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A Joint Multi-Criteria Utility-Based Network Selection Approach for Vehicle-to-Infrastructure Networking

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***Abstract*— The emerging technologies for connected vehicles have become hot topics. In addition, connected vehicle applications are generally found in heterogeneous wireless networks. In such a context, user terminals face the challenge of access network selection. The method of selecting the appropriate access network is quite important for connected vehicle applications. This paper jointly considers multiple decision factors to facilitate vehicle-to-infrastructure networking, where the energy efficiency of the networks is adopted as an important factor in the network selection process. To effectively characterize users' preference and network performance, we exploit energy efficiency, signal intensity, network cost, delay, and bandwidth to establish utility functions. Then, these utility functions and multi-criteria utility theory are used to construct an energy-efficient network selection approach. We propose design strategies to establish a joint multi-criteria utility function for network selection. Then, we model network selection in connected vehicle applications as a multi-constraint optimization problem. Finally, a multi-criteria access selection algorithm is presented to solve the built model. Simulation results show that the proposed access network selection approach is feasible and effective.**

***Index Terms*— Heterogeneous wireless networks, energy efficiency, network selection, handover decision making, vehicle-to-infrastructure networking.**

I. Introduction

WITH advanced information and communication technologies being successfully applied, connected vehicle applications have received extensive attention. As mentioned in [1]–[3], the emerging technologies for connected vehicles have become hot topics. However, connected vehicle applications are generally used in heterogeneous wireless networks. In such a context, user terminals (without loss of generality, we use the term "user terminals" to denote licensed user terminals) face the challenge of access network selection [4], [5]. Moreover, high energy consumption is an important problem in current communication networks [6]–[11]. For example, with the extensive utilization of videos and big data, vehicle communication terminals need more energy to finish the communication process. Therefore, how to select the appropriate access network is significantly important for connected vehicle applications. This paper studies a vehicle-to-infrastructure networking approach for these applications.

In vehicle-to-infrastructure networking, user terminals (vehicles) have multiple available networks, such as Wireless Local Area Networks (WLAN), cellar networks, and other wireless networks, which they can select as their access networks. It is very difficult for user terminals to select the appropriate network from multiple available networks. Xie *et al.* proposed a wireless network selection scheme with a parallel transmission capability [4]. Aymen *et al.* used fuzzy logic and multi-attribute decision making to present a new network selection algorithm [5]. Prabhavathi and Nithyanandan proposed a distributed reinforcement learning strategy to select the WLAN and WiMAX networks [12]. Xing *et al.* used neural network theory to design a network selection algorithm [13]. However, these methods face many difficulties in selecting an effective access network.

A. Motivation and Contributions

The motivation of this paper is to effectively select the appropriate access network in heterogeneous wireless vehicular networks by considering the multi-criteria utilities. As mentioned in [14] and [15], the high energy consumption of a vehicular network is an important challenge in connected vehicle applications. More importantly, with the emerging requirements and fast-paced development of smart cities, smart transportation, and in-car entertainment, multimedia videos, pictures, photos, real-time traffic and vehicle information, weather information etc. must be quickly uploaded to the data treatment platform for these applications via wireless vehicular networks. For example, when a vehicle accident occurs, quickly reporting the location of an accident to a smart

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transportation platform in real time is helpful in saving lives and avoiding the traffic congestion; through in-car terminals, individual mobile phones and other individual mobile devices such as iPads and laptops, users can download and upload entertainment data such as videos and photos to/from their social networks to share them with their friends. Moreover, transportation congestion controls and transportation traffic scheduling based on vehicle-to-infrastructure networking are very helpful in improving city transportation and implementing smart transportation. All these applications need to deliver greater amounts of data. In this paper, we study network selection for vehicle-to-infrastructure networking. In such a case, terminal devices consume more energy. In particular, when there exist multiple mobile devices in a vehicle, the interference among them can lead to higher receiving and transmitting power consumptions. As discussed in [16]–[19], energy efficiency has become an important metric for vehicular networks. Thereby, in this paper we consider the energy efficiency utility in the network selection process.[1] In contrast to previous papers, this makes our work more consistent with practical cases. We combine energy efficiency, signal intensity, network cost, delay, and bandwidth metrics to establish the appropriate utility function to capture users' preferences and network performance. Additionally, dedicated short-range communications (DSRC), which are one-way or two-way short-range to medium-range wireless communication technologies, are used for vehicle-to-vehicle communications in vehicular networks [20]. However, in contrast to DSRC applications in vehicle-to-vehicle communications, in this paper, we mainly study the communication performance of vehicle-to-infrastructure networking.

According to the analysis above, we jointly consider multiple decision factors to effectively achieve vehicle-to-infrastructure networking. In this paper, the energy efficiency of networks is adopted as an important factor to perform network selection. We propose a multi-constraint optimization model to characterize the multi-criteria network selection problem in vehicle-to-infrastructure heterogeneous wireless networks. A heuristic algorithm is proposed to seek the optimal solution to the model. Our main contributions in this paper are as follows:

- In contrast to previous network selection methods, we take the energy efficiency of networks as an important decision factor. Then, we propose a framework for network selection under the energy efficiency metric. To obtain the weight of each decision factor, we use the hierarchy analysis method to propose a weight generation algorithm after considering the energy efficiency of the networks.
- Multiple decision factors, including energy efficiency, signal intensity, network cost, delay, and bandwidth, are jointly considered in the vehicle-to-infrastructure networking. Their utility functions are built to characterize the users' preferences and network performance. Simultaneously, we give a detailed proof about these utility functions.
- Multi-criteria utility theory is used to construct an energy-efficient network selection approach. The design strategies are proposed to establish a joint multi-criteria utility function for network selection. According to the design strategies, we give the design requirements for the multi-criteria utility function. Then, the corresponding multi-criteria utility function is correctly designed, and a detail proof is given. The network selection for connected vehicle applications is modeled as a multi-constraint optimization problem. Then, we present a heuristic multi-criteria access network selection algorithm to obtain the optimal solution to the model. Finally, we conduct detailed simulation experiments to validate the proposed network selection approach.

[1] In this paper, we use the term "user terminals" or "terminals" loosely to refer to mobile devices accessing networks via vehicle-to-infrastructure networking. Here, energy efficiency is taken as an important metric, although we know that in reality these devices can be charged or powered by the vehicle's battery and alternator. However, to deliver larger data flows, terminals require higher energy consumptions. This leads to great loads on vehicles. In turn, bad network selection can increase the transmitting power on the infrastructure side (such as base stations) in vehicle-to-infrastructure networking. As mentioned in [14], energy efficiency plays a key role in the optimal design of vehicular techniques deployed in vehicle-to-infrastructure scenarios.

B. Related Work

To improve the network selection performance, Abid *et al.* [21] and Lahby and Adib [22] used multiple criteria to build network selection algorithms, namely the Simple Addition Weight (SAW) algorithm and the Random Access Selection (RAS) algorithm. Their studies have shown that SAW and RAS provided a better network selection ability. Kang *et al.* [23] used DS evidence theory to build a network selection scheme. By constructing the appropriate DS evidence, they could choose the optimal network from many available networks. Tang *et al.* [24] studied access network selection in multi-cognitive wireless networks. They exploited user preferences, business requirements and network performance to propose an integrated weighting network access selection algorithm. Additionally, Wang and Kuo [25] discussed the mathematical modeling of the network selection. Goudarzi *et al.* [26] used an artificial bee colony to seek the optimal solution to the vertical-handover problem, where an iterative process was used to find the optimal solver. Chinnappan and Balasubramanian [27] exploited fuzzy logic controllers to perform the vertical handover and used the mobile terminal speed, network load and service cost to decide the users' satisfaction degrees. Gharsallah *et al.* [28] proposed a new scheme to select the most appropriate wireless access network for each application. Ahuja *et al.* [29] took the available bandwidth as a time-varying parameter to perform network selection in heterogeneous wireless contexts. However, these methods do not jointly consider multiple decision factor. Moreover, these methods also do not consider the networks' energy efficiency. As mentioned in [30], energy efficiency has an important impact on network performance. Therefore, these methods face difficulties in achieving the optimal network selection. Our approach jointly consider multiple decision factors and regards the access networks' energy efficiency as a selection metric.

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Xu *et al.* [31] studied network selection between LTE and WiFi. They proposed a context-aware method to choose the network. Skondras *et al.* [32] proposed a network selection approach by estimating the weights of decision factors. In each selection process, they considered the impact and dynamic changes in different decision factors. Then, by performing a weight estimation process, they selected the network that satisfied their requirements. Goyal and Kaushal [33] exploited the analytic hierarchy process to perform network selection for moving vehicles. Ting *et al.* [34] studied network selection in the backhaul capacity of small cells and presented a dynamic backhaul-capacity-sensitive network selection method. They took the backhaul capacity and capacity sensitivity as important selection factors. Kuboniwa *et al.* [35] studied the cell selection in small cells. They exploited the positioning and map information to develop a new selection scheme.Simultaneously, they considers traffic load information and employed the expected throughput and location to select a network. Mah *et al.* [36] used the Markov Decision Process and related shadow prices to develop a network selection method. Their method exploited operators' and users' utilities to jointly consider users' and operators' objectives. Accordingly, their method could obtain a better network selection performance. In contrast to these methods, we build a multi-criteria utility function and model to characterize the network selection problem in heterogeneous wireless networks.

The remainder of this paper is organized as follows. Section 2 discusses network selection for vehicle-to-infrastructure networking. Section 3 derives the utility functions of all the decision factors. In Section 4, we present and discuss a multi-criteria access network selection approach. Section 5 presents the simulation results and analysis. Finally, we conclude our work in Section 6.

II. Network Selection for Vehicle-to-Infrastructure Networking

In the section, we will discuss the network selection for vehicle-to-infrastructure networking.

A. Network Selection

To allow user terminals to access the appropriate network, a complex mechanism is required. In the mechanism, user terminals need to find available access networks, and an appropriate scheme is built to select an optimal access network for users. Moreover, we also need to guarantee continuous communication for the users.

For the vehicle-to-infrastructure networking case, it is significantly important to select the appropriate available network. Therefore, network selection has an important impact on users' quality of experience. In this paper, the network selection framework for vehicle-to-infrastructure networking is shown in Fig. 1, which includes the modules for data collection, network filtering, the calculation of energy efficiency, and the generation of the fitted values. First, the data collection module collects and provides all the parameters that the network selection algorithm needs. In our framework, we collect the parameters about users' configuration, traffic demands, QoS requirements, and configuration of operator networks, where traffic demands denote the demands for download and upload traffic. In our framework and method, users decide on and input the QoS requirements. The user terminals or vehicle terminals collect these requirements. Based on these parameters, the measurement metrics about energy efficiency, signal intensity, delay, and cost can be calculated appropriately. Second, the network filtering module chooses the networks that satisfy the given constraints and parameter thresholds. Through the network filtering process, the set of available networks is built. Simultaneously, the computational complexity and the decision time can be effectively reduced. Third, we use the module for the calculation of the energy efficiency to compute the energy efficiency of the available networks according to the network parameters and traffic types. Fourth, the fitted value generation module calculates the selection weight of the available networks. To generate the appropriate and correct selection weight for each metric, we use the hierarchy analysis method to obtain the expected network weight as discussed in [33].

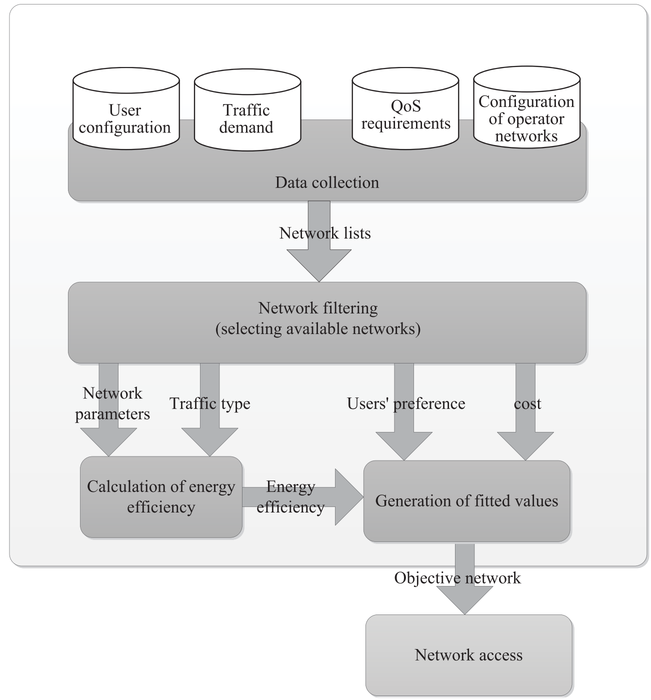

Fig. 1. The framework of the network selection in vehicle-to-infrastructure networking.

B. Network Weight

In this paper, the decision factors of the network selection include the networks' energy efficiency, signal intensity, delay, cost, and bandwidth. Signal intensity can be determined by the user terminals, while other metrics need to be obtained by network sensing and information collection [24].

To access the optimal network, the network weight is exploited to characterize the network performances and users' preferences. We use the hierarchy analysis method to allocate the appropriate weight to each selection metric. The steps and flow chart of the hierarchy analysis algorithm are shown in Algorithm 1 and in Fig. 2, respectively.

Algorithm 1 Hierarchy Analysis Algorithm

Input: user demands: bandwidth demand b_u,
cost demand c_u, delay demand d_u, signal
intensity demand d_u; parameters of access
network i: available bandwidth b_i of access
network i, cost c_i of access network i, delay
d_i of access network i, signal intensity s_i of
access network i;
Output: Output: Decision factor weights of
access network i: energy efficient weight w_i^e,
cost weight w_i^c, signal intensity weight w_i^s,
delay weight w_i^d, bandwidth weight w_i^b;
Procedure:
According to bandwidth demand b_u, cost
demand c_u, delay demand d_u, signal
intensity demand s_u, build decide hierarchy
structure $H = h_1, h_2, \ldots, h_n$; let $j = 1$;
Loop1: Construct decision matrix R;
Loop2: Calculate the weight of hierarchy j;
then attain energy efficient weight $w_{i,j}^e$,
cost weight $w_{i,j}^c$, signal intensity weight
$w_{i,j}^s$, delay weight $w_{i,j}^d$, bandwidth weight
$w_{i,j}^b$ of hierarchy j;
decide whether hierarchy j is consistent; If
not, go back to **Loop1**;
if $j < n$, go back to **Loop2**;
calculate the total weights; then attain energy
efficient weight w_i^e, cost weight w_i^c, signal
intensity weight w_i^s, delay weight w_i^d,
bandwidth weight w_i^b of access network i;
decide whether the whole hierarchy is
consistent; if not, go back to **Loop1**;
Exit the procedure;

III. Utility Function

To effectively evaluate the decision factors of network selection, we design utility functions to map different decision factors to the corresponding utility metrics. According to utility theory, the utility function is satisfied with twice differentiability, monotonicity, and concavity-convexity. Only when three properties are satisfied, can we find the optimal point according to the designed utility functions. In the following, we design the utility function corresponding to each decision factor.

A. Utility Function of Energy Efficiency

Here, we define energy efficiency of networks as

$$EE = \frac{T}{E} = \frac{\sum b}{\sum (\alpha r_t + (1-\alpha) r_d b)} \tag{1}$$

where T denotes the throughput (namely, the maximum amount of mutual information delivered), in units of bits,

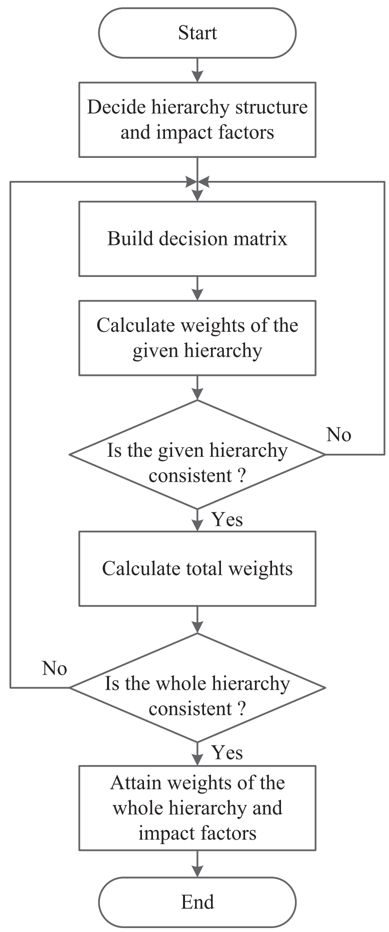

Fig. 2. The flow chart of the hierarchy analysis method.

E expresses the energy consumption in units of joules; α is a parameter, where $0 < \alpha < 1$; r_d denotes the energy consumption to transmit K bytes; r_t represents the user terminal's circuit energy consumption per second; b denotes the average transmission rate of the users' traffic, in units of $Kbyte/s$; and $(\sum b) \leq B$, where b denotes the network bandwidth. In Equation (1), r_t denotes the basic circuit energy consumption that guarantees that the terminal circuits will perform normally when the terminal is idle, while r_d describes the energy consumption only related to the terminal loads when the terminal sends network data.

As mentioned in [30], the sigmoidal function is a good threshold function and is continuous, smooth, and strictly monotonic. Therefore, we use the sigmoidal function to characterize the utility metric of the networks' energy efficiency.

Theorem 1: The sigmoidal utility function, namely

$$y = \frac{1}{1 + \beta \exp \gamma_1 (x_0 - x)},$$

is twice differentiable, monotonic, and concavity-convex.

Proof: In the following, we use the mathematical method to prove that the utility function has twice differentiability, monotonicity, and concavity-convexity.

For the utility function

$$y = \frac{1}{1 + \beta \exp \gamma_1 (x_0 - x)}, \tag{2}$$

its first derivative can be denoted as

$$y' = \frac{\gamma_1 \beta \exp \gamma_1 (x_0 - x)}{(1 + \beta \exp \gamma_1 (x_0 - x))} > 0, \tag{3}$$

where $\gamma_1 > 0$ and $\beta > 0$.

Therefore, according to Equation (3), we can prove that the utility function is monotone.

According to Equation (3), we obtain its second derivative as follows:

$$y'' = \frac{2\gamma_1^2 \beta^2 \exp \gamma_1 (2x_0 - 2x)}{(1 + \beta \exp \gamma_1 (x_0 - x))^3} - \frac{\gamma_1^2 \beta \exp \gamma_1 (x_0 - x)}{(1 + \beta \exp \gamma_1 (x_0 - x))^2}. \tag{4}$$

According to Equation (4), we know that the utility function in Equation (2) is twice differentiable.

Let $y'' \leq 0$; then, the following equation is obtained:

$$\frac{2\gamma_1^2 \beta^2 \exp \gamma_1 (2x_0 - 2x)}{(1 + \beta \exp \gamma_1 (x_0 - x))^3} \leq \frac{\gamma_1^2 \beta \exp \gamma_1 (x_0 - x)}{(1 + \beta \exp \gamma_1 (x_0 - x))^2}. \tag{5}$$

Then, we obtain the following equation:

$$x \leq x_0 - \ln \frac{1}{\beta}. \tag{6}$$

Let $y'' \leq 0$; then, the following equation holds:

$$\frac{2\gamma_1^2 \beta^2 \exp \gamma_1 (2x_0 - 2x)}{(1 + \beta \exp \gamma_1 (x_0 - x))^3} \geq \frac{\gamma_1^2 \beta \exp \gamma_1 (x_0 - x)}{(1 + \beta \exp \gamma_1 (x_0 - x))^2} \tag{7}$$

Accordingly, we obtain the following equation:

$$x \geq x_0 - \ln \frac{1}{\beta} \tag{8}$$

According to Equations (5)-(8), we can derive that when $x \leq x_0 - \ln \frac{1}{\beta}$, the utility function in Equation (2) is a concave function, but when $x \geq x_0 - \ln \frac{1}{\beta}$, it is convex. Therefore, it is concavity-convex.

The proof is concluded.

Thus, according to the above discussion, we define the utility function of the network's energy efficiency as

$$u(e) = \frac{1}{1 + \beta \exp(\gamma_1 (e_{avg} - e))}, \quad e > 0 \tag{9}$$

where e and e_{avg} denote the network's energy efficiency and average energy efficiency and γ_1 (where $\gamma_1 \geq 2$) represents the sensitivity of the user's traffic to the energy efficiency, which determines the curve steepness of the utility function. A steeper γ_1 results in a higher sensitivity.

The utility function for energy efficiency is plotted in Fig. 3. From Fig. 3, we can see that the utility function is monotonic and concavity-convex. The physical meaning of Equation (9) is that a higher network energy efficiency e results in a larger utility function $u(e)$ and a more preferable network. This shows that the defined utility function $u(e)$ can effectively be used for decision making in network selection.

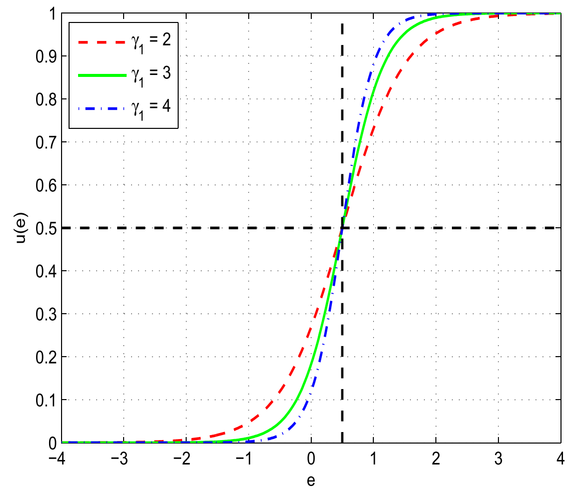

Fig. 3. The utility function for energy efficiency.

B. Utility Function of Signal Intensity

Generally, when the received signal is lower than a certain threshold, it can be considered that the network cannot guarantee normal operation. In such a case, the utility value for the signal intensity is 0. Moreover, the received signal has an upper limit.

The received signal determines the intensity scope. If assuming x_α as a lower limit and x_β as an upper limit, we need to consider the upper and lower limits in the utility function. Therefore, for the utility function of the signal intensity, we introduce the following additional conditions:

$$u(x) = 0 \quad \forall x \leq x_\alpha \tag{10}$$

$$u(x) = 1 \quad \forall x \geq x_\beta \tag{11}$$

$$u(x_{mid}) = 0.5, \quad x = x_{mid} \tag{12}$$

where

$$x_{mid} = \frac{(x_{\min} + x_{\max})}{2} \tag{13}$$

Theorem 2: For the below utility function

$$u(x) = \begin{cases} 0 & x < x_{\min} \\ \dfrac{\left(\frac{x}{x_{mid}}\right)^{\gamma_2}}{1 + \left(\frac{x}{x_{mid}}\right)^{\gamma_2}} & x_{\min} \leq x \leq x_{mid} \\ 1 - \dfrac{\left(\frac{x_{\max} - x}{x_{\max} - x_{mid}}\right)^{\gamma_2}}{1 + \left(\frac{x_{\max} - x}{x_{\max} - x_{mid}}\right)^{\gamma_2}} & x_{mid} \leq x \leq x_{\max} \\ 1 & x > x_{\max} \end{cases} \tag{14}$$

where $\gamma_2 \geq 2$ and

$$x_{mid} = \frac{(x_{\min} + x_{\max})}{2},$$

is twice differentiable, monotonic, and concavity-convex. In addition, it satisfies with the constraints in Equations (10)-(12).

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Proof: According to Equation (14), we can observe that the utility function satisfies the constraints in Equations (10)-(12). Next, we prove that it is twice differentiable, monotonic, and concavity-convex.

To prove the twice differentiability, we only need to prove that the second and third equations in Equation (14) are differentiable.

According to Equation (14), the following equation holds:

$$\lim_{x \to x_{mid}^{+}} u'(x) = \frac{\gamma_2}{4(x_{mid} - x_{\min})} \tag{15}$$

$$\lim_{x \to x_{mid}^{-}} u'(x) = \frac{\gamma_2}{4(x_{\max} - x_{mid})} \tag{16}$$

Therefore, we can obtain the following equation

$$\lim_{x \to x_{mid}^{+}} u'(x) = \lim_{x \to x_{mid}^{-}} u'(x)$$

As a result, the utility function in Equation (14) is twice differentiable. Simultaneously, we can easily find that it is also monotonic and concavity-convex.

The proof is concluded.

Here, we obtain the utility function of the signal intensity as follows:

$$u(s) = \begin{cases} 0 & s < s_{\min} \\ \dfrac{\left(\frac{s}{s_{mid}}\right)^{\gamma_2}}{1 + \left(\frac{s}{s_{mid}}\right)^{\gamma_2}} & s_{\min} \le s \le s_{mid} \\ 1 - \dfrac{\left(\frac{s_{\max}-s}{s_{\max}-s_{mid}}\right)^{\gamma_2}}{1 + \left(\frac{s_{\max}-s}{s_{\max}-s_{mid}}\right)^{\gamma_2}} & s_{mid} \le s \le s_{\max} \\ 1 & s > s_{\max} \end{cases} \tag{17}$$

where s_{min} and s_{max} denote the lower and upper limits of the signal intensity, respectively; γ_2 (where $\gamma_2 \ge 2$) represents the sensitivity; and

$$s_{mid} = \frac{(s_{\min} + s_{\max})}{2}$$

The physical meaning of Equation (17) is that a higher signal intensity s results in a larger utility function $u(s)$ and a more preferable network. This shows that the defined utility function $u(s)$ can effectively be used for network selection. Fig. 4 shows the utility function for signal intensity.

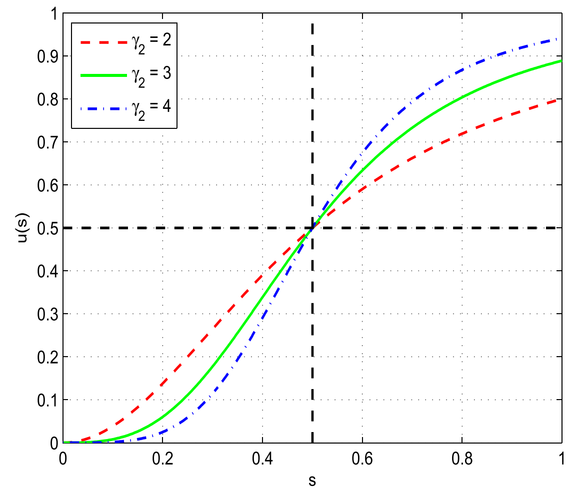

Fig. 4. The utility function for signal intensity.

C. Utility Function of Cost

Network cost is a more intuitive metric for the user. The cost of different networks can be compared directly with each other. In this paper, we use a linear function to denote the utility function of cost. Hence, it can be expressed as

$$u(c) = 1 - u'(c) \tag{18}$$

where

$$u'(c) = \begin{cases} \dfrac{c}{c_{\max}}, & 0 \le c \le c_{\max} \\ 1, & c > c_{\max} \end{cases}$$

c is the current cost of the network, and c_{max} is the maximum cost acceptable to the user.

The physical meaning of Equation (18) is that a lower cost c results in a larger utility function $u(c)$ and a more preferable network. This shows that the defined utility function $u(c)$ can effectively be used for network selection. Fig. 5 plots the utility function for the cost.

D. Utility Function for Network Delay

Generally, network delay should have a maximum value. When designing the utility function, we expect that a larger network delay has a lower the corresponding utility value. The network delay criterion is a decreasing metric. Therefore, we define the utility function for the network delay as

$$u(d) = 1 - u'(d)$$

$$u'(d) = \begin{cases} \dfrac{\left(\frac{d}{d_m}\right)^{\gamma_3}}{1 + \left(\frac{d}{d_m}\right)^{\gamma_3}} & 0 \le d \le d_m \\ 1 - \dfrac{\left(\frac{d_{\max}-d}{d_{\max}-d_m}\right)^{\gamma_3}}{1 + \left(\frac{d_{\max}-d}{d_{\max}-d_m}\right)^{\gamma_3}} & d_m \le d \le d_{\max} \\ 1 & d > d_{\max} \end{cases} \tag{19}$$

where d_{max} represents the maximum delay, d_m is half of the maximum delay, and γ_3 (where $\gamma_3 \ge 2$) denotes the sensitivity. A greater value of γ_3 results in a greater sensitivity.

The utility function for the network delay is similar to that for the signal intensity, which is twice differentiable, monotonic, and concavity-convex. Due to space limitations, the detailed proof process is not given. The physical meaning of Equation (19) is that a higher cost d results in a larger utility function $u(d)$ and a more preferable network. This shows that the defined utility function $u(d)$ can effectively be used for network selection.

E. Utility Function for Network Bandwidth

When the network bandwidth is lower than the minimum requirements of the user's traffic, this will cause a loss of the user's requests. This is very difficult for users to tolerate.

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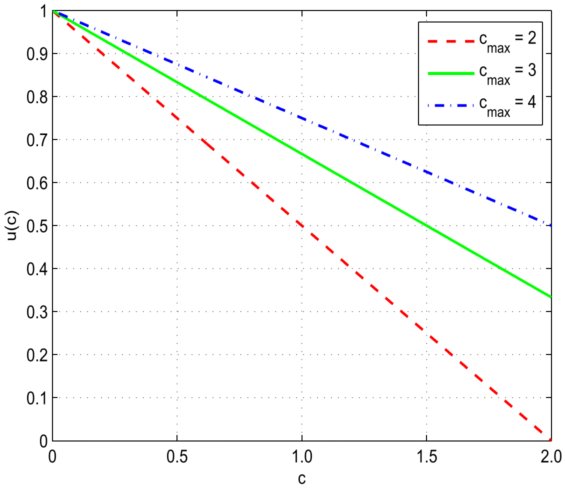

Fig. 5. The utility function for cost.

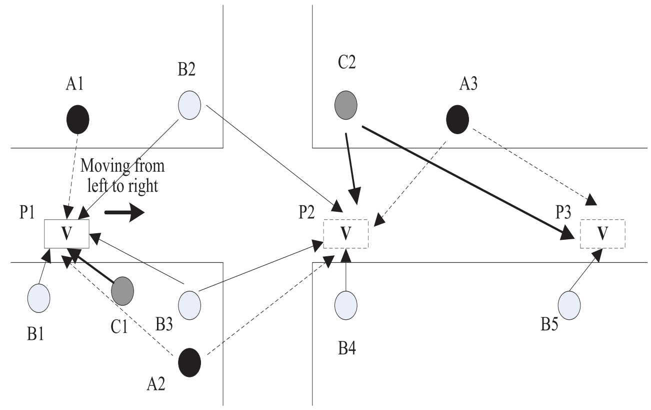

Fig. 6. Access selection for multiple available networks in vehicle-to-infrastructure networking, where gray circles denote WLAN APs, blue circles represent 3G towers, green circles indicate WiMax towers, and the red rectangle denotes the vehicle moving from left to right.

When the network bandwidth is higher than the maximum requirements of the user's traffic, the user's satisfaction degree will not increase further. Therefore, we define the following utility function for network bandwidth:

$$u(b) = \begin{cases} 0 & b \le b_{\min} \\ \dfrac{\left(\frac{b}{b_m}\right)^{\gamma_4}}{1+\left(\frac{b}{b_m}\right)^{\gamma_4}} & b_{\min} \le b \le b_m \\ 1 - \dfrac{\left(\frac{b_{\max}-b}{b_{\max}-b_m}\right)^{\gamma_4}}{1+\left(\frac{b_{\max}-b}{b_{\max}-b_m}\right)^{\gamma_4}} & b_m \le b \le b_{\max} \\ 1 & b > b_{\max} \end{cases} \tag{20}$$

where b_{min} and b_{max} represent the minimum and maximum network bandwidths, respectively, and b denotes the bandwidth of the user's demands. The utility function for the network delay is similar to that for the signal intensity. Due to space limitations, the detailed proof process is not given. The physical meaning of Equation (20) is that a higher cost b results in a larger utility function $u(b)$ and a more preferable network. This shows that the defined utility function $u(b)$ can effectively be used for network selection.

Thus, according to the above discussion and design, for metric factors concerning energy efficiency, signal intensity, network cost, delay, and bandwidth, we can effectively design corresponding utility functions that are twice differentiable, monotonic, and concavity-convex. As a result, according to these designed utility functions, we can select the appropriate access network.

IV. Multi-Criteria Access Selection

In this section, we will derive our network selection approach: Multi-Criteria Access Selection (MCAS). For connected vehicle applications in vehicle-to-infrastructure networking as shown in Fig. 6, where V denotes the moving vehicle, when the vehicle V is moving to position $P1$ from left to right, there are six available networks, including three WLAN networks, two 3G networks and one WiMax network. At Position $P1$, it seems that it is the most appropriate for vehicle V to select network $B1$. However, if there exists greater interference and channel congestion, other networks may be better suited for the vehicle V. When vehicle V moves from position $P1$ to positions $P2$ and $P3$, the available networks are different at these different positions. In such a case, many factors, including energy efficiency, signal intensity, network cost, delay, and bandwidth, are considered.

Therefore, when designing the multi-criteria utility function, we need to consider how multiple selection metrics affect each other in the decision process. Therefore, we propose the following design strategies:

Strategy 1: If one of the multiple metrics of the network has a weight value of greater than zero, the multi-criteria utility function can characterize the impact between multiple metrics on network selection.

Strategy 2: If one of the multiple metrics of the network has a weight value of zero, the multi-criteria utility function can reflect this feature of the network. In addition, the multi-criteria utility value can effectively be used to perform decision making in network selection.

Strategy 3: The utility function can reflect the monotonicity of each metric. In addition, it ensures that the utility value cannot be greater than one.

Strategy 4: The utility function is used to avoid the zero-cost effect. It can correctly reflect the selection preferences of users.

According to the design strategies above, we define the following design requirements for the multi-criteria utility function:

$$\frac{\partial U(\mathbf{x})}{\partial u_i} \ge 0 \tag{21}$$

$$sign\left(\frac{\partial U(\mathbf{x})}{\partial x_i}\right) = sign\left(u_i'(x_i)\right) \tag{22}$$

$$\lim_{u_i \to 0} U(\mathbf{x}) = 0, \quad \forall i = 1, \ldots, n \tag{23}$$

$$\lim_{u_i, u_2, \ldots, u_n \to 1} U(\mathbf{x}) = 1 \tag{24}$$

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Equation (21) ensures that the multi-criteria utility function increases with monotonic increases in each utility function. In such a case, our multi-criteria utility function can sufficiently characterize the impact of each selection factor. Equation (22) indicates that the multi-criteria utility function decreases with monotonic decreases in each utility function. Equation (23) shows that the multi-criteria utility function trends to zero when one of multiple metrics gradually becomes zero. Equation (24) guarantees that the multi-criteria utility function trends to one when all multiple metrics gradually become one. Specifically, this illustrates that all utility metrics are based on the users' expectations. Finally, we set the weight concerning the users' preferences to reflect their individual preferences.

A. Multi-Criteria Utility Function

In this section, we propose a new multi-criteria utility function and prove that it satisfies all the requirements in Equations (21)-(24) and is built according to the utility functions of the five decision factors in Equations (1)-(20).

Theorem 3: For the multi-criteria utility function

$$U\left(x\right)=\prod_{i=1}^{n}\left[u_i\left(x_i\right)\right]^{\varpi_i} \tag{25}$$

where n is the number of dimensions of vector x, ϖ_i denotes the initial weight of metric i (where $(\sum_{i=1}^{n}\varpi_i)=1$), $u_i(x_i)$ stands for the utility value of metric i, it satisfies the constraints in (21)-(24).

Proof: For $\forall j=1,\ldots,n$, when $u_j\rightarrow 0$, $U\left(x\right)=\prod_{i=1}^{n}u_i(x_i)^{\varpi_i}=0$.

Therefore, the utility function in (25) satisfies the constraint in Equation (23).

When $u_1,\ldots,u_n\rightarrow 1$, $U\left(x\right)=\prod_{i=1}^{n}u_i(x_i)^{\varpi_i}=1$. This indicates that Equation (25) satisfies the constraint in Equation (24).

The partial differential of the utility function in (25) with respect to u_j is calculated as follows:

$$\frac{\partial U\left(x\right)}{\partial u_j}=\varpi_j\left[u_j\left(x_j\right)\right]^{\left(\varpi_j-1\right)}\prod_{i\neq j}^{n}\left[u_i(x_i)^{\varpi_i}\right]\geq 0 \tag{26}$$

Therefore, the utility function in Equation (25) satisfies the constraint in Equation (21).

The partial derivative of $U(x)$ in Equation (25) with respect to x_j can be obtained as follows:

$$\frac{\partial U\left(x\right)}{\partial x_j}=\left(\varpi_j\left[u_j\left(x_j\right)\right]^{\left(\varpi_j-1\right)}\prod_{i\neq j}^{n}\left[u_i\left(x_i\right)\right]^{\varpi_i}\right)u_j'\left(x_j\right) \tag{27}$$

This illustrates that the utility function in Equation (25) satisfies the constraint in Equation (22).

Therefore, from Equations (26)-(27), we can know that when each utility function monotonically increases or decreases, the multi-criteria utility function possesses the same monotonic properties.

Finally, it is proved that the multi-criteria utility function can be used to reflect the users' preferences. The logarithmic transformation cannot cause a change in the priority. Therefore, $U(x)$ in Equation (25) is logarithmically transformed. Then, we obtain the following equation:

$$V\left(x\right)=\ln\left(u\left(x\right)\right)=\sum_{i=1}^{n}\varpi_i\ln\left(u\left(x\right)\right) \tag{28}$$

According to Equation (28), let $\upsilon_i\left(x_i\right)=\ln u_i\left(x_i\right)$. It is clear that $\upsilon_i\left(x_i\right)=\ln u_i\left(x_i\right)$ is also a one-metric utility function. Then, the following equation can be obtained:

$$V\left(x\right)=\sum_{i=1}^{n}\varpi_i\upsilon_i\left(x_i\right)\sim U\left(x\right) \tag{29}$$

From Equation (29), it can be known that the users' preferences can be reflected by setting appropriate weight values. This indicates that the utility function in Equation (25) can effectively characterize users' preferences.

The proof is concluded.

According to Theorem 3, the utility function in Equation (25) satisfies the requirements of the multi-criteria utility function and can be used to build our multi-criteria utility function for vehicle-to-infrastructure networking. In the following, we will discuss our access selection model for this application.

B. Access Selection Model

According to the discussion above, we propose the following access selection model:

$$\max\sum_{k=1}^{N}\varphi_k\prod_{i=1}^{n}\left[u_i\left(x_i\right)\right]^{\varpi_i} \tag{30a}$$

$$s.t.\ \sum_{k=1}^{N}\varphi_k=1,\quad \varphi_k\in\{0,1\} \tag{30b}$$

$$\sum_{i=1}^{n}\varpi_i=1 \tag{30c}$$

$$0<\varpi_i<1 \tag{30d}$$

$$0<\alpha<1 \tag{30e}$$

$$0<b_u\leq b_{\max} \tag{30f}$$

$$0<c_u\leq c_{\max} \tag{30g}$$

$$s_{\min}<s_u\leq s_{\max} \tag{30h}$$

$$0<d_u\leq d_{\max} \tag{30i}$$

$$\gamma_1\geq 2,\quad \gamma_1\in Z^+ \tag{30j}$$

$$\gamma_2\geq 2,\quad \gamma_2\in Z^+ \tag{30k}$$

$$\gamma_3\geq 2,\quad \gamma_3\in Z^+ \tag{30l}$$

$$\gamma_4\geq 2,\quad \gamma_4\in Z^+ \tag{30m}$$

where φ_k is the $0-1$ variable; $u_i(x_i)$ denotes the utility value of each metric; ϖ_i is the initial weight calculated by the hierarchy analysis method; α is a parameter, where $0<\alpha<1$; b_u, c_u, s_u, and d_u denote the user demand bandwidth, demand cost, intensity of received signals, and demand delay, respectively; b_{max}, c_{max}, s_{max}, and d_{max} denote the maximum user demand bandwidth, maximum demand cost, maximum intensity of received signals, maximum demand delay, respectively; s_{min} stands for the minimum intensity of received signals; and n denotes the number of access networks.

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Equation (30) describes an optimal model, Equation (30a) denotes the objective function obtained according to the multi-criteria utility function in Equation (25), Equation (30b) indicates the constraints of the normalized coefficients of n access networks, Equations (30c-30d) give the weight constraints of network i, Equation (30e) denotes the constraint of parameter α, Equation (30f) is the bandwidth constraint, Equation (30g) represents the cost constraint, Equation (30h) is the constraint for the signal intensity, Equation (30i) stands for the delay constraint, and Equations (30j-m) denote the constraints of parameters r_1 and r_2.

C. Selection Algorithm

The optimal model of network selection in Equation (30) is built according to the utility functions of five decision factors in Equations (1)-(20), which is a multi-constraint optimal model. It is quite difficult to solve the optimal model. Therefore, we propose a heuristic Multi-Criteria Access Selection (MCAS) algorithm. The flow chart of MCAS is shown in Fig. 7. The steps of the MCAS algorithm are detailed as follows:

Algorithm 2 Attaining the Available Network List

Input: user demands: bandwidth demand b_u,
  cost demand c_u, delay demand d_u, signal
  intensity demand d_u; parameters of n access
  networks, namely: available bandwidth b_i of
  access network i, cost c_i of access network i,
  delay d_i of access network i, signal intensity
  s_i of access network i, where $i = 1, 2, \ldots, n$;
Output: Available network list l_{an};
Procedure:
According to parameters of n access networks,
  build access network list $l_{an} = \{l_1, l_2, \ldots, l_n\}$;
for $i = 0$ to n do
    if $b_i \leq b_u$ or $c_i \geq c_u$ or $d_i \geq d_u$ or
        $s_i \leq s_u$ then
        delete access network i from the list l_{an};
        update the access network list l_{an} into
            $\hat{l}_{an} = \{\hat{l}_1, \hat{l}_2, \ldots\}$;
        let $l_{an} = \hat{l}_{an}$;
    end
end
output the available network list l_{an};

Step 1: Collect networks' information; obtain the parameter list $l_{np} = \{p_1, p_2, \ldots, p_n\}$ of n access networks, namely available bandwidth b_i of access network i, cost c_i of access network i, delay d_i of access network i, signal intensity s_i of access network i, where $p_i = \{b_i, c_i, d_i, s_i\}$ and $i = 1, 2, \ldots, n$; initialize parameters α, β, r_1 and r_2.

Step 2: Collect users' information; attain the demand list $l_d = \{q_1, q_2, \ldots, q_k\}$ of k users, namely the uth user's bandwidth demand b_u, cost demand c_u, delay demand d_u, signal intensity demand s_u, where $q_u = \{b_u, c_u, d_u, s_u\}$ and $u = 1, 2, \ldots, k$. Let $m = 1$.

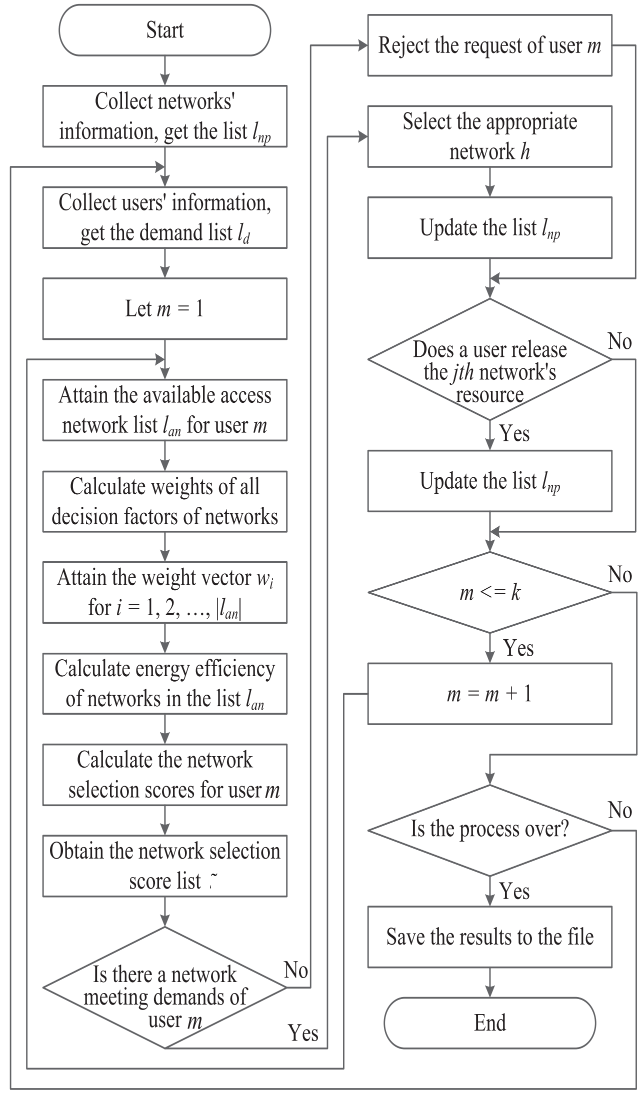

Fig. 7. The flow chart of the MCAS algorithm.

Step 3: According to the network parameter list l_{np}, the demand list l_d, and Algorithm 2, attain the available access network list l_{an} for user m.

Step 4: Calculate the weights of all decision factors of access networks in the available access network list l_{an}. According to Algorithm 1 and the list l_{an}, attain the weights of decision factors in access network i in the list l_{an}, namely energy efficient weight w_i^e, cost weight w_i^c, signal intensity weight w_i^s, delay weight w_i^d, bandwidth weight w_i^b; obtain weight vector $w_i = \{w_i^e, w_i^c, w_i^s, w_i^d, w_i^b\}$ of access network i, where $i = 1, 2, \ldots, |l_{an}|$.

Step 5: According to Algorithm 3 and the list l_{an}, calculate energy efficiency of available networks in the list l_{an}.

Step 6: According to Algorithm 4 and the list l_{an}, calculate the network selection scores for user m.

Step 7: Obtain the network selection score list $\tilde{s}$.

Step 8: Ifthe current network satisfies the requirements of user m, select the appropriate available access network h (where $h = 1, 2, \ldots, |l_{an}|$) according to the network selection score list $\tilde{s}$. Or reject the request of user m, and go to Step 10.

Step 9: Update the network parameter list l_{np} according to the selected access network h.

Step 10: If users release the resource of access network j (where $j = 1, 2, \ldots, n$), update the network parameter list l_{np} according to access network j.

Step 11: If $m <= k$, let $m = m + 1$ and go to Step 3.

Step 12: If network selection is completed, exit and save the results to the file; otherwise go back to Step 2 to repeat the process.

Algorithm 3 Calculating Energy Efficiency of Available Networks

Input: Available network list l_{an}; parameters
of access networks in the list l_{an}; initialize
the transaction duration time t (namely the
duration of the application), energy
consumption rate r_d (where unit is $J/Kbyte$)
of data transmission, and terminals' energy
consumption r_t (where unit is W) per
unit of time;
Output: Energy efficiency list e of available
networks in the list l_{an};
Procedure:
According to available network list l_{an}, get
the number $z = |l_{an}|$ of available networks
in the list l_{an};
for $i = 0$ to z do
calculate energy efficiency e_i of access
network i in the list l_{an};
end
get energy efficiency list $e = \{e_1, e_2, \ldots, e_z\}$
of all available networks in the list l_{an};
output the energy efficiency list
$e = \{e_1, e_2, \ldots, e_z\}$;

V. Simulation Results and Analysis

In this section, we conduct a series of tests to validate our MCAS algorithm for vehicle-to-infrastructure networking applications using the NS3 simulation platform. The simulation scenario is such that the user is in the coverage areas of three types of wireless access networks, namely, the 3G cellular network, WLAN network and WiMAX network. As mentioned in [21], [22], [26], [27], and [37], the basic parameters of the three networks are listed in Table 1, where the notations "si" and "bw" denote "signal intensity" and "bandwidth". As shown in Table 1, for 3G, WiMAX, and WLAN, their bandwidths (in Mbps) are 3, 12, and 6, respectively; their transmitting power values (W) are 0.86687, 0.90000, and 0.62815, respectively; and their energy efficiency values (J/KB) are 0.01540, 0.02000, and 0.00412, respectively. From Table 1, we can see that each network possesses different advantages and disadvantages. The WiMAX access network is expensive, although it provides a larger bandwidth and lower network delay. The 3G access network is cheap, but its performance is not satisfactory. The WLAN access network provides a generally good performance, and it requires a lower energy consumption.

TABLE I
The Basic Parameters of Three Networks

network type	si (dBm)	cost	bw (Mbps)	delay (ms)	r_t (W)	r_d (J/KB)
3G	-55	1.0	3	100	0.86687	0.01540
WiMAX	-55	1.5	12	80	0.90000	0.02000
WLAN	-45	0.5	6	120	0.62815	0.00412

Algorithm 4 Generating Network Selection Score

Input: Available network list l_{an}; parameters of
access networks in the list l_{an}; energy
efficiency list $e = \{e_1, e_2, \ldots, e_z\}$ of available
networks in the list l_{an}; weight vector $w_i =$
$\{w_i^e, w_i^c, w_i^s, w_i^d, w_i^b\}$ of available network i in
the list l_{an}, where $i = 1, 2, \ldots, |l_{an}|$;
Output: Available network selection score
list $\tilde{s}$;
Procedure:
According to available network list l_{an}, get
the number $z = |l_{an}|$ of available networks in
the list l_{an};
get the combination scheme set
$l_c = \{l_{c,1}, l_{c,2}, \ldots, l_{c,z}\}$ of all decision factors
of z available networks.
for $i = 1$ to z do
for $j = 1$ to $|l_{c,i}|$ do
calculate utility values u_{ij}^e, u_{ij}^c, u_{ij}^s,
u_{ij}^d, and u_{ij}^b;
get network selection score
$u_{ij} = (u_{ij}^e)^{w_{ij}^e} (u_{ij}^c)^{w_{ij}^c} (u_{ij}^s)^{w_{ij}^s} (u_{ij}^d)^{w_{ij}^d}$
$(u_{ij}^b)^{w_{ij}^b}$;
end
get the utility set $u_i = \{u_{i1}, u_{i2}, \ldots, u_{i|l_{c,i}|}\}$
of available network i in the list l;
find the maximum utility $u_{i,\max} =$
$\max\ (u_i)$ in the utility set u_i;
end
get the utility set $u = \{u_{1,\max}, u_{2,\max}, \ldots,$
$u_{z,\max}\}$ of available networks in the list l;
rank the utility set u from the largest to
the smallest;
get the network selection score $\tilde{s} = rank(u)$;
output the network selection score list $\tilde{s}$;

In the simulation scenario, we analyze four different types of applications, including voice, video, web downloads, and online games. Without loss of generality, all the required bandwidth and duration times are fixed. As mentioned in [21] and [37]–[39], the detailed parameters of all the applications are listed in Table 2, where the notations "du", "bwd", and "sod" denote "duration", "bandwidth demand", and "sensitivity of delay", respectively. As listed in Table 2, for voice,

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TABLE II
DEMAND PARAMETERS

metrics	voice	video	download	game
du(min)	5	10	10	20
bwd(Mbps)	0.1−0.2	1 − 2	0 − 0.2	0.4−0.8
sod	middle	middle	low	high

video, downloads, and games, their duration values (in min) are 5, 10, 10, and 20, respectively, while their bandwidth demand values (Mbps) are 0.1 − 0.2, 1 − 2, 0 − 0.2, and 0.4 − 0.8, respectively. It is reported that the SAW and RAS algorithms achieve good network selection performance for wireless access applications [21], [22]. These algorithms are two important multi-criteria utility network selection algorithms for heterogeneous wireless environments. SAW and RAS could obtain better performances in the network selection process, but they still suffers from certain disadvantages. First, SAW used $U(x) = \sum_{i=1}^{n} w_i u_i(x_i)$ (where $\sum_{i=1}^{n} w_i = 1$) to calculate the selection weight, while it independently used each decision factor to select the target network. Accordingly, SAW could avoid selecting a network with a certain utility value being zero, namely, $\exists i \in \{1, 2, \ldots, n\}$: $\lim_{u_i(x_i)\to 0} U(x) \neq 0$. Second, RAS exploited the acceptance probability $A(u, p) = 1 - \exp\left(-Cu^{\mu} p^{-\varepsilon}\right)$ to decide whether the satisfaction degree of utility u could be accepted after expending a certain cost p, where $\mu > 0$ and $\varepsilon > 0$ denoted the users' sensitivity to the utility u and cost p, and C was a positive constant representing the referred satisfaction degree. RAS avoided the shortcoming of SAW, although it suffered from the zero cost effect: $\sum_{p\to 0} A(u, p) = 1$ (where $\forall u > 0$). Furthermore, RAS only considered a single metric in calculating the utility u. Additionally, RAS could use the utility function to reflect the users' preference. To validate the performance of our MCAS algorithm, we compare MCAS with those two algorithms. Mah *et al.* [36] discussed the energy consumption of android phones, whereas in this paper, we validate our method according to the simulation parameters in Tables 1 and 2.

A. Performance Analysis

Fig. 8 shows the users' traffic allocation on different access networks under the MCAS algorithm. When traffic requests are low, the WLAN undertakes most of the traffic requests. When the number of traffic requests increases, the percentage of traffic allocated to the WLAN gradually decreases, while that of the WiMAX access network increases. In such a case, the percentage of traffic allocated to the 3G access network initially increases but then decreases. It is very interesting that the WLAN is always in charge of delivering substantially more traffic requests that the 3G and WiMAX access networks. In contrast to WLAN and 3G access networks, WiMAX forwards the fewest traffic requests. This is reasonable because the WLAN has the lowest cost and energy consumption as well as higher bandwidth compared to the other two access networks. Moreover, MCAS takes energy

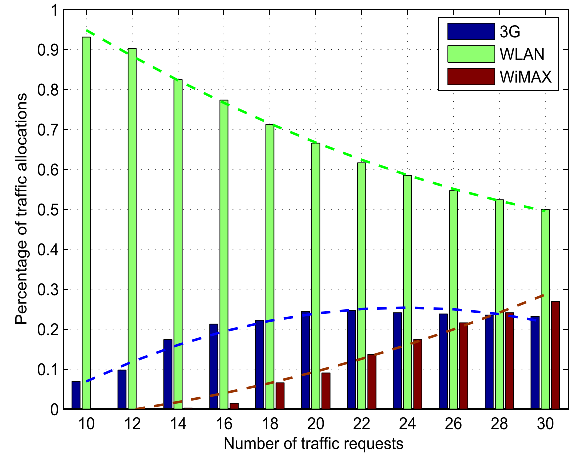

Fig. 8. Users' traffic allocations on different access networks.

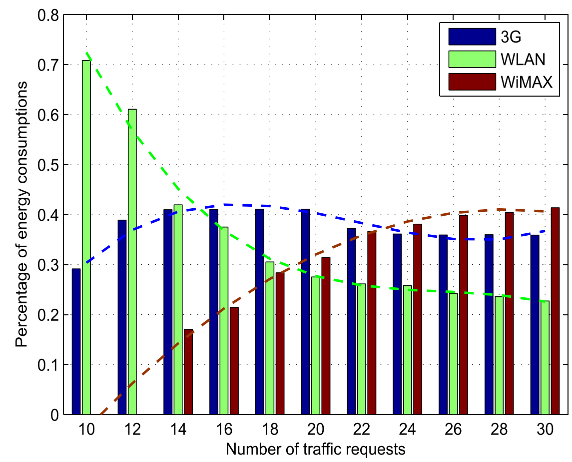

Fig. 9. Energy consumption distribution on different access networks.

efficiency as an important selection metric in the network selection process. Therefore, MCAS always allocates traffic requests to the WLAN as a priority. When the number of traffic requests increases, the WLAN does not have sufficient network resources to provide to user terminals. In such a case, some of the traffic requests are allocated to the 3G and WiMAX networks. This indicates that MCAS achieves a better performance for network selection.

Next, we analyze the energy consumption of MCAS for different access networks. Fig. 9 plots the energy consumption distribution when the number of traffic requests gradually increases. It is very clear that when traffic requests increase, the energy consumption of the WLAN slowly decreases. However, in such a case, the energy consumption of WiMAX gradually increases, while that of the 3G access network first increases and then slowly decreases. More importantly, when the number of traffic requests is greater than 18, the energy consumption of the WLAN is lower than those of the other two access networks. When there are between 16 and 22 traffic requests, the energy consumption of the 3G access network is larger than that of the WLAN and WiMAX. When there are fewer than 16 traffic requests, the WLAN shows the highest energy consumption. According to Table 1, we can see that

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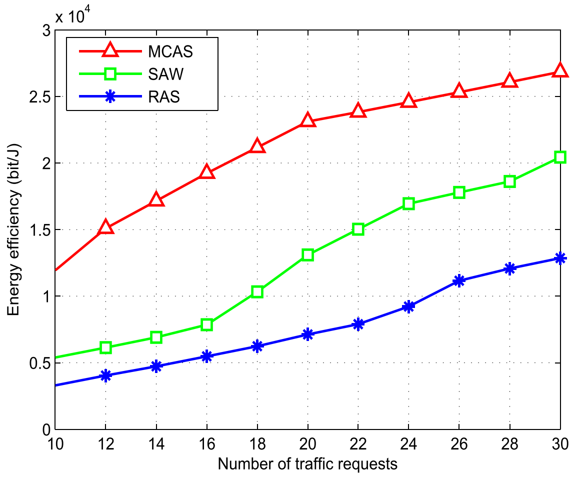

Fig. 10. Energy efficiency of three algorithms.

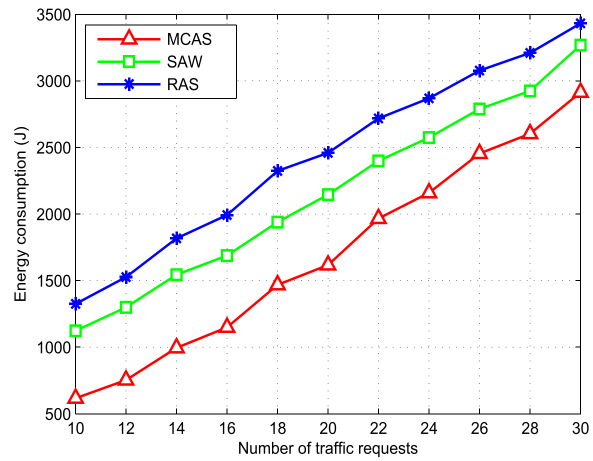

Fig. 11. Energy consumption of three algorithms.

when the number of traffic requests is smaller, MCAS first selects the WLAN as the optimal available access network. Because the WLAN undertakes most of the traffic requests in such a case, it expends the highest amount of energy. In addition, MCAS uses multiple metrics as the optimal utility value to select the optimal access network. Thereby, when faced with many traffic requests, some traffic requests will be allocated to the two other access networks according to the multi-criteria selection strategies. Compared to the two other access networks, the percentage of energy consumption of the WLAN will decrease slowly. This illustrates that MCAS can indeed select the appropriate access network to facilitate data packet delivery to achieve energy savings.

B. Performance Comparison

Now, we compare the performance of three algorithms under different numbers of traffic requests. Here, we discuss their energy efficiency, energy consumption, average satisfaction degree, and failure times during network selection. Fig. 10 plots the energy efficiency of three algorithms when the number of traffic requests changes. From Fig. 10, we can see that for different numbers of traffic requests, the energy efficiency curve of MCAS is always higher than those of the SAW and RAS algorithms, while that of RAS is at the bottom. This is because MCAS considers the energy efficiency as a decision metric in the network selection process, while SAW and RAS do not consider the energy efficiency metric in their network selection processes. Moreover, with increasing traffic requests, the energy efficiency of the three algorithms also gradually increases. Fig. 10 demonstrates that MCAS possesses a better energy efficiency performance than SAW and RAS.

Fig. 11 analyzes the energy consumption performance of the three algorithms for different numbers of traffic requests. Because MCAS takes energy efficiency as a decision factor in network selection, Fig. 11 indicates that MCAS achieves the lowest energy consumption when the number of traffic requests increases. SAW exhibits a higher energy consumption, while RAS expends the most energy of the three algorithms. Furthermore, it is very clear that when the number of traffic requests is increasing, the energy consumption of the three algorithms also increases. This is because more traffic requests leads to more energy necessary to finish the data packet delivery. In contrast to RAS and SAW, MCAS expends much less energy for different traffic request scenarios. This further indicates that MCAS provides a better energy savings performance than other two algorithms.

To more effectively compare the performance of the three algorithms, we discuss the average satisfaction degree of the users. Fig. 12 plots the users' average satisfaction degree under the three algorithms with gradually increasing numbers of traffic requests. When the number of traffic requests becomes large, the average satisfaction degree of the three algorithms gradually decreases. This is because additional network resources are required when additional traffic requests are introduced. In such a case, this necessarily degrades the satisfaction degree of the users. However, the average satisfaction degree of SAW decreases quickly, while MCAS and RAS show nearly no change for different traffic request scenarios. Moreover, in contrast to RAS, MCAS shows a lower change in the average satisfaction degree of the users. This is because the multi-criteria utility function of MCAS considers the multiple decision factors and the preferences of the users. In addition, RAS thinks that the individual decision factors are independent, while SAW uses the acceptation probability to characterize users' satisfaction degrees. Accordingly, Fig. 12 also indicates that when the number of traffic requests is increasing, MCAS achieves the largest average satisfaction degree. Compared to MCAS, SAW exhibits a lower average satisfaction degree, while RAS's average satisfaction degree is the lowest. This illustrates that MCAS can effectively select an appropriate access network to meet the users' requirements and preferences. In addition, it can provide users with a higher quality of experience.

Finally, to verify the correctness of network selection and the stability of the algorithms, we repeatedly run a scenario with 30 traffic requests 10-100 times. This is equivalent to 300-3000 executions of the network selection process. Fig. 13 shows the failure times of the network selection

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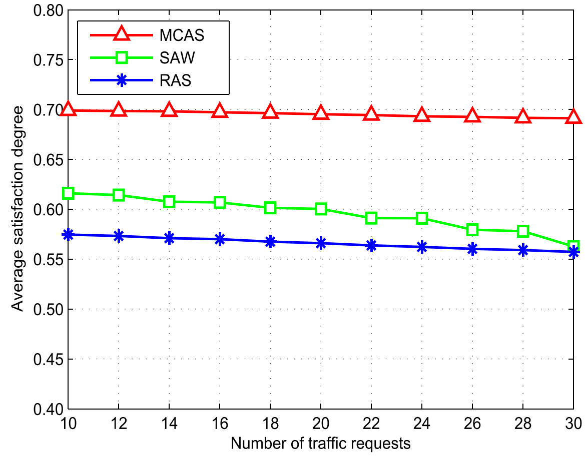

Fig. 12. Average satisfaction degree of three algorithms.

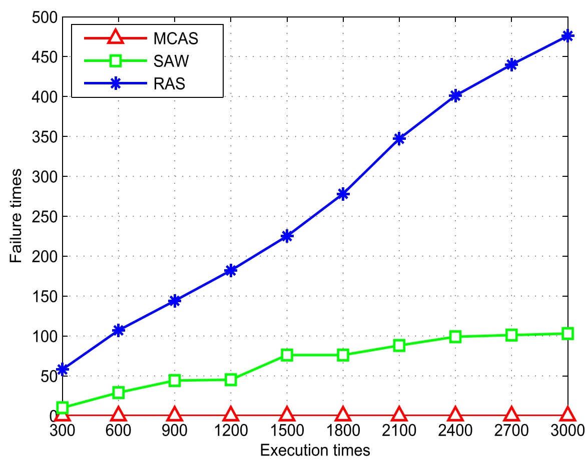

Fig. 13. Failure times of network selection for three algorithms.

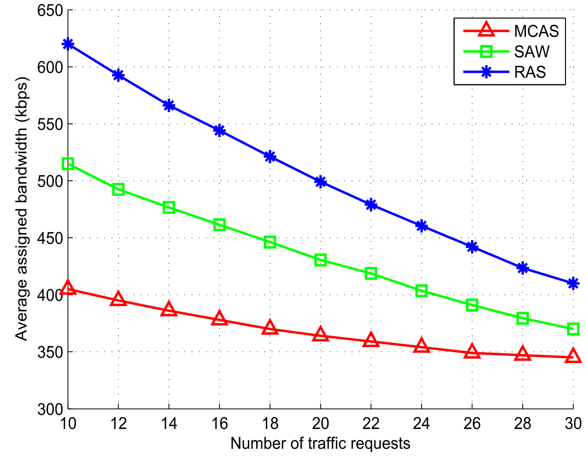

Fig. 14. Average assigned bandwidth of three algorithms.

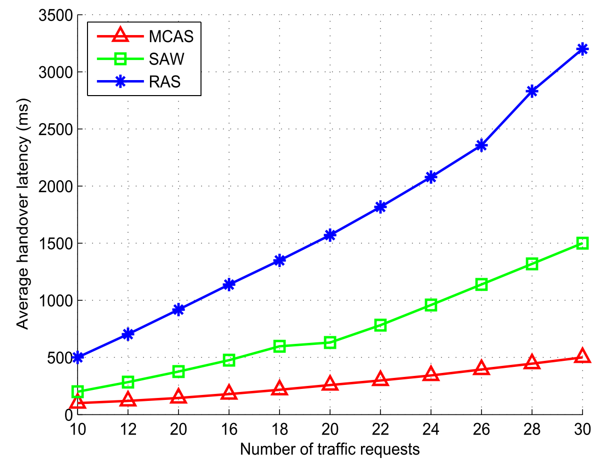

Fig. 15. Average handover latency of three algorithms.

process for the three algorithms in such a case. From Fig. 13, we can find that in this process, MCAS has no failures during network selection, while SAW and RAS present more failure times. In particular, when the number of executions increases, the failure times of SAW slowly increase, while those of RAS increase quickly. This is because MCAS jointly consider the mutual impact of multiple decision factors. In contrast to MCAS, RAS independently uses the individual decision factors, while SAW also independently considers each utility metric and suffers from the zero-cost utility problem. Therefore, this indicates that MCAS provides a much better network selection ability and better stability than SAW and RAS.

C. Handover Cost

Next, we discuss the handover cost generated by the three network selection algorithms. As mentioned in [40] and [41], the average assigned bandwidth and average handover latency are used to characterize the network handover performance. Fig. 14 plots the average assigned bandwidth of the three algorithms with gradually increasing the number of traffic requests. Here, the average assigned bandwidth denotes the bandwidth that is assigned to users or vehicle terminals under the constraints of meeting traffic request demands. To avoid the effects of outliers, we run 100 simulations for each algorithm to obtain the average assigned bandwidth. A lower average assigned bandwidth means that we assign to users or vehicle terminals lower bandwidth to finish traffic requests. Accordingly, the lower average assigned bandwidth shows that the network selection algorithms can effectively utilize fewer network resources to complete traffic requests. With increasing numbers of traffic requests, the average assigned bandwidth of the three algorithms gradually decreases. This is because more network resources are required to deliver more requests. As a result, each request is necessarily assigned less network bandwidth. It is clear that the average assigned bandwidth of SAW and RAS is quickly decreasing, while that of MCAS is only gradually decreasing. Moreover, compared to SAW and RAS, MCAS shows a smaller bandwidth change. This is because MCAS jointly consider multiple utility factors in the network selection process. Moreover, Fig. 14 shows that when the number of traffic requests is increasing, MCAS provides the lowest average assigned bandwidth. In contrast to MCAS, SAW exhibits a larger average assigned bandwidth, while RAS shows the largest average assigned bandwidth. This illustrates that MCAS can effectively select the appropriate access network, leading to the lowest handover cost.

Fig. 15 indicates the average handover latency under the three network selection algorithms. From Fig. 15, we can see that the average handover latency of the three algorithms is increasing with increasing numbers of traffic requests. It is interesting that MCAS leads in terms of handover latency with gradual changes, while that of SAW and RAS increase quickly. Additionally, Fig. 15 shows that MCAS achieves the lowest handover latency, followed by SAW and then RAS. This is because MCAS jointly considers the mutual impact of multiple decision factors. Moreover, If the networks satisfy the users' requirements, MCAS does not perform network selection, which avoids the handover process without affecting the users' demands and accordingly reduces the handover cost. Therefore, this shows that MCAS provides a substantially better network selection performance.

VI. Conclusion

This paper studies the network selection problem in heterogeneous wireless networks for vehicle-to-infrastructure networking. In contrast to previous methods, we jointly consider multiple decision factors to facilitate vehicle-to-infrastructure networking. The energy efficiency of the networks is taken as an important factor in the network selection. We regard energy efficiency, signal intensity, network cost, delay, and bandwidth as decision factors. Their utility functions are built to characterize the users' preferences and network performance. Multi-criteria utility theory is used to construct an energy-efficient network selection approach. We propose several design strategies to construct a joint multi-criteria utility function for network selection. We also present a multi-constraint optimal model to describe the network selection for connected vehicle applications. A multi-criteria access selection algorithm is presented to solve the model. The simulation results show that the proposed access network selection approach is promising.

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References

[1] M. Amadeo, C. Campolo, and A. Molinaro, "Information-centric networking for connected vehicles: A survey and future perspectives," *IEEE Commun. Mag.*, vol. 54, no. 2, pp. 98–104, Feb. 2016.

[2] Z. Zhu, J. Loo, Y. Chen, K. K. Chai, and T. Zhang, "Recent advances in connected vehicles via information-centric networking," in *Proc. ICV*, 2016, pp. 1–8.

[3] H. Zhou *et al.*, "TV white space enabled connected vehicle networks: Challenges and solutions," *IEEE Netw.*, vol. 31, no. 3, pp. 6–13, May/Jun. 2017.

[4] G. Xie, H. Chen, L. Xie, and K. Wang, "A user-preference-aware terminal-controlled access network selection scheme in heterogeneous wireless networks," in *Proc. VTC*, Sep. 2013, pp. 1–5.

[5] B. Z. Aymen, M. Ayadi, and S. Tabbane, "A fuzzy logic algorithm for RATs selection procedures," in *Proc. ISNCC*, Jun. 2014, pp. 1–5.

[6] T. S. Asha and N. J. R. Muniraj, "Network connectivity based energy efficient topology control scheme for MANET," in *Proc. ICOSS*, Jul. 2013, pp. 1–7.

[7] D. Jiang, Z. Xu, W. Li, and Z. Chen, "Network coding-based energy-efficient multicast routing algorithm for multi-hop wireless networks," *J. Syst. Softw.*, vol. 104, no. 2, pp. 152–165, 2015.

[8] B. Wang, W.-P. Wang, and L.-M. Chen, "Research on Chinese energy consumption network between industrial sectors," in *Proc. ICMSE*, Aug. 2014, pp. 1600–1607.

[9] B. Makki, A. Graell i Amat, and T. Eriksson, "Green communication via power-optimized HARQ protocols," *IEEE Trans. Veh. Technol.*, vol. 63, no. 1, pp. 161–177, Jan. 2014.

[10] X. Zhang *et al.*, "Macro-assisted data-only carrier for 5G green cellular systems," *IEEE Commun. Mag.*, vol. 53, no. 5, pp. 223–231, May 2015.

[11] D. Jiang, Z. Xu, J. Liu, and W. Zhao, "An optimization-based robust routing algorithm to energy-efficient networks for cloud computing," *Telecommun. Syst.*, vol. 63, no. 1, pp. 89–98, 2016.

[12] P. Prabhavathi and L. Nithyanandan, "Network selection in wireless heterogeneous networks," in *Proc. ICCSP*, Apr. 2013, pp. 357–361.

[13] H. Xing, D. Mu, X. Ge, and R. Chai, "An NN-based access network selection algorithm for heterogeneous networks," in *Proc. WOCC*, May 2013, pp. 378–383.

[14] D. Tian, J. Zhou, Z. Sheng, and V. C. M. Leung, "Robust energy-efficient MIMO transmission for cognitive vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 6, pp. 3845–3859, Jun. 2016.

[15] T.-D. Nguyen, O. Berder, and O. Sentieys, "Energy-efficient cooperative techniques for infrastructure-to-vehicle communications," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 3, pp. 659–668, Sep. 2011.

[16] C. Yang, Y. Fu, Y. Zhang, S. Xie, and R. Yu, "Energy-efficient hybrid spectrum access scheme in cognitive vehicular ad hoc networks," *IEEE Commun. Lett.*, vol. 17, no. 2, pp. 329–332, Feb. 2013.

[17] T. Han, X. Liu, L. Wang, J. Wang, K. S. Kwak, and Q. Li, "Energy saving of base stations sleep scheduling for multi-hop vehicular networks," in *Proc. ICC*, Jun. 2016, pp. 1–5.

[18] A. A. Hammad, T. D. Todd, G. Karakostas, and D. Zhao, "Downlink traffic scheduling in green vehicular roadside infrastructure," *IEEE Trans. Veh. Technol.*, vol. 62, no. 3, pp. 1289–1302, Mar. 2013.

[19] M. Shojafar, N. Cordeschi, and E. Baccarelli, "Energy-efficient adaptive resource management for real-time vehicular cloud services," *IEEE Trans. Cloud Comput.*, to be published.

[20] J. Jang, "Outlier filtering algorithm for travel time estimation using dedicated short-range communications probes on rural highways," *IET Intell. Transp. Syst.*, vol. 10, no. 6, pp. 453–460, 2016.

[21] M. Abid, T. A. Yahiya, and G. Pujolle, "A utility-based handover decision scheme for heterogeneous wireless networks," in *Proc. CCNC*, 2012, pp. 650–654.

[22] M. Lahby and A. Adib, "Network selection mechanism by using M-AHP/GRA for heterogeneous networks," in *Proc. WMNC*, Apr. 2013, pp. 1–6.

[23] J. Kang, L. Ma, and Y. Xu, "A heterogeneous network access control algorithm based on DS evidence theory," in *Proc. ICCCNT*, Jul. 2014, pp. 1–5.

[24] T. Tang, W. Wu, Y. Deng, and W. Feng, "Access network selection algorithm in heterogeneous multi-cognitive wireless networks coexistence environment," in *Proc. LEMCS*, 2015, pp. 1266–1271.

[25] L. Wang and G.-S. G. S. Kuo, "Mathematical modeling for network selection in heterogeneous wireless networks—A tutorial," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 1, pp. 271–292, 1st Quart., 2013.

[26] S. Goudarzi *et al.*, "Artificial bee colony for vertical-handover in heterogeneous wireless networks," in *Advanced Computer and Communication Engineering Technology* (Lecture Notes in Electrical Engineering), vol. 362. Springer, 2015, pp. 307–322.

[27] A. Chinnappan and R. Balasubramanian, "Complexity–consistency trade-off in multi-attribute decision making for vertical handover in heterogeneous wireless networks," *IET Netw.*, vol. 5, no. 1, pp. 13–21, 2016.

[28] A. Gharsallah *et al.*, "Network selection in heterogeneous wireless system environments," *J. Netw.*, vol. 10, no. 12, pp. 633–641, 2015.

[29] K. Ahuja, B. Singh, and R. Khanna, "Network selection based on available link bandwidth in multi-access networks," *Digit. Commun. Netw.*, vol. 2, no. 1, pp. 15–23, 2016.

[30] D. Jiang, Z. Xu, W. Li, and Z. Chen, "Topology control-based collaborative multicast routing algorithm with minimum energy consumption," *Int. J. Commun. Syst.*, vol. 30, no. 1, p. e2905, 2014.

[31] L. Xu, J. Xie, X. Xu, and S. Wang, "Enterprise LTE and WiFi interworking system and a proposed network selection solution," in *Proc. ANCS*, 2016, pp. 137–138.

[32] E. Skondras, A. Sgora, A. Michalas, and D. D. Vergados, "An analytic network process and trapezoidal interval-valued fuzzy technique for order preference by similarity to ideal solution network access selection method," *Int. J. Commun. Syst.*, vol. 29, no. 2, pp. 307–329, 2016.

[33] R. K. Goyal and S. Kaushal, "Network selection using AHP for fast moving vehicles in heterogeneous networks," in *Advances in Intelligent Systems and Computing*, vol. 395. Springer, 2015, pp. 235–243.

[34] A. Ting, D. Chieng, K. H. Kwong, I. Andonovic, and K. D. Wong, "Scalability study of backhaul capacity sensitive network selection scheme in LTE-WiFi HetNet," *Trans. Emerg. Telecommun. Technol.*, vol. 28, no. 4, p. e3013, 2016.

[35] J. Kuboniwa *et al.*, "High efficient network selection scheme using location information for heterogeneous wireless system," in *Proc. WCNCW*, Mar. 2015, pp. 391–396.

[36] F. Mah, Z. Dziong, and J.-C. Grgoire, "Economic access network selection in heterogeneous wireless networks environment," in *Proc. CoCoNet*, Dec. 2015, pp. 124–130.

[37] K. Andersson, "On access network selection models and mobility support in heterogeneous wireless networks," Ph.D. dissertation, Dept. Comput. Sci. Electr. Eng., Luleå Univ. Technol., Luleå, Sweden, 2010.

[38] K. S. Balamurugan and B. Chidhambararajan, "Fast and secure intelligence re-authentication mechanism for next generation subscribers," *Int. J. Comput. Technol. Appl.*, vol. 9, no. 9, pp. 4175–4189, 2016.

[39] G. Kalic, I. Bojic, and M. Kusek, "Energy consumption in Android phones when using wireless communication technologies," in *Proc. MIPRO*, May 2012, pp. 754–759.

[40] R. Balakrishnan and I. Akyildiz, "Local anchor schemes for seamless and low-cost handover in coordinated small cells," *IEEE Trans. Mobile Comput.*, vol. 15, no. 5, pp. 1182–1196, May 2016.

[41] Z. Du, Q. Wu, and P. Yang, "Dynamic user demand driven online network selection," *IEEE Commun. Lett.*, vol. 18, no. 3, pp. 419–422, Mar. 2014.

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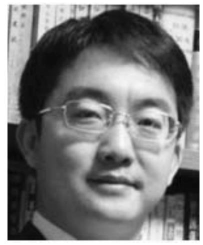

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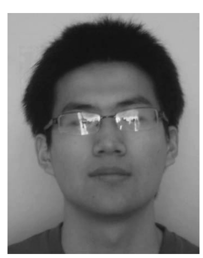

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