,

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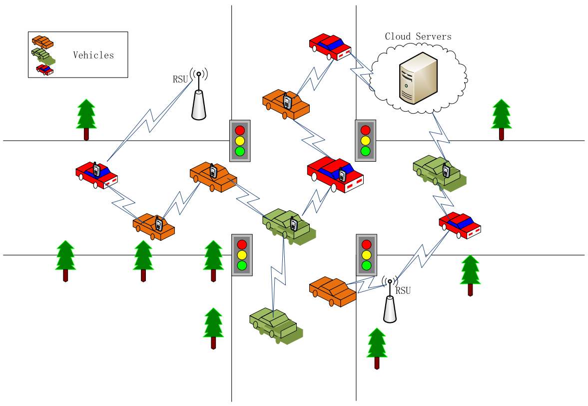


FIGURE 1. Vehicular networks architecture.

RSU, cloud servers. It is challenging to ensure reliable data scheduling due to high dynamic of vehicular networks. Many scheduling algorithms have been proposed to solve this problem, however, most of them did not consider to guarantee the stability of the links and fair allocation of available channel resources at the same time. Some works [11]–[15] quantify the expected path delay by using carry-and-forward mechanism and operate data scheduling cooperatively via the hybrid of V2I and V2V communication or pure V2V communication, which is often used for advertising. However, they ignore the problem of the stability of the link and fair allocation of available channel resources. Some works [2], [7], [16]–[18] schedule the data by disseminating in large-scale VANETs, e.g., emergency information. They focus on the problem of congestion control and utility maximization, which also involves fair allocation of channel resources. However, their fairness is not enough to support reliable data transmission. They didn't consider stability of link in vehicular communications. Moreover, some works [6], [8], [19], [20] transmit the information by multi-hop probabilistic forwarding, which can support safety applications on highways. They exploite travelling information and matching-based user association approach for data forwarding and achieve stable data scheduling in the way of network coding in low-speed mobility networks. However, they also didn't consider stable scheduling in vehicular networks.

It is challenging to realize stable and fair data scheduling in vehicular networks. Firstly, the vehicles drive with different speeds and vary from time to time and road to road. The communication time among the vehicles is different according to the number of fast vehicles in vehicular networks. Secondly, the topology of network changes as time goes on. It is unstable as the topology of network changes for the communication among vehicles or between vehicles and RSU. Moreover, data dissemination in vehicular networks is not easy to be guaranteed due to different communication time among vehicles. Allocation of available channel resources is not evenly distributed on the basis of different contact opportunities among vehicles or between vehicles and RSU, cloud servers.

In this paper, we propose an algorithm, called SF-NUM, to realize stable data scheduling and fair allocation of available channel resources in vehicular networks. In particular, SF-NUM consists of two phases: back-pressure vector based stable scheduling and distributed computing based fair allocation. In the back-pressure vector based scheduling part, we first determine the stability of the average rate, and then compute the preferred service vector according to the back pressure vector. We notice that the linear variation of the difference between the input queue length and the output queue length tends to infinity. We apply the Logarithmic function to make the data scheduling tend to be stable. If the queue length is average-rate stable, the virtual queue length, the intermediate virtual queue length, the intermediate actual queue length, and the actual queue length are updated. The cloud servers compute the total number of null activities based on the intermediate actual queue length. Through the comprehensive estimation of the weight value, the utility function achieves the goal of fair distribution, which maximizes the utility function under the condition of adaptive selecting transmission probability in a certain range. The proposed algorithm is general and can be used in communication among vehicles on urban roads.

The main contributions of this work are summarized as follows:

- We propose to utilize opportunistic scheduling for stable transmission in vehicular networks. Based on the back pressure vector, we have proposed a new way to determine the stability.
- We develop a novel network utility maximization model to analyze the fair allocation of SF-NUM in a distributed computing way.
- We conduct extensive simulations to evaluate the performance of SF-NUM. The experimental results show that SF-NUM outperforms other algorithms in terms of the probability of data transmission, the packet receiving probability and service ratio.

The remainder of the work is presented as follows. Section II gives an overview of some related works in recent literature. The system model is described in Section III. The problem analysis is presented in section IV. Section V provides an analysis of stability scheduling of vehicular networks and the fairness of available channel resources. Section VI evaluates the performance of the proposed algorithm. Finally, the conclusion of the paper is presented in Section VII.

II. RELATED WORK

Many works focus on reducing channel load to avoid congestion. D'Aronco *et al.* [16] proposed a new distributed delay-constrained congestion control algorithm that can adapt the sending rate to both loss and delay-based congestion events. Lovewell *et al.* [21] designed the packet-scale paradigm for end-to-end congestion control protocols. Specifically, it can continually probe for available bandwidth at short timescales, and adapt to the data sending rate so as to avoid overloading the network. The analysis showed that it gains high performance along several dimensions. The network load can be reduced further in some cases by introducing optimization of latency. Lee *et al.* [17] proposed a DX algorithm to perform fine-grained control to achieve very low queuing delay. This method aims to perform practical and fine-grained congestion control and reflect the one-way queuing delay in single packet level. Egea-Lopez and Pavon-Marino [10] was motivated by the observations that the problem of controlling the beaconing rate on each vehicle can be modeled as a Network Utility Maximization (NUM) problem. Thus, the proposed algorithm in [10] employs a particular scaled gradient projection algorithm to solve the dual of the NUM problem. However, they ignore fair allocation of available channel resources.

Some schemes detect network load using either opportunistic communication or distributed method. Pan *et al.* [22] proposed a distributed re-routing system to offload a large part of the rerouting computation at the vehicles. It is a hybrid system due to that a server and Internet communication are still used to determine an accurate global view of the traffic. Han *et al.* [23] proposed to exploit opportunistic communications to facilitate information dissemination and reduce the amount of mobile data traffic in the mobile social network. It successfully alleviates the load problem in the mobile network, and the target-set selection problem is investigated for information delivery as a case study. Tong *et al.* [24] presented an analytical study of adaptive approach, which aims to find a small set of seed users that are able to maximize the spread of the influence. This is called the influence maximization problem. However, stable scheduling have not been exploited for achieving global optimization of vehicular networks.

Some works focus on optimizing information transmission problem. Zhang and Valaee [2] proposed Distributed Network Utility Maximization (D-NUM) algorithm that the transmission probability is superior than the PULSAR algorithm. They take the safety benefit of packets transmitted on each wireless link into account for the adaptation of transmission probability. The performance evaluation showed that the algorithm can respond quickly when vehicles change the driving environment. While Kuo and Wang [19] proposed an opportunistic scheduling solution that is provably optimal for time varying channels, using the corresponding stability region to match the optimal Shannon capacity. Then, a queue length-based scheduling scheme was developed. The proposed algorithm is also generalized to include the capability of rate adaptation. Chiti *et al.* [6] used the user association methods to optimize the information dissemination in Internet of Vehicle (IoV). To solve the user association problem, the authors considered the vehicles' quality of service (QoS) requirement and the information gained through communication, which is also formulated as a mix integer liner programming (MILP) problem. While Baron *et al.* [25] proposed an embedding algorithm that computes an offloading overlay to alleviate the ever growing traffic load by offloading. Specifically, the data transfer assignment problem was formulated as a novel linear programming model. Employing the model, the optimal logical paths which match the performance requirements of data transfer can be determined. However, the algorithm cannot provide a fair allocation of available channel resources in the network. Furthermore, problems such as the adaptive selecting transmission probability and the fairness of the resource utilization should be considered. In this paper, we exploit fair allocation of available channel resources and stable scheduling to achieve global optimization in vehicular networks.

III. SYSTEM MODEL

In this section, we present the communication model of vehicular networks.

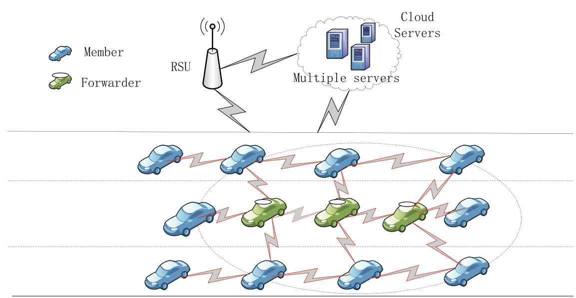


FIGURE 2. Communications of vehicular networks.

Figure 2 shows the communication in hybrid vehicular networks. The system consists of RSU, Cloud Servers, Vehicles (member vehicles and forward vehicles). The RSU is intended to collect and distribute information, and the cloud server handles information in the vehicular networks. The member vehicles are common vehicles that need to send or receive information, while the forward vehicles are the vehicles that are capable of transmitting information as quickly and accurately as possible to the destination vehicles.

A scheduling period consists of three phases:

- At the first phase, all vehicles are set to V2I mode, and broadcast their heartbeat messages so that each vehicle is able to discover the neighboring vehicles.
- At the second phase, all vehicles switch to the V2V mode. They communicate with the RSU and the cloud servers. Each vehicle informs the RSU with its updated information, including the list of its current neighbors, and the identifiers of the retrieved and newly requested data items [26], [27]. This information is transmitted into the Probe Vehicle Message as defined in SAE J2735 [20]. Each request contains only one data item, and the request is valid as long as the corresponding data item is retrieved via either V2I or V2V communication [28].
- At the third phase, each vehicle is involved in V2I or V2V communication mode according to the scheduling decision. Multiple instances of data transmission may occur simultaneously at this phase [29]. Specifically, some vehicles will be instructed to enter the V2I mode and retrieve data items from RSU and cloud

computing, while other vehicles will be instructed to enter the V2V mode for data transmission or reception.

In order to achieve the collaborative data transmission of V2I and V2V, the proposed algorithm is expected to make the following scheduling decisions. Firstly, the vehicles are divided into two groups, one runs the V2I communication mode and the other runs the V2V communication mode. Secondly, the algorithm selects a data item to be sent from the RSU or the cloud server so that the vehicle in the V2I group can retrieve the data item through the V2I service channel [30]. Thirdly, for the vehicle in the V2V group, the algorithm confirms a set of vehicles and the sender according to the corresponding data items of transmission of each sender vehicle. The neighbors of each sender vehicle have the opportunity to retrieve the requested data items via V2V mode. We assume that these vehicles remain in the same community in a short time.

We model the vehicular network with an undirected graph $G(V, E)$, where $V = \{1, 2, \ldots, n\}$ represents the set of vehicles and n is the total number of vehicles, and E is the set of communication edges among vehicles. It is supposed that the communication range of a vehicle is r_0. There is an edge $E(i, j)$ between vehicle i and vehicle j and $E(i, j) = 1$ if their distance $c(i, j)$ is smaller than r_0, otherwise, there is no edge and $E(i, j) = 0$. Let N_i denote the set of neighbor vehicles of vehicle i, so we have $N_i = \{j | c(i, j) \leq r_0 \;\&\; j \neq i\}$. Note that the topology changes as the vehicles' movement, so we let $G_t(V, E)$ denote an instantaneous graph at time period t.

IV. PROBLEM FORMULATION

In this section, we present the problem as a Network Utility Maximization (NUM) problem.

The notations used in this paper are summarized in table 1. We assume that each incoming packet gets a value from a finite field and a session denotes that there are data transmission between two vehicles. At the beginning of each time period t, there are $n_1(t)$ session-1 packets and $n_2(t)$ session-2 packets waiting for the response of the source node s. It is assumed that $n_1(t)$ and $n_2(t)$ are integer-valued random variables with mean M_1 and M_2 respectively. For time-varying channels, the time-varying channel quality is simulated as a Markovian random process $MP(t)$ that determines the probability of reception of the broadcast. It can be seen that our scheme can also be applied directly to Markovian random process $MP(t)$. Let SM represent the support of $MP(t)$ and we assume that the $|SM|$ is limited. For any constant number $\lambda \in SM$, we use f_λ to represent the steady state frequency of $MP(t) = \lambda$. It is assumed that $f_\lambda > 0$ for all $\lambda \in SM$ [19].

Our network utility contains the concept of packet delay and security benefits among neighbors, where the latter is a multiplicative weight. The utility function $u_{i,j}(\alpha)$ is expressed as:

$$u_{i,j}(\alpha) = -w_{i,j} E[D_{i,j}]$$

Where $E[D_{i,j}]$ is the minimum expected delay, $w_{i,j}$ is the non-negative multiplicative weight. It shows that under the conditions of minimization expected delay and stability of transmission, the network utility is maximized on the basis of ensuring fair allocation of available channel resources. It is necessary to consider the weight of different factors and the delay problem. The packet delay from the sending node i to receiving node j is determined by many factors, including the distance among vehicles, relative velocity and the trend of the movement. This delay in number of time slots is represented as random variable $D_{i,j}$ [2].

TABLE 1. Summary of notations.

Notataions	Descriptions
$G(V, E)$	The undirected graph of vehicular networks
V	The set of vehicles
$E_{i,j}$	An edge between vehicle i and vehicle j
N_i	The set of neighbor vehicles of vehicle i
r_0	The communication range of a vehicle
$c_{i,j}$	The distance between vehicle i and vehicle j
$G_t(V, E)$	Instantaneous graph of vehicular network at time period t
$n_1(t)$	The number of session packets between source node and relay node
$n_2(t)$	The number of session packets between source node and another relay node
M_1	Mean of Integer-valued random variables $n_1(t)$
M_2	Mean of Integer-valued random variables $n_2(t)$
$MP(t)$	A Markovian random process
SM	The support of $MP(t)$
λ	A constant number
f_λ	The steady state frequency of $MP(t) = \lambda$
$E[D_{i,j}]$	The minimum expected delay
$w_{i,j}$	The non-negative multiplicative weight
$D_{i,j}$	The delay in number of time slots
α_i	The adaptive selecting transmission probability
α_{min}	The minimum adaptive selecting transmission probability
α_{max}	The maximum adaptive selecting transmission probability
$q(t)$	A queue length
$E[q(t)]$	The expected queue length
$x^*(t)$	The preferred service vector
$d(t)$	The back pressure vector
Ψ	The set of vectors that contains all Dirac delta vectors and the all-zero vectors
SA	Service Activity
SA^*	Preferred Service Activity
$\overline{B^{in}(MP(t))}$	The mean of number of packets entering queue
$\overline{B^{out}(MP(t))}$	The mean of number of packets leaving queue
$q_k(t+1)$	Virtual queue length at $(t+1)$
$q_k^{inter}(t+1)$	Intermediate virtual queue length at $(t+1)$
$Q_k(t+1)$	Actual queue length at $(t+1)$
$Q_k^{inter}(t+1)$	Intermediate actual length at $(t+1)$
m	The movement of the vehicle
v	The speed of the movement of the vehicle
c	The distance between the vehicle and the RSU or another vehicle
S_c	The coefficient of Λ
SCH_{avg}	Stable Scheduling based on average departure rate
$\mu_{out,k}$	The amount of packets "coming out of queue k"
$\mu_{in,k}$	The amount of packets "entering queue k"
$N_{NA,k}(t)$	The aggregate number of null activities occurred at queue k up to time t
$S_{i,j}$	Successfully receiving probability
$u_{i,j}(\alpha)$	The network utility function
τ_j	The clear channel probability
q_i	The first part of utility maximization function
γ_j	The messages of its one-hop interferers
b_i	The second part of utility maximization function
I_n	The collection of the input queues of SA(Service Activity) n
O_n	The collection of the output queues of SA(Service Activity) n
$p_{i,j}$	The packet receiving probability on link $i \rightarrow j$ in the absence of interference
e_i	The information entropy to measure the value of information of transmission

The problem is that how to maximize the network utility in vehicular networks in a certain range of adaptive selecting transmission probability. Vehicular networks can acquire reliable communication by the way of fair allocation of available channel resources. The network utility is determined by the safety weight and the expected successful transmission of the node. we formulate the problem as a NUM optimization problem:

$$\max \sum_{i \in \Omega} \sum_{j \in N_i} u_{i,j}(\alpha)$$
$$s.t. \; \alpha_{min} \leq \alpha_i \leq \alpha_{max}$$

where α_i is the adaptive selecting transmission probability, α_{min} is the minimum adaptive selecting transmission probability, i.e., the minimum probability of data transmission under the influence of speed, distance, movement trend, and channel conditions. α_{max} is the maximum adaptive selecting transmission probability, i.e., the maximum probability of data transmission under the influence of speed, distance, movement trend, and channel conditions. The objective is to maximize network utility in vehicular networks under the condition of stable transmission of data. The constraint indicates that the vehicle transmits data with a certain probability.

V. STABILITY WITH FAIRNESS NETWORK UTILITY MAXIMIZATION (SF-NUM)

In this section, we aim to derive the optimal scheduling policy, which can provide stable data scheduling and realize fair allocation of available channel resources by using safety weight distribution.

We design an algorithm of stable data scheduling with fairness by exploiting sensor information of vehicular networks, named Stability with Fairness Network Utility Maximization (SF-NUM). The algorithm works in both connected and intermittently connected networks. When the vehicle is in connected networks, the algorithm routes a packet along the shortest path. Otherwise, stability scheduling based on Dirac function and queue lengths is used. The Dirac delta is used to model a tall narrow spike function (an impulse), and other similar abstractions such as a point charge, point mass or electron point [31]. We point out that the results obtained in this section are based on the assumption that the energy level of the transmitter is stable [32]. We design our algorithm by scheduling resources and queues for a given source-destination pair. We consider the operation of the system on the block, which corresponds to the total number of channels used [33]. The SF-NUM mainly consists of two parts. One part is the queue length based stable scheduling, which is used to ensure the stable state of the communication process. The other part is the fair allocation of the available channel resources, which ensures that an increasing amount of data can be transmitted in the vehicular networks.

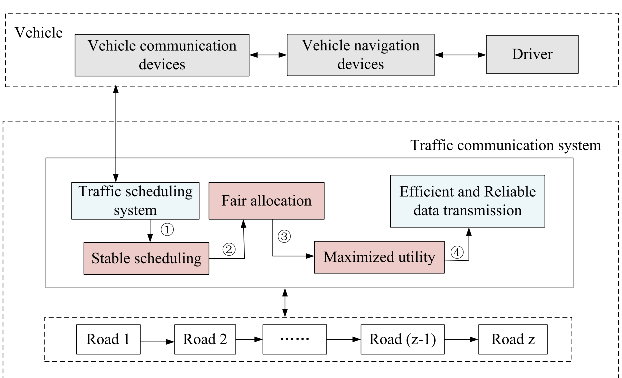


FIGURE 3. The overview of the scheduling algorithm.

A. THE OVERVIEW OF SF-NUM

SF-NUM mainly consists of two parts, one is stable scheduling and the other is fair allocation. As shown in Figure 3 and Algorithm 1. In the part of stable scheduling, firstly, if the queue length is mean-rate stable, the SF-NUM computes the "preferred service vector" and determines the stability of the queue. Secondly, we update the virtual queue length, the intermediate virtual queue length, the intermediate actual queue length and the actual queue length. Thirdly, we consider the conditions that the empty activity of the queue needs to be satisfied. In the part of fair allocation, we first compute the probability of successful communication through probability of transmission, probability of receiving and information entropy. Then we compute the expected probability of successful transmission and the different weight values among different factors. At last, the clear channel probability is computed and the utility maximization function is distributed into two parts.

In the following, we first describe the stability scheduling and then achieve part of the fair allocation.

Algorithm 1 Stability With Fairness Network Utility Maximization (SF-NUM)

Input: The adaptive transmission probability α_i, The packet receiving probability $p_{i,j}$, Information entropy e_i

Output: The maximum of the utility function $u_{i,j}(\alpha)$

1: Determine the stability of the queue according to the formula (4);
2: If the queue is stable, the algorithm updates the virtual queue length of the next moment according to the formula (3). Otherwise, no data transmission is needed;
3: Update the intermediate virtual queue length according to formula (5);
4: Update the intermediate actual queue length according to formula (9);
5: Update the actual queue length according to the formula (10) when the service vector is infeasible;
6: Calculate the number of null activities based on formula (11);
7: Calculate the probability of successful transmission of the vehicle according to the formula (13);
8: Calculate the expectation of the probability of successful transmission of the vehicle according to the formula (14);
9: Calculate the utility function formula (15) according to the weight and expectation;
10: Calculate the weight factor according to the formula (16)(17)(18);
11: Calculate $u_{i,j}(\alpha)$ according to problem formulation;

B. BACK PRESSURE VECTOR-BASED STABILITY SCHEDULING

In this section, we present the stable scheduling based on back pressure vector.

A queue length $q(t)$ is mean-rate stable if

$$\lim_{(t_2-t_1)\to\infty} \frac{E[q(t_2)]-E[q(t_1)]}{t_2-t_1}=0 \tag{1}$$

We compute the "preferred service vector" by

$$x^*(t) = arg \max_{x \in \Psi} d^T(t).x \tag{2}$$

where $d(t) = (\overline{B^{in}(MP(t))} - \overline{B^{out}(MP(t))})^T .q(t)$ is the back pressure vector that focuses on communication networks. The packets in networks come from multiple data streams and should be delivered to appropriate destinations; $q(t)$ is the vector of the virtual queue lengths; and we suggest that the notations $\overline{B^{in}(MP(t))}$ and $\overline{B^{out}(MP(t))}$ are the expectations when the channel quality $MP(t) = \lambda$.

Let Ψ denote the set of vectors that contains all Dirac delta vectors and the all-zero vectors, i.e., those vectors that can be activated at any given time slot, because we assume that each vector in Ψ has less than 1 non-zero coordinate. We can find the preferred Service Activity (SA) SA^* in time t through $x^*(t)$ and $d(t)$. We then check whether the preferred SA is feasible. It is acknowledged that SA a is feasible if at time t and queue k has at least one packet for all. Otherwise, it is infeasible at time t. If so, we officially schedule the preferred service activity SA^*. If not, we let the system be idle, the actually scheduled service vector $x(t) = 0$ is now all-zero. Let m represent the movement of the vehicle, v indicate the speed of movement of the vehicle and c represent the distance between the vehicle and the RSU. Regardless of whether the preferred SA SA^* is feasible or not. The movement, speed, distance of different vehicles and the transmission probability, receiving probability, information entropy of different vehicles constitute different three-dimensional column vectors, replacing it with the following formula for matrix operations. we update $q(t)$ by:

$$q(t+1) = q(t) + log(mv) + (\overline{B^{in}(MP(t))} - \overline{B^{out}(MP(t))}).x^*(t) \tag{3}$$

Note that the actual queue length $Q_k(t)$ is updated in a way different from $q(t+1)$. If the preferred SA SA^* is not feasible, the system remains idle and $Q_k(t)$ changes if and only if any new packet arrives. If the preferred SA SA^* is feasible, $Q_k(t)$ is updated based on the actual packet movement. While the actual queue length $Q_k(t)$ is always greater or equal to 0, the virtual queue length $q(t)$ can be strictly negative when updated via $q(t-1)$.

Define Λ to be the convex hull of Ψ and let Λ^0 be the interior of Λ. The movement m and the speed of the movement v can be mean-rate stabilized, only if there exist $S_\lambda \in \Lambda$ for all $\lambda \in SM$ such that

$$log(mv) + \sum_{\lambda \in SM} f_\lambda.\overline{B^{out}(\lambda)}.S_\lambda = \sum_{\lambda \in SM} f_\lambda.\overline{B^{in}(\lambda)}.S_\lambda \tag{4}$$

Let each queue k keep another two real-valued counters $q_k^{inter}(t)$ and $Q_k^{inter}(t)$, and they are termed as the intermediate virtual queue length and the intermediate actual queue length. Thus, there are four different queue length values $q_k(t)$, $q_k^{inter}(t)$, $Q_k^{inter}(t)$, and $Q_k(t)$ for each queue k. To prove $Q(t)$, the vector of the actual queue length can be stabilized. We will show that both $Q_k^{inter}(t)$and $|Q_k(t) - Q_k^{inter}(t)|$ can be mean-rate stabilized by SCH_{avg} (Stable Scheduling based on average departure rate) [19] for all k. Since the summation of mean-rate stable random processes is still mean-rate stable, $Q(t)$ can thus be mean-rate stabilized by SCH_{avg}.

With the above road map, we now specify the update rules for $q_k^{inter}(t)$ and $Q_k^{inter}(t)$. Initially, $q_k^{inter}(1)$ and $Q_k^{inter}(1)$ are set to 0 for all k. At the end of each time t, we compute $q^{inter}(t+1)$ using the preferred schedule $x^*(t)$ which is chosen by SCH_{avg}:

$$q^{iner}(t+1) = q^{inter} + log(mv) + (B^{out}(MP(t)) - B^{in}(MP(t))).(x^*(t)) \tag{5}$$

Comparing $q^{inter}(t+1)$ and $q(t+1)$, we can see that $q^{inter}(t)$ is updated by the realization of the input/output service matrices while $q(t)$ is updated by the expected input/output service matrices. We can rewrite $q^{inter}(t+1)$ in the following equivalent form:

$$q_k^{inter}(t+1) = q_k^{inter} - \mu_{out,k}(t) + \mu_{in,k}(t) \tag{6}$$

$$\mu_{out,k}(t) = \sum_{n=1}^{N} (\beta_{k,n}^{in}(MP(t)).x^*(t)) \tag{7}$$

$$\mu_{in,k}(t) = \sum_{l=1}^{M} (log(m_{k,l})v_l(t)) + \sum_{n=1}^{N} (\beta_{k,n}^{out}(MP(t)).x^*(t)) \tag{8}$$

Here, $\mu_{out,k}$ is the amount of packets "coming out of queue k", which is decided by the "input rates of SA a". Similarly, $\mu_{in,k}$ is the amount of packets "entering queue k", which is decided by the "output rates of SA a" and the packet arrival rates. We now update $Q^{inter}(t+1)$ by

$$Q_k^{inter}(t+1) = (Q_k^{inter}(t) - \mu_{out,k}(t))^+ + \mu_{in,k}(t), \forall k \tag{9}$$

The difference between $q_k^{inter}(t)$ and $Q_k^{inter}(t)$ is that the former can be strictly negative when updated via $q_k^{inter}(t-1)$, while we enforce the latter to be non-negative. To compare $Q_k^{inter}(t)$ and $Q_k(t)$, we observe $Q_k^{inter}(t+1)$ and $Q_k^{inter}(t)$, which are updated by the preferred service vector $x^*(t)$ without considering whether the preferred SA SA^* is feasible or not. In contrast, the update rule of the actual queue length $Q_k(t)$ is quite different. For example, if SA SA^* is infeasible, the system remains idle and we have noted that $Q_k(t+1)$ differs significantly from $Q_k^{inter}(t+1)$. For example, initially we let $Q_k(t) = 0$. When SA SA^* is infeasible, the aggregate increase of $Q_k(t)$ depends only on the new packet arrivals by equation 10. But the aggregate increase of $Q_k^{inter}(t)$ assuming $Q_k^{inter} = 0$ depends on the service rates of the preferred $x_n^*(t)$ as well.

We focus on the absolute difference $|Q_k(t) - Q_k^{inter}(t)|$. We use $SA(t)$ to denote the preferred SA suggested by the back-pressure scheduler in $x^*(t)$ and $d(t)$. We now define an event, which is called the null activity of queue k at time t. We say that the null activity occurs at queue k if $k \in I_n(t)$ and $Q_k^{inter}(t) < \beta_{k,n(t)}^{in}(MP(t))$. That is, the null activity describes the event that the preferred SA shall consume the packets in queue k (since $k \in I_n(t)$), but $Q_k^{inter}(t) < \beta_{k,n}^{in}(MP(t))$ at the same time. Note that the null activity is defined based on comparing the intermediate actual queue length $Q_k^{inter}(t)$ and the actual realization of the packet consumption $\beta_{k,n(t)}^{in}(MP(t))$. For comparison, whether the SA $a(t)$ is feasible depends on the fact that whether the actual queue length $Q_k(t)$ is larger or less than 1. Therefore the null activities are not directly related to the event that SA $a(t)$ is infeasible. If the preferred SA SA^* is infeasible, the system remains idle and we have

$$Q_k(t+1) = Q_k(t) + \sum_{l=1}^{M} log(m_{k,l}v_l(t)) \tag{10}$$

Let $N_{NA,k}(t)$ be the aggregate number of null activities occurred at queue k up to time t. That is,

$$N_{NA,k}(t) \triangleq \sum_{i=1}^{t} I(k \in I_n(t)).I(Q_k^{inter}(\tau) < \beta_{k,n(\tau)}^{in}(MP(\tau))) \tag{11}$$

where $I(.)$ is the indicator function. We then have

$$E(|Q_k(t) - Q_k^{inter}(t)|) \leq \sum_{\bar{k}=1}^{K} E(N_{NA,\bar{k}}(t)) \tag{12}$$

for all t = 1 to ∞.

In summary, the data scheduling of vehicular networks tends to be stabilized by the above-mentioned scheduling scheme based on the queue length, and it also considers the influence of the factors of the trend of the movement, the relative speed and the relative distance.

C. FAIR ALLOCATION OF AVAILABLE CHANNEL RESOURCES

We assume that the adaptive selecting transmission probability α_i for each individual node i within a range $[\alpha_{min}, \alpha_{max}]$. Let $\alpha_i' = \{\alpha_i | i \in V\}$ be the vector of transmission probability assignments for the network, $V = \{1, 2, \ldots, n\}$ denotes the set of vehicular nodes. We denote the set of nodes whose transmission may collide at node j as M_j.

Recall that the packet receiving probability on link $i \to j$ in the absence of interference is denoted as $p_{i,j}$. We use the information entropy e_i to measure the value of information transmission. Accounting for collisions, the probability that a packet from i is transmitted and successfully received at neighbor j in a certain time slot is

$$S_{i,j} = p_{i,j}e_i\alpha_i \prod_{k \in M_j \setminus i} (1-\alpha_k) \tag{13}$$

The operation of the network in each time slot can be viewed as an independent Bernoulli trial with successful probability $S_{i,j}$. We define the delay to be the time interval between consecutive successful packet receptions on a given link. This metric has alternately been known as the inter-packet reception time. The delay on the $i \to j$ link has a geometric distribution and its expected value is

$$E[D_{i,j}] = \frac{1}{S_{i,j}} = \frac{1}{p_{i,j}e_i\alpha_i \prod_{k \in M_j \setminus i}(1-\alpha_k)} \tag{14}$$

A natural definition of the network utility of a certain transmission rate allocation α' is the negative expected delay of each logical link $i \to j$. Maximizing this utility would result in a global allocation where the expected delay is minimized for all links. To allow for the incorporation of the movement of the vehicle, relative velocity, and the distance of safety into the utility function, we add a non-negative multiplicative weight of $w_{i,j}$ to denote the importance of different factors. Thus, let the network utility of the $i \to j$ link under transmission rate α' be

$$u_{i,j}(\alpha') = -w_{i,j}E[D_{i,j}] = \frac{-w_{i,j}}{p_{i,j}e_i\alpha_i \prod_{k \in M_j \setminus \quad i}(1-\alpha_k)} \tag{15}$$

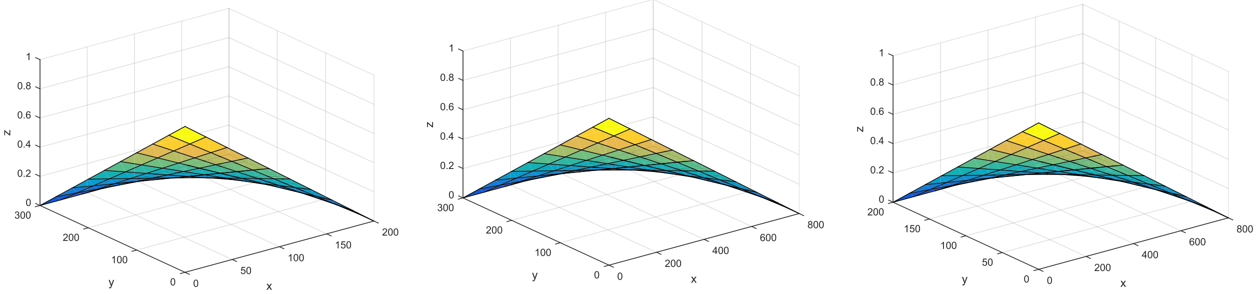
The safety weight should express the greater importance of packets from closer neighbors versus farther neighbors, and vehicles which are approaching versus those who are retreating. Let the range of values for the link distance between nodes i and j, $c_{i,j}$ be $[0, c_{max}]$. We denote the relative velocity between two vehicles i and j with $v_{i,j}$, such that a negative value denotes a decrease in distance over time and a positive value denotes an increase. Let v_{max} be the maximum magnitude of the relative velocity, which can be determined by doubling the physical or legal maximum speed of road vehicles. The value $v_{i,j}$ is in the range of $[-v_{max}, v_{max}]$. Let the range of values for the movement trend of the vehicle $m_{i,j}$ be $[-m_{max}, m_{max}]$. we consider the two factors among them as the safety weight such as $w_{i,j}^1$, $w_{i,j}^2$, $w_{i,j}^3$.

$$w_{i,j}^1 = f(v_{i,j}, c_{i,j}) = (1 - \frac{v_{i,j}}{v_{max}})(1 - \frac{c_{i,j}}{c_{max}}) \tag{16}$$

$$w_{i,j}^2 = f(c_{i,j}, m_{i,j}) = (1 - \frac{c_{i,j}}{c_{max}})(1 - \frac{m_{i,j}}{m_{max}}) \tag{17}$$

$$w_{i,j}^3 = f(v_{i,j}, m_{i,j}) = (1 - \frac{v_{i,j}}{v_{max}})(1 - \frac{m_{i,j}}{m_{max}}) \tag{18}$$

The functions of distance, relative velocity and movement are illustrated in Figure 4, for $c_{max} = 300m$, $v_{max} = 200m/s$ and $m_{max} = 800m$. It is noted that the weight function reaches a maximum value of 0. 3 when the velocity or the movement tendency of the vehicles reaches the three fourths of the maximum and the distance of the vehicle reaches the maximum. The weight function also reaches a maximum value of 0.3 when the two vehicles are moving toward each other at their maximum velocity and the movement tendency of the vehicle reaches three fourths of a maximum. This occurs when a vehicle is about to pass an oncoming vehicle in an adjacent lane. Although this is possible safety weight function, it illustrates that the safety context of a vehicle may change more dramatically than the dynamic of the network mobility.



(a) (b) (c)

FIGURE 4. The safety weight function as velocity, distance and movement. (a) Safety weight function as velocity and distance. (b) Safety weight function as movement and distance. (c) Safety weight function as velocity and movement.

We denote the clear channel probability at node j as:

$$\tau_j = \prod_{k \in M_j} (1 - \alpha_k)(1 - \frac{1}{e_k}) \tag{19}$$

which can be estimated by counting the number of unoccupied time slots within a sliding window of time slots. This value is disseminated to all one-hop neighbors.

q_i and b_i are the parts of the network utility maximization function. The expression q_i can then be evaluated at node i using τ_j. $\forall j \in N_i$, q_i would require two rounds of packet exchanges to be updated

$$q_i = \sum_{j \in N_i} w_{i,j} p_{i,j}^{-1} \tau_j^{-1} (1 - \alpha_i)(1 - \frac{1}{e_j}) \tag{20}$$

In order to compute b_i, each node j will calculate an intermediate value summed over all links for which node j is the receiver and disseminate the value to their first hop neighbor:

$$\gamma_j = \sum_{l \in N_j} w_{l,j} p_{l,j}^{-1} \alpha_l^{-1} e_l (1 - \alpha_l) \tau_j^{-1} \tag{21}$$

Since the value of the weights $w_{i,j}$ only depends on the position and mobility information of the nodes i and j, the γ_j can be computed by both nodes along with the value of $p_{i,j}$. We also disseminate the current probability assignment α_i to one-hop neighbors. Thus, the message γ_j can be calculated using local information available at each node j. It is also disseminated to all of its one-hop neighbors.

The value of b_i can then be computed using the messages of its one-hop interferers γ_j, $\forall j \in M_i$,

$$b_i = (1 - \alpha_i)[\gamma_i + \sum_{j \in M_i} (\gamma_j - \frac{w_{i,j} e_j (1 - \alpha_i)}{p_{i,j} \alpha_i \tau_j})] \tag{22}$$

Note that depending on the difference between transmission range R_N and interference range R_I, the γ_j messages of interferers outside of the transmission range may require two-hop forwarding.

VI. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed algorithm and compare it with the Fair Adaptive Beaconing Rate for Intervehicular Communications (FABRIC) algorithm and the Distributed Network Utility Maximization (D-NUM) algorithm.

TABLE 2. Parameters of the simulation.

Description	Value
Simulation Area	8.0km, 10.0km
Communication Range	1500m
Interference Range	1000m
Node Speed	36m/s
Max Speed	72m/s
Simulation Time	100s, 200s
Packet Size	1k bytes
Time slot	1ms

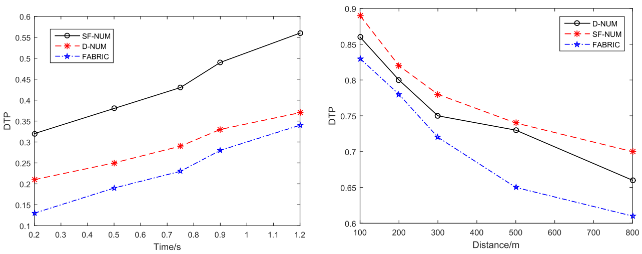
The simulation model is built based on the system architecture described in Section III. It is assumed that all nodes are synchronized in both time slots and transmission frames [34], [35]. The simulation parameters are listed in Table 2 and A Nakagami fading channel model is used.

We implemented two benchmark algorithms for performance comparison. One is the FABRIC algorithm [10], which uses a particular scaled gradient projection algorithm to solve the duality of the NUM problem. The other is the D-NUM algorithm [2], which solved the NUM problem that takes the driving context into account. Both the FABRIC algorithm and the D-NUM algorithm have considered the fairness problem from different perspective. The FABRIC algorithm solved the fairness problem by controlling the beaconing rate on each vehicle, while the D-NUM algorithm solved the fairness problem by allocating available channel resources. In addition, they are also competitive solutions to the stated problem. Our algorithm gives more comprehensive solution to the issue of fairness.

A. METRICS

Although the queue length and the back off supervision are sometimes used in Mobile Ad Hoc Networks, they are effective only in the case of low mobility networks. In the context of vehicular networks, due to the high mobility of nodes and their short connectivity cycles, we have considered that the use of the above metrics is unrealistic [34]. We use the following metrics to quantitatively analyze the algorithm performance.

- Data transmission probability (DTP): The relay node adaptively selects the probability of transmission for the data that needs to be transmitted according to different environmental conditions.
- Packet receiving probability (PRP): Probability of the vehicle receiving the complete packet in the high speed dynamic vehicle networking.
- Service ratio (SR): Given the total number of served requests n_s and the total number of submitted requests n by all vehicles, the service ratio is computed by n_s/n.
- Service delay (SD): It measures the waiting time of served requests, which is the duration from the time when the request is submitted to the time when the corresponding data item is retrieved.

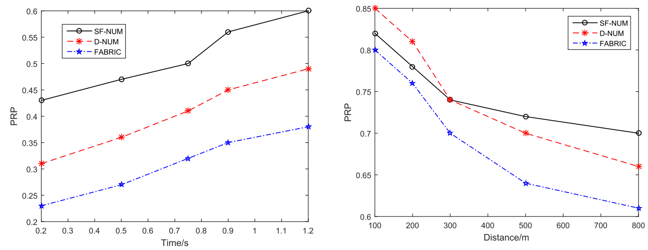


(a) (b)

FIGURE 5. The Probability of Data Transmission under different times and distances. (a) The Probability of Data Transmission under different times. (b) The Probability of Data Transmission under different distances.

B. SIMULATION RESULTS

Figure 5(a) and Figure 5(b) show the performance comparison of the three algorithms on the probability of data transmission under different times and different distances respectively. We can observe that SF-NUM has the best performance, and FABRIC has the worst performance. The reason is as follows. The SF-NUM transmits the data by stable scheduling and fair allocation of available channel resources, so it can satisfy the nodes' requirements when transmitting data in Vehicular networks. D-NUM also achieves the fair allocation of available channel resources, but it ignores the problem of stable scheduling and the trend of vehicle's movement, so its data transmission probability is lower than SF-NUM. Unlike D-NUM, FABRIC did not explore the fair allocation of available channel resources. Instead, FABRIC uses the attribute value of the algorithm to establish the desired fairness concept in the allocation. However, compared with SF-NUM that relies on stability and fairness, FABRIC may not always be able to transmit the data in an uniform state since it is possible to transmit large or small amount of data, so its data transmission probability is the lowest.



(a) (b)

FIGURE 6. The Packet Receiving Probability under different times and distances. (a) The Packet Receiving Probability under different times. (b) The Probability of Data Transmission under different distances.

As shown in Figure 6(a) and Figure 6(b), SF-NUM achieves the highest packet receiving probability among all, D-NUM has lower packet receiving probability while FABRIC is the lowest. The SF-NUM's packet receiving probability is the highest. The reason is as follows. The SF-NUM transmits the data by stable scheduling and fair allocation of available channel resources, so it can receive the data of vehicle in stable state. D-NUM also achieves the fair allocation of available channel resources to some extent, but it ignores the problem of stable scheduling and the trend of vehicle's movement, so its packet receiving probability is lower than SF-NUM. Unlike D-NUM, FABRIC did not explore the fair allocation of available channel resources. Instead, FABRIC uses the attribute value of the algorithm to establish the desired fairness concept in the allocation. However, compared with SF-NUM that relies on stability and fairness, FABRIC may not always be able to receive the data completely since it is possible to receive part of the data or null data. Because the data transmission is not fully conducted, leading to the lowest packet receiving probability. Another observed trend for all approaches is that the packet receiving probability increases when the rounds of process of data transmission increase. This is because the longer the process of data transmission, the higher the probability that the data will be received over the channel.

Figure 7(a) and Figure 7(b) show the service ratio of algorithms changes with different times and different distances. As observed, the service ratio among the algorithms decline to a certain extent when the traffic workload starts to get heavier. As time and distance increase, the amount of data transmission is growing and the resources that need to be consumed will increase, the service ratio of all the algorithms keep reducing. The reasons are explained as follows. At the beginning, all algorithms can achieve reasonable good performance due to the small number of data. When the vehicle arrive rate starts to increase, although the velocity drops accordingly, the increased number of data transmission dominates the performance, which results in the decline of the service ratio. As shown in Figure 7(a), the service ratio of D-NUM is lower than that of SF-NUM as time increases,

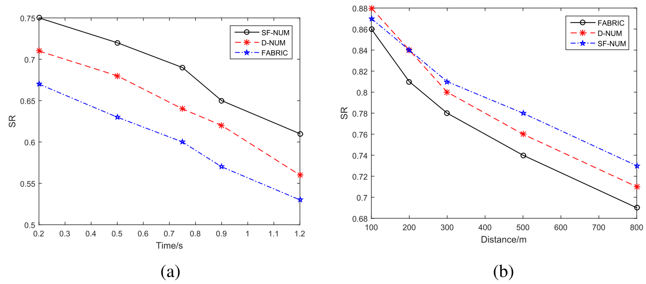


FIGURE 7. The Service Ratio under different times and distances. (a) The Service Ratio under different times. (b) The Service Ratio under different distances.

while it is higher than FABRIC. This is due to the fact that stable scheduling gradually play a useful role in efficient range of communication coverage, the service ratio of SF-NUM is better than D-NUM, and the performance of D-NUM is higher than FABRIC. This demonstrates the advantages of stable scheduling strategy adopted by SF-NUM. As shown in Figure 7(b), the service ratio of SF-NUM is lower than that of D-NUM as distance increases, while it is higher than FABRIC at the beginning. This is due to the fact that stability scheduling is not obvious in the case of a small amount of data transmission. Also, the computation of SF-NUM is larger than that of D-NUM. FABRIC is a fair adaptive control of beacon rate, so the performance of FABRIC is the lowest. After a while, stable scheduling gradually play a useful role, the service ratio of SF-NUM is better than D-NUM, and the performance of D-NUM is higher than FABRIC. This demonstrates the advantages of stable scheduling strategy adopted by SF-NUM.

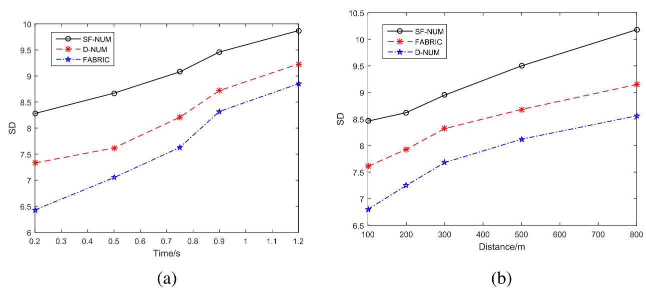


FIGURE 8. The Service Delay under different times and distances. (a) The Service Delay under different times. (b) The Service Delay under different distances.

In the last round of experiments, we study the effect of times and distances on the service delay of the above algorithms. Figure 8(a) and Figure 8(b) show the service delay of algorithms changes with different times and different distances. In Figure 8(a), we can observe that the proposed SF-NUM scheme achieves a worse service delay, the performance of D-NUM is lower, while FABRIC's service delay is the lowest. This is because that the computation of SF-NUM is more complexity, as it needs to schedule through queues and distributes resources fairly by weight calculation. While D-NUM calculates weight factors less than SF-NUM, so its service delay is better than SF-NUM. Furthermore, as FABRIC focuses on controlling beacon rate, solving the problem of duality of network utility maximization, while compared with D-NUM, its calculation is less. Therefore, its service delay is better than D-NUM.

In Figure 8(b), we can observe that the proposed SF-NUM scheme achieves a worse service delay, the performance of FABRIC is lower, while D-NUM's service delay is the lowest. This is because that the computation of SF-NUM is more complexity, as it needs to schedule through queues and distributes resources fairly by weight calculation. While FABRIC calculates weight factors less than SF-NUM, so its service delay is better than SF-NUM. Furthermore, as D-NUM consider the effect of the distance which is a factor of safety weight. Therefore, its service delay is better than FABRIC. The benefit of data transmission achieved by SF-NUM is more significant in a heavy traffic environment. Although the performance of SF-NUM is worse than the other two algorithms, the SF-NUM is superior when transmitting and receiving data in Vehicular networks.

VII. CONCLUSION

This paper presents a novel stable scheduling based algorithm and a corresponding data dissemination in vehicular networks by allocating the available channel resources fairly. To the best of our knowledge, this is the first study that applies queue lengths based stable scheduling techniques to vehicular networks. The back pressure vector is introduced into stable scheduling and entropy value is introduced into fair allocaton of available channel resources. The proposed algorithm maintains the stability of vehicular networks communications and improves the probability of successful data transmission compared to existing algorithms.

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LIBING WU received the B.Sc. and M.Sc. degrees in computer science from Central China Normal University, Wuhan, China, in 1994 and 2001, respectively, and the Ph.D. degree in computer science from Wuhan University, Wuhan, in 2006. He was a Visiting Scholar with the Advanced Networking Lab, University of Kentucky, USA, in 2011. He is currently a Professor with the Department of Computer Science, Wuhan University. His research interests include wireless sensor networks, network management, and distributed computing.

YOUHUA XIA received the B.Sc. degree in computer science from Yichun University, Yichun, China, in 2012, and the M.Sc. degree in computer science from Fujian Normal University, Fuzhou, China, in 2016. He is currently pursuing the Ph.D. degree with the Department of Computer Science, Wuhan University, Wuhan, China. His main research interests include distributed computing, clustering methods, and vehicular networks.

ZHIBO WANG (M'14) received the B.E. degree in automation from Zhejiang University, China, in 2007, and the Ph.D. degree in electrical engineering and computer science from the University of Tennessee, Knoxville, TN, USA, in 2014. He is currently an Associate Professor with the School of Computer, Wuhan University. His research interests include wireless sensor networks and mobile sensing systems. He is a member of the ACM.

HAO WANG received the bachelor's degree in hydrogeology and engineering geology and the master's degree from the China University of Geosciences, Wuhan, in 1993 and 1996, respectively, and the Ph.D. degree in solid mechanics from the Graduate School of the Chinese Academy of Sciences in 2007. He is currently with the Institute of Rock and Soil Mechanics, Chinese Academy of Sciences. His main research interests include data modeling, risk analysis, and geotechnical information engineering.