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A Secure Resource Optimization Strategy Based on Utility Dominant in Vehicular Networks

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ABSTRACT Prospectively, vehicular networks are envisioned to support vehicular-based, road-based, and traffic-based data sensing, transmitting and processing for intelligent transportation system applications, and eventually evolve towards a new paradigm, named vehicular networks (VNs), which bundle the characteristics of networks into vehicular networks. In VNs, since the conflict between resource utility and the quality of service (QoS), it remains an ongoing challenge about how to reasonably and effectively allocate resources that can meet QoS and fairness requirements at the same time which causes security problem because of the conflicts. To this end, we propose a utility-based dominant resource allocation optimization strategy in this paper to achieve security in VNs. We first establish a mapping model between user QoS requirements and resource demands, and then apply the improved dominant resource fairness scheme to obtain optimal allocation results. The effectiveness of this security strategy is proved theoretically through the constructed utility function and the mapping model. Experimental results demonstrate that our security strategy can not only maximize the ratio of provision over demand of users and the satisfied degree of services but also achieve the QoS and fairness requirements of users.

INDEX TERMS Vehicular networks, security, resource allocation, utility function, QoS.

I. INTRODUCTION

In recent years, ITS and vehicles, especially cars, has developed a lot. More and more sensors and communication technologies (e.g., cloud computing) are integrated with cars, which opens up a new design space for vehicular-based applications [1], [2]. Prospectively, vehicular networks are envisioned to support vehicular-based, road-based and traffic-based data sensing, transmitting and processing for ITS applications, and eventually evolve towards a new paradigm, named Vehicular Networks (VNs), which bundle the characteristics of networks into vehicular networks. Thus, VNs has become an important way for users to obtain information and entertainment [3].

Vehicular networks have attracted great interest in the research community recently. Many potentially useful applications have been envisioned in vehicular networks [4]. These range from safety applications, such as vehicle collision avoidance, to other valuable applications such as realtime traffic estimation for trip planning, information retrieval, and media content sharing [5]. Moreover, vehicular networks also have the prospect of improving sensing and wireless coverage in the future. For example, by embedding sensors in vehicles, a mobile sensor network can be established to monitor road states and other environmental conditions in large areas. The vehicular networks can also act as ''delivery networks'' to transfer data from remote sensor networks to Internet servers [6].

Current VNs serve the last mile connection to the Internet for various wireless devices with diverse QoS requirements: large user numbers [7], high data transmission volume and multiple types of services. From the perspective of system operators [8], they want to maximize resource utilization and access more vehicles without increasing their investment. However, the users hope to obtain sufficient resources for their access anytime, anywhere, and higher quality of services. Because of the continuous emergence and rapid update of multimedia real-time applications, users become more and more strict with QoS guarantees. Due to the exponential growth of mobile vehicles, the system cannot meet all QoS requirements with limited network resources [9]–[11]. When many vehicles come together to provide services, the resource allocation/sharing becomes an important issue. The continuous traffic also makes the competition among the shared links become increasingly fierce. Optimized allocation of resources for users can not only meet the differentiated QoS requirements, but also achieve fairness. Therefore, how to maximize resource utilization has become a problem that needs to be solved.

In this paper, we focus on analyzing QoS and fairness requirements of users in resource allocation, and propose an allocation optimization security strategy that can satisfy both QoS and requirements. We evaluate the service quality through a utility metric, which characterizes the perceived service quality of users with diverse QoS requirements. We establish a mapping model, which makes QoS metrics (packet delay and packet loss) the independent variables and resource quantities (bandwidth and buffer) the dependent variables. This model can transform QoS requirements into network resource demands. We model the queuing buffer at the Access Point(AP) and derive the mapping model based on it. By modifying the existing dominant existing resources fairness scheme, we can achieve a fair distribution among users while maximize the utility.

The rest of this paper is organized as follows. section II, the related work is reviewed. The construction of Qos utility function is defined in section III. The Qos requirements and resource mapping model is described in section IV. section V is about the utility-based dominant resource allocation optimazation security strategy. The proof of the algorithm fair property is described in section VI. The experimental results and analysis is shown in section VII. We provide the conclusion in section VIII.

II. RELATED WORK

When studying the issue of resource allocation, fairness is a key factor to be considered. Since the unfair distribution of resources between different individuals can lead to resource starvation, waste or redundancy, and severely decrease resource utilization and use efficiency. At present, there are two most widely used fair resource allocation strategies: maximum and minimum fairness and proportional fairness. Max-min Fairness is a simple and effective fairness rule that can maximize the needs of the user with the least resources [12]. It was originally used in the window flow control protocol and later widely used in the bandwidth [13], channel and power allocation issues [14]–[18]. The weighted maximum-minimum fairness strategy introduces the concept of weights on it, enabling users to obtain resource shares corresponding to the weights [19]. Since this method gives absolute priority to users with less resource requirements, it is highly likely to affect other users. Therefore, Proportional Fairness has been proposed [20]. It focuses more on the proportionate change in resource allocation. However, this method is mainly applied to the elastic traffic services and the utility function constructed by it is only a single logarithmic function [21], so that cannot adapt to a variety types of service.

In order to make more efficient use of resources and adapt to different applications' quality of service requirements [22], scholars have made relevant researches on utility theories in microeconomics and applied them to resource allocation problems in network systems. The utility function is usually used to reflect how satisfied users are with services [23]. Shenker detail analyzed the characteristics and requirements presented by different applications in [24], designed different utility function curves according to different application classifications, and pointed out that the non-linear relationship between application performance and bandwidth should be considered when allocating network resources and providing QoS guarantees. The unified utility function of different traffic flows was studied in [25], and a resource allocation optimization model was established. The proposed heuristic algorithm can guarantee the QoS demand of real-time traffic and provide a trade-off between throughput and fairness for the best-effort traffic. There are also many literatures that combine the utility and fairness criteria and propose the methods of utility max-min fairness and utility proportional fairness to achieve the purpose of user fairness and optimal utility [26]–[29].

In current VNs, resources are mostly allocated separately, and nowadays mobile applications usually require multiple resources; thus single resource allocation design can no longer meet differentiated QoS requirements. Through in depth analysis of QoS performance, it can be found that different QoS requirements are closely related to different network resource requirements in the VNs. For example, for a certain user, the packet delay in the radio access network is mainly affected by the wireless bandwidth it obtains, that is, the maximum rate that the user can use to transmit the packet on the shared radio channel; the packet loss is mainly due to the fact that the cache capacity of network devices is limited. In order to satisfy the user's service experience, it is critical to allocate these network resources fairly among wireless devices [30]. Therefore, the joint scheduling and optimization of multiple resources have attracted people's attention.

The most common multi-resource allocation method is per-resource fairness (PF), which can balance the user's share of each type of resource without considering the diverse needs of users. On the other hand, the non-fair allocation (NF) only considers user demands and ignores fairness. Specifically, for each user, NF allocates each type of resource with an amount proportional to his or her demands in the corresponding resource. Although it strikes equivalent QoS utility values for every user, it ignores fairness because a user with higher resource demands will get more shares, encouraging users to bluff about their true demands. Another multi-resource allocation scheme is bottleneck fairness (BF) [31]. It decides which type of resource is the most bottlenecked (i.e., the resource type with the highest demand to supply ratio), and then distributes such resources equally among users. The other types of resources are allocated to each user in proportion to the resource demand. It is fair because it equalizes user shares in the bottleneck resource, while taking into account diverse user demands. However, it is vulnerable to attack from a malicious user, who may lie about his true resource demands in order to shift the bottleneck resource from one to another, thereby gain more shares of resources.

Dominant Resource Fairness (DRF) is also used to study the issue of multiple resource allocation [32]. Different from PF, NF and BF, it can achieve a good balance between fairness and the diversity of user demands, and prevent the attacks of malicious users who lie about their true resource demands. In DRF, the resource share of a certain resource type is defined as the ratio of the total amount of resources acquired by the user to the total amount of the resource. The dominant share of each user is defined as the maximum share of resources among all types of resources. The purpose of DRF is to equalize the share of all users' dominant resources. It is an extension of the max-min fairness from single resource allocation to the max-min fairness of multiple resources, and it has the following desirable properties: pareto-optimality, envy-freeness and strategy-proofness.

Pareto-optimality means that for any user, his or her own overall resource share cannot be increased without either increasing the total resource capacity or decreasing the resource share of other user. Envy-freeness means that no users are willing to exchange their own share of resources with other users. That is, their resource share is already optimal. This will ensure fairness.

Strategy-proofness means that no user can concurrently increase his resource shares in all resource types by lying about his true resource demand, and encourage users to participate with honesty. It is worth noting that DRF does not always allocate the dominant shares fairly. If the resource requirements of certain users are fully satisfied, the remaining resources of these users can be used to further meet the the unsatisfactory demands of other users.

Therefore, resources in the system can be used more efficiently. However, this method is mainly aimed at the cloud computing environment and pursues a fair distribution of the dominant resources without considering other resources [33]. If it is applied to a VNs system, the user QoS requirements also need to be considered.

Our work studies the multiple resource allocation problem in VNs, and proposes a resource allocation optimization strategy that can meet user QoS requirements and fairness simultaneously through using the utility function and improving the DRF scheme. Based on the literature [34], the definition of the weight of user priority is introduced to allocate the remaining resources, so that it can satisfy more users.

III. CONSTRUCTION OF QoS UTILITY FUNCTION

In our VNs system, we consider two performance parameters when evaluating user QoS, that is, packet end-to-end delay and loss rate. Although objective QoS metrics are often desirable for a certain flow type, it is more challenging when multiple types of flows exist and need to compare with each other in the scenario of resource management in this paper. Furthermore, both subjective and objective factors should be considered in judging the perceived QoS. So we construct a utility function with the packet delay and packet loss as independent variables, as shown in equation (1):

$$U\left(d_0, r_0, d, r\right) = min\left(\frac{d_0}{d}, \frac{1-r}{1-r_0}\right) \quad (1)$$

Where d_0 and d are requested and perceived packet end-to-end delay by the user, r_0 and r are requested and perceived packet loss rate, respectively. In equation (1), $\frac{d_0}{d}$ is called the delay ratio, which is the ratio of the requested delay to actual delay. If the system can fully meet the delay requirement for the user, then we have $\frac{d_0}{d} = 1$; otherwise we have $\frac{d_0}{d} < 1$. Therefore, the value of the delay ratio reflects the user's satisfaction with the delay requirement. A large delay ratio indicates that the actual end-to-end delay is short, and user satisfaction is higher, and vice versa. Similarly, $(1-r)/(1-r_0)$ is called the loss ratio, which is the ratio of the actual transmission rate to the requested transmission rate, and reflects the extent to which the system meets the packet loss rate requirements. The QoS utility function U is defined as the minimum of the delay ratio and the loss ratio, which indicates that the overall utility is affected by the bottleneck of one of the two QoS indicators, when one of the two is less satisfied than another, choosing a smaller one will truly reflect the perceived quality of the user.

IV. QoS REQUIREMENTS AND RESOURCE MAPPING MODEL

Although the DRF scheme can ensure the fairness of resource quantities, it cannot guarantee that the final allocation results can meet user QoS requirements. In other words, it is more concerned with fairness than utility. In order to improve it, maximizing utility will be the optimization goal in our security strategy, so as to make resource allocation more reasonable and efficient. In order to realize our purpose, a mapping model that transforms different QoS requirements into multiple resource requirements needs to be established. To achieve the mapping relationship between the two, it is necessary to establish a corresponding function. Here, QoS performance indicators (packet delay and packet loss rate) are used as independent variables, and resource quantities (wireless bandwidth and queue buffer) are used as dependent variables. In the VNs system shown as Figure 1, the AP serves as a bridge connecting the wired network and the wireless network and needs to receive a large number of service

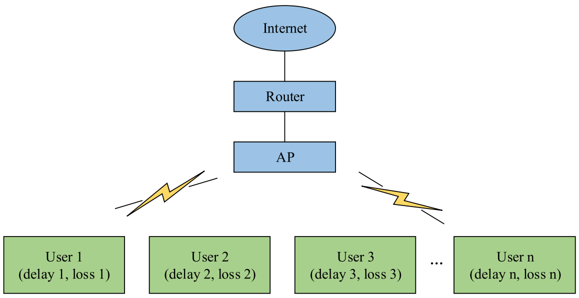

FIGURE 1. The topology of VNs system.

requests from the wireless devices, and packets may suffer significant queuing delays in their buffer queues. Therefore, we estimate the packet end-to-end delay as the sum of the transmission delay of the wireless channel and the queuing delay in the buffer. For the calculation of the packet loss rate, the packet loss caused by the wireless channel fading or the MAC layer random access collision can be compensated through the retransmission mechanism. Therefore, only the packet loss caused by the overflow of the queuing buffer on the AP is considered. Since the uplink device that AP connects is a network layer device, we do not consider packet loss at the physical layer or MAC layer.

We use a M/D/1 queuing model for the queuing buffer at the AP, assuming that all traffic flows have a fixed packet size P. The service flow requested by each user has a packet delay and packet loss rate that represent QoS performance, denoted as $< d, r >$. The VNs resources assigned to the corresponding user (wireless bandwidth and queued cache) are denoted by $< BW, L >$, and the transmission delay of the node's packets in the wireless link d_t is expressed as:

$$d_t = \frac{P}{BW} \tag{2}$$

Suppose the packet arrival follows the Poisson distribution with an arrival rate $\lambda = BW/P$ and the service rate of the queue α,that denotes the number of packets that are served by the queue in a time unit, we define $\rho = \lambda/\alpha$ as the traffic load. In general, $\rho < 1$, because the service rate is larger than the flow arrival rate. Otherwise, serious congestion may occur and the system cannot operate normally. According to the queuing model, the average queuing delay d_q is

$$d_q = \frac{2-\rho}{2\alpha(1-\rho)} \tag{3}$$

Therefore, the end-to-end packet delay d is

$$d = d_t + d_q = \frac{1}{\lambda} + \frac{2-\rho}{2\alpha(1-\rho)} \tag{4}$$

Packet loss due to queue buffer overflow can be calculated according to the model and the average queuing length is

$$E[Q] = \frac{\rho(2-\rho)}{2(1-\rho)} = \rho + \frac{\rho^2}{2(1-\rho)} \tag{5}$$

However, the M/D/1 model assumes an infinite buffer size. There will be packet loss if $E[Q] > \frac{L}{P}$, which indicates that the average queuing length is larger than the allocated buffer size. Here L should be normalized by packet size P when it compares with $E[Q]$, as L has the unit of bit while $E[Q]$ has the unit of packets. From this, we can define an approximate packet loss rate r as follows:

$$r = \frac{E[Q] - \frac{L}{P}}{E[Q]} \tag{6}$$

We assume the traffic load ρ is a constant value. When the traffic load is heavy, it can be approximately equated to $\frac{C}{C_b}$, where C is the wireless channel capacity and C_b is the capacity of the wired link connected to the router. Based on this assumption we have

$$\lambda = \frac{S}{d} \tag{7}$$

where

$$S = 1 + \frac{\rho(2-\rho)}{2(1-\rho)} \tag{8}$$

Similarly,

$$BW = \lambda P = \frac{SP}{d} \tag{9}$$

Because $E[Q]$ is a function of ρ, it can also be regarded as a constant for the user. According to formula (6), it can be deduced that the allocated queuing buffer length is:

$$L = PE[Q](1-r) \tag{10}$$

From Equation (9) and (10), it can be seen that the bandwidth is inversely proportional to the packet delay, and the buffer length is also inversely proportional to the packet loss rate. This is in line with the reality. To have a shorter packet delay, the system should provide a faster transmission rate; to have a smaller packet loss rate, the system should provide a larger buffer length.

V. UTILITY-BASED DOMINANT RESOURCE ALLOCATION OPTIMIZATION SECURITY STRATEGY

A. FORMULATION OF THE OPTIMIZATION PROBLEM

Assume that in a VNs system shown in Figure 1, the wireless channel capacity is C, the queuing buffer is L_Q, and M users compete for network resources. For each user i, their QoS requirements are represented as $\langle d_{i0}, r_{i0}\rangle$ and the corresponding resource demand vector as $\langle BW_{i0}, L_{i0}\rangle$. We define $\mu_i = max\left\{\frac{BW_{i0}}{C}, \frac{L_{i0}}{L_Q}\right\}$ as the dominant share required by the user i. If $\mu_i = \frac{BW_{i0}}{C}$, indicates that user i is bandwidth-dominant, otherwise user i is buffer-dominant. Without loss of generality, it is assumed that the first K of the M users are bandwidth-dominated and the remaining users are buffer-dominant. We can derive that

$$\mu_i = \begin{cases} \frac{BW_{i0}}{C} & i = 1, 2, \cdots, K \\ \frac{L_{i0}}{L_Q} & i = K+1, K+2, \cdots M \end{cases} \tag{11}$$

We define $\alpha = \frac{L_Q}{C}$ as the ratio of total queuing buffer size over wireless channel capacity and $m_i = \frac{L_{i0}}{BW_{i0}}$ as the resource demand ratio of user i. According to the definition of dominant share, we also have

$$\begin{cases} m_i \leq a & i = 1, 2, \cdots, K \\ m_i \geq a & i = K+1, K+2, \cdots, M \end{cases} \tag{12}$$

The allocated resource shares and actual perceived QoS performance of user i under the improved DRF scheme are denoted as $\langle BW_i, L_i \rangle$ and $\langle d_i, r_i \rangle$, respectively. We denote $x_i = \frac{BW_i}{BW_{i0}} = \frac{L_i}{L_{i0}}$ as the ratio of provision over demand of user i. Since DRF aims to balance the actual dominant share of all users, we further defined $q = \mu_i x_i, (i = 1, 2, \cdots, M)$ as the actual dominant share of any user. Through the above definition, we make some modify and improve the DRF scheme in [19], and formulate the '

$$\begin{aligned} &\text{maximize } (x_1, x_2, \cdots, x_M) \\ &\text{subject to } \sum\nolimits_{i-1}^{M} BW_i = \sum\nolimits_{i-1}^{M} x_i BW_{i0} \leq C \\ &\qquad \sum\nolimits_{i-1}^{M} L_i = \sum\nolimits_{i-1}^{M} x L_{i0} \leq L_Q \\ &\qquad \mu_1 x_1 = \mu_1 x_2 = \cdots = \mu_M x_M \end{aligned} \tag{13}$$

In the above formulation, we maximize the share of all users subject to resource constraints in bandwidth and queuing buffer and the DRF constraint which equalizes users' actual dominant shares. The following results can be obtained by calculation:

$$q = min\left(\frac{1}{K + a\sum_{i-K+1}^{M}\frac{1}{m_i}}, \frac{a}{\sum_{i-1}^{K} m_i + a(M-K)}\right) \tag{14}$$

$$BW_i = x_i BW_{i0} = \begin{cases} qC & i = 1, 2, \cdots, K \\ \dfrac{qL_Q}{m_i} & i = K+1, K+2, \cdots, M \end{cases}$$

$$L_i = x_i L_{i0} = \begin{cases} m_i qC & i = 1, 2, \cdots, K \\ qL_Q & i = K+1, K+2, \cdots, M \end{cases} \tag{15}$$

Since all fairness properties of QoS are related to utility, all DRF fairness properties are described from the perspective of resources. Therefore, in order to prove that our security strategy can satisfy QoS and fairness at the same time, we first need to derive the utility function with the resource quantities as an independent variable. According to equation (9) and (10) and (1), the utility function related to resources can be obtained,

$$U_i = min\left(\frac{BW_i}{BW_{i0}}, \frac{L_i}{L_{i0}}\right) \tag{16}$$

Here again, it can be linked to the ratio of provision over demand of users,

$$U_i = x_i \tag{17}$$

That is to say, the user's satisfaction with the service can be expressed as the ratio of provision over demand of the allocated resources, and the more satisfying the user's QoS requirements, the higher user utility.

B. ALGORITHM DESCRIPTION

After the user establishes a connection with the AP, if a service flow request is initiated, the QoS requirement of each service flow of each user is mapped to the network resource requirement.

1) ADAPTIVE FLOW DEMAND AGGREGATION

If a node creates multiple service flows, to ensure the fairness of each node, it is necessary to aggregate the multiple service flows of the user so that per-node fairness is achieved. This is because a node can obtain more resources by transmitting multiple flows.

Suppose the user creates J flows. The QoS requirement of each service flow j is represented as $\langle d_{j0}, r_{j0} \rangle$. According to the mapping model proposed in this paper, the corresponding resource requirement for each service flow is $\langle BW_{j0}, L_{j0} \rangle$. The node's aggregate resource requirement denotes as $\langle BW_0, L_0 \rangle$, can be expressed as

$$BW_0 = \sum\nolimits_{j-1}^{J} BW_{j0}, \quad L_0 = \sum\nolimits_{j-1}^{J} L_{j0} \tag{18}$$

Therefore, the user can use the above total demand to compete for resources. Because one-time traffic demand aggregation cannot adapt well to changing user requirements, dynamic calculations need to be performed based on changes in user traffic. If the user creates a new service flow or ends an existing service flow, it needs to update the corresponding user QoS requirements and adjust the resource allocation result.

2) DEFINITION OF USER PRIORITY WEIGHTS

After the on-demand allocation is performed, there are still resources left, and then the final allocation needs to be made according to the user priority weights, so that users with large demand and unsatisfied can obtain more resources as much as possible. This article defines the following weights to measure the user's overall priority in all resource types:

$$\omega_i = \sum_R \left(\frac{\mu_{iR}}{\mu_R}\right), \quad R \in \{BW, L\} \tag{19}$$

where $\mu_R = arg\ max\ \mu_{iR}\ , i \in M$ represents the collection of the largest dominant resource for all users on resource R. The algorithm not only allocates the local importance of the resource requested by the user, but also further considers the overall priority of the resource requested by the user, so that after satisfying the user with a small amount of resource demand, the user with the most resource demand is satisfied as much as possible in order to maximize the reasonable allocation of resources. Moreover, DRF does not always balance the user's dominant resource share. If the user gets more resources than he needs, after meeting his needs, additional resources will be reassigned to other users. Taking the scenario in Figure 1 as an example, the overall resource allocation algorithm steps can be described as follows:

(1) Firstly, the QoS requirements of the service flow created by the user are acquired, and the QoS requirement is

converted into a required amount of resources according to a mapping model. If the user creates multiple service flows, traffic demand aggregation is required;

(2) At this time, all users have only one service QoS request, and then they are converted into resource quantities according to the mapping model, and their respective dominant resource shares and user priority weights are calculated, according to formulas (13), (14) and (15) Calculate optimal distribution results;

(3) Calculate the utility of each user according to formula (16). A user whose utility is greater than 1 will acquire his or her resource amount as needed, and for other users, it will use the remaining network resources to perform the operation in (2) again. Repeat this process until no user can obtain a utility greater than 1 or all users satisfy their resource requirements, or if one of the resource types is completely allocated, terminate execution and output the final allocation result;

(4) If there are still remaining resources and the user's requirements have not been met, they are assigned to users with insufficient resources in descending order of user priority weights until the remaining resources are consumed, and the execution stops and the final result is output. Assignment results;

(5) If there is a change (addition or deletion) of the user's service flow after that, the demand is modified according to the corresponding change, and the above-mentioned distribution process is performed again. According to the above algorithm steps, the flow chart shown in Figure 2 is drawn.

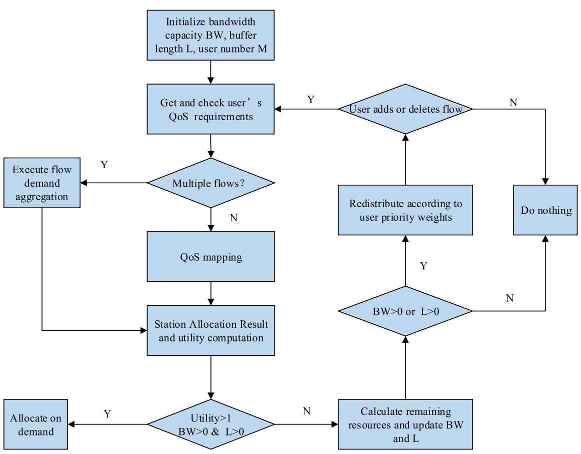

FIGURE 2. **Utility-based dominant resource allocation optimization algorithm.**

VI. PROOF OF THE ALGORITHM FAIR PROPERTY

According to the previous introduction, it is learned that DRF can provide fairness based on the amount of resources. Although the mapping model between user QoS requirements and the number of resources is established in this paper, after the mapping is completed, whether the fairness attributes still valid still need to be verified. According to formula (14), one of the values is proved here. Taking $q = \frac{1}{K+a\sum_{i-K+1}^{M}\frac{1}{m_i}}$ as an example, another case can be similarly proved.

Theorem 1: The algorithm satisfies the Pareto-optimality, that is, in a given amounts of all types of network resources in VNs, the user can only increase its utility by reducing the utility of any other user.

Proof: Assume that among the M users, the user i increases his utility, and the utility of any other node (such as node j) does not decrease. According to formula (17), it can be inferred that x_i increase and x_j remain unchanged. However, according to the derivation of DRF, at least one resource in the system is fully utilized by the user. Without losing the generality, it is assumed that the bandwidth is completely consumed, that is $\sum_{i-1}^{M} x_i BW_{i0} = C$. Because of the x_i increase, the single component $x_i BW_{i0}$ will increase accordingly, while the other nodes x_j will remain unchanged, so the final total will be greater than C, contradicting the actual situation. The reason for this is that the wrong assumption was made that the user can increase $U_i (i \neq j)$ without reducing U_j. From this, it can be proved that the algorithm satisfies Pareto optimality.

Theorem 2: The algorithm satisfies envy-freeness, that is, users will not envy QoS performance of any other user. This property indicates that the utility of a user will not increase if this user exchanges his QoS performances with another user's.

Proof: Because the QoS performance and the amount of resources are one-to-one mapping, the exchange of QoS performance is equivalent to the exchange of actual resource shares. Assume that the two users i and j have obtained the number of resources for $\langle BW_i, L_i \rangle$ and $\langle BW_j, L_j \rangle$, and the corresponding utility values for the two users are U_i and U_j. The user is bandwidth-dominant after mapping his QoS requirements to resource requirements. According to formula (15) of DRF distribution results, there are $BW_i = qC$. If the user j is also bandwidth-dominant, then there is $BW_j = BW_i = qC$. Otherwise, if the user j is cache-dominant, there is $BW_j = \frac{qL_Q}{m_j}$. By calculating the ratio between the two,

$$\frac{BW_j}{BW_i} = \frac{L_Q}{m_j C} = \frac{a}{m_j} \tag{20}$$

Since the user j is cache-dominant, it can be known from equation (12) that $m_j \geq a$ and so

$$\frac{BW_j}{BW_i} = \frac{a}{m_j} \leq 1 \Rightarrow BW_j < BW_i \tag{21}$$

Combining the two cases can prove that when the user i is dominant in bandwidth, the actual bandwidth share he will receive will not be less than any other user.

$$BW_i \geq BW_j, \quad \forall j \neq i \tag{22}$$

If the user i exchanges his own resource share with the user j, the user i has a new utility value U_i^{new}, which can be expressed as

$$U_i^{new} = min(\frac{BW_j}{BW_{i0}}, \frac{L_j}{L_{i0}}) \tag{23}$$

In the previous derivation $BW_j < BW_i$, if $L_j < L_i$, the number of all resources of the user j is less than the user i, obviously there is $U_i^{new} < U_i$; if $L_j > L_i$, according to formula (17) available

$$U_i^{new} = min(\frac{BW_j}{BW_{i0}}, \frac{L_j}{L_{i0}}) = \frac{BW_j}{BW_{i0}} \leq \frac{BW_i}{BW_{i0}} = x_i = U_i \quad (24)$$

When the user is buffer-dominant, this case is the same. Hence, it can be shown that the algorithm satisfies envy-freeness.

Theorem 3: The algorithm satisfies strategy-proofness, that is, users can not increase their own utility by falsely reporting their true QoS requirements.

Proof: Suppose the user's real QoS requirement is $\langle d_{i0}, r_{i0} \rangle$. The actual perceived QoS performance after resource allocation using the DRF scheme can be expressed as $\langle d_i, r_i \rangle$, and its corresponding utility value is U_i. If the user provides false QoS requirements $\langle d_{i0}^*, r_{i0}^* \rangle$, his actual QoS performance and utility values change to $\langle d_i^*, r_i^* \rangle$ and U_i^*, respectively. Then, the prevention of strategic policing attributes that satisfy QoS can be expressed as the following inequality:

$$U_i(d_{i0}, r_{i0}, d_i, r_i) \geq U_i^*(d_{i0}^*, r_{i0}^*, d_i^*, r_i^*) \quad (25)$$

Represent the user's real resource requirements as $\langle BW_{i0}, L_{i0} \rangle$. Corresponding to the real and false QoS requirements provided by the user, the actual resource shares allocated to them are $\langle BW_i, L_i \rangle$ and $\langle BW_i^*, L_i^* \rangle$, respectively. According to the DRF's prevention of strategic manipulative attributes based on the amount of resources, the number of user resources cannot increase at the same time. Without loss of generality, if $BW_i^* > BW_i$, there are $L_i^* \leq L_i$, similar to the proof of innocence satisfying QoS, available according to formula (17)

$$U_i^* = min(\frac{BW_i^*}{BW_{i0}}, \frac{L_i^*}{L_{i0}}) = \frac{L_i^*}{L_{i0}} \leq \frac{L_i}{L_{i0}} = x_i = U_i \quad (26)$$

It can be seen that the calculations U_i^* in the above formula are based on the real needs of the user $\langle BW_{i0}, L_{i0} \rangle$ and are not related to the spurious needs of the false reports. Therefore, they will not have any impact on the final utility, which means that the algorithm satisfies strategy-proofness.

VII. EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the validity of the proposed algorithm (here the improved DRF is abbreviated as DRF), the results are analyzed by running simulation experiments and are consistent with the PF, NF, and BF which compare the fairness and user utility. The simulation parameters set in the experiment are shown in Table 1.

TABLE 1. Simulation parameters configuration.

Parameter	Value
Bandwidth	5 Mbps
Queuing buffer	20 Mb
Packet size	12 kb
Packet delay	[0.1 s, 5]
Packet loss	[1%,50%]

In order to differentiate service types, the session and stream classes are defined as delay sensitive applications. The packet delay and packet loss rate ranges are [0.1s, 2s] and [10%, 50%], respectively. The interaction class and background class are defined as packet loss sensitive applications. The packet delay and packet loss rate ranges are [2s, 5s] and [1%, 10%], respectively. Correspondingly, different application types use different performance values. We use Matlab as the simulation tool and generate QoS requirement randomly. Three different traffic load scenarios are selected to represent the situation when the system is under different load.

Figure 3 shows the results of four different allocation schemes when the traffic load is 0.3. It can be seen from the figure that the system is in a light load state at this time, and the red line represents the resource requirement after mapping the QoS requirements of different service flows. According to the randomly generated data in the experiment, the bandwidth requirements of all users are larger than the buffer requirements. This is because the total difference between the two is relatively large. Therefore, after the function mapping calculation is performed, the dominant resources and bottleneck resources of all users are bandwidth. It can be seen that both PF and BF divide the total bandwidth capacity equally among all users, that is, the bandwidth can be divided into 2.5 Mbps. The NF has a similar shape to the user request resource curve, because it is allocated to the user in proportion, so the amount of resources obtained is more because of a large amount of demand, for example, the user index of 11,13,15,19. The DRF also has a similar trend with the amount of resources requested, but compared with the NF, it is obviously more consistent with the actual resource requirements of the users, almost coincident, indicating that it will not provide an unlimitedly high share for high demand users. Instead, it allocates on demand, which reduces the distribution gap between users and also saves system resources.

For the buffer resource, the PF still divides the resources equally among the users, that is, they all obtain 1Mb; at this time, the buffer resources do not belong to the bottleneck resources in the BF allocation scheme, so the proportional allocation is performed, and thus the allocation result overlap with the NF. The DRF allocation scheme still performs on-demand allocation even if the system has enough remaining resources. This is in line with the marginal utility theory, it is not always true that the more resources allocated to users, the greater their satisfaction with the service will continue to increase. If a certain service only needs to satisfy a certain QoS requirement, it can provide a good service experience, then allocating more resources will only result in a waste of resources and also affect the users behind. Therefore, following the principle of on-demand allocation can greatly improve the system's resource utilization.

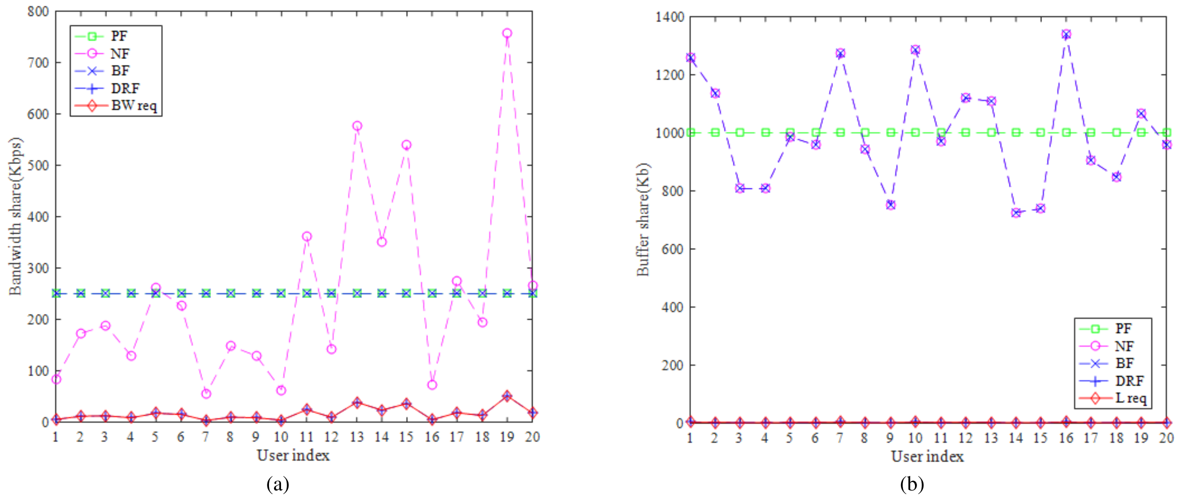

FIGURE 3. The allocation results of different schemes when traffic load is 0.3, a is bandwidth and b is buffer.

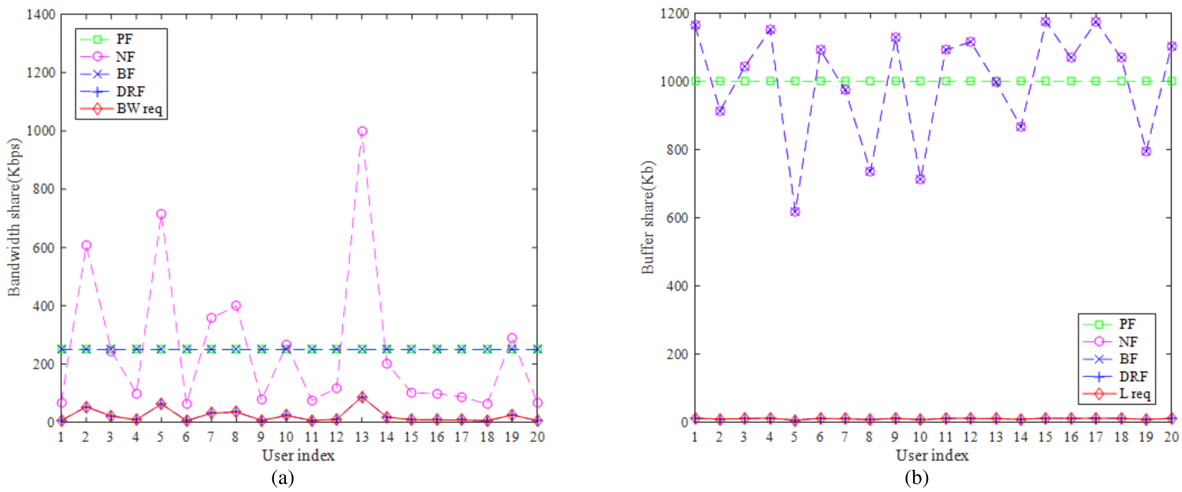

FIGURE 4. The allocation results of different schemes when traffic load is 0.6, a is bandwidth and b is buffer.

Figure 4 shows the allocation result when the system traffic intensity is 0.6. At this time, the system is in a medium load state, and the amount of resources requested by the user increases. Similar results can be observed. However, PF and BF cannot satisfy the bandwidth requirement average value at this time. NF and DRF curves are very close to the user's request, indicating that the higher the system load, the higher the resource utilization.

Figure 5 shows the distribute result when the traffic load is 0.9. At this time, the system is in a heavy load state. The amount of resources requested by the user reaches 600 Kbps at the highest. All kinds of allocation schemes are close to the actual user requirements, which means that the system load is heavier, and less likely the resources are over-allocated. In this case, the actual resource requirements of some users exceed the average 2.5 Kbps, such as user 7 and user 17, then the PF and BF schemes cannot meet the user's needs, while NF and DRF can be well satisfied with the different needs of users, because each user has obtained the amount of resources he needs, and achieves fairness among users. NF means that the more user needs, the more it is allocated, hence it does not achieve fairness very well.

From the experimental results above, we can see that the PF scheme is absolutely fair, but it does not consider the needs of different users. NF only considers the different requirements of users in proportion, and thus ignores the fairness among users. DRF and BF consider both fairness and user demand, but the results obtained are different. BF divides the bottleneck resources equally and then allocates another bottleneck resource according to the user's needs. This results in users having absolute fairness on one type of resource and a large share of the gap on another type of resource. The difference is that DRF allocates two kinds of resources in a consistent manner, which not only considers the diversity of user needs,

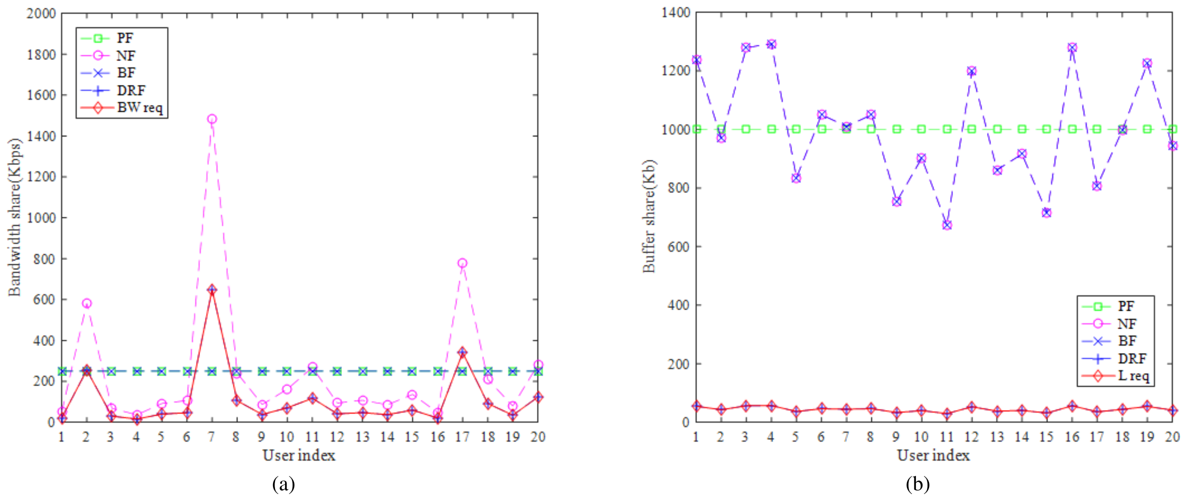

FIGURE 5. The allocation results of different schemes when traffic load is 0.9, a is bandwidth and b is buffer.

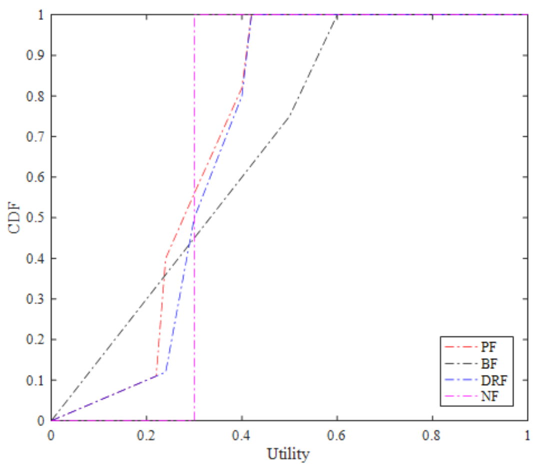

FIGURE 6. CDF of user utilities when traffic load is 0.9.

but also controls the differentiation of allocation shares to some extent. Therefore, it can be concluded that the DRF balance the contradiction between fairness and utility well, which not only maximizes the satisfaction of the user, but also maximizes the utilization of system resources.

Comparing the efficiency of these schemes in using network resources, Figure 6 is a cumulative distribution function graph of user utility when the traffic load is 0.9, which describes the probable distribution of utility. From this figure, it can be seen that under the NF scenario, all users have the same utility value, and PF performs the worst among the four scenarios because PF allocates resources equally and does not consider the diversity of user needs. BF and DRF perform better than PF and NF, but DRF is more focused on median utility than BF, which means that the number of users with too high or too low utility under DRF scheme is less than that of BF scheme, making DRF scheme not only adaptable to different user requests, but also possible to maximize network user utility under limited resources, and reduce the number of resource gaps between users. The conclusion is consistent with the above experiment.

VIII. CONCLUSION

This paper presents a resource allocation optimization security strategy and algorithm that can meet the QoS and fairness requirements of users simultaneously by comparing and analyzing existing resource allocation strategies. The mapping relationship among bandwidth, buffer resources, packet delay and packet loss rate was discovered. Through constructing the utility function and the deduced mapping model, it was proved that the algorithm can well meet the fairness attributes required for resource allocation and allocate resources to achieve security in VNs. The optimization problem was formalized. Finally, a simulation experiment was conducted to make comparisons among PF, NF and BF. The results show that the proposed security strategy can balance the relationship between user utility and fairness, and can maximize the ratio of provision over demand of users. While meeting the QoS requirements of users, the effectiveness of resources is realized as well.

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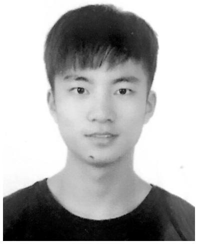

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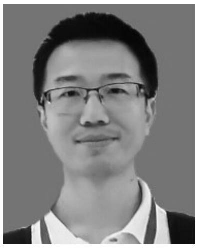

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