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FRRF: A Fuzzy Reasoning Routing-Forwarding Algorithm Using Mobile Device Similarity in Mobile Edge Computing-Based Opportunistic Mobile Social Networks

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ABSTRACT The arrival of 5G is accompanied by massive data transmission between mobile devices (MDs) and huge transmission energy consumption in the wireless networks. Therefore, how message applications select the appropriate relay MDs to complete the efficient data transmission process in the opportunistic mobile social networks (OMSNs)? At present, designing an efficient routing–forwarding algorithm is extremely challenging. Some routing–forwarding algorithms choose appropriate nodes as relay nodes based on the similarity between nodes, but most existing routing–forwarding algorithms only consider a few similar factors and even completely ignore the importance of movement similarity in data transmission of the node. In particular, existing routing–forwarding algorithms will bring extra energy consumption to the nodes in the wireless networks, and excessive energy consumption will further affect the delay and data transmission efficiency. In order to solve the problems in the existing strategies, we apply the mobile edge computing (MEC) to OMSNs, and we propose the fuzzy reasoning routing–forwarding (FRRF) algorithm that integrates the movement and social similarity in the MEC-based OMSNs. In detail, the fuzzy evaluation of the movement and social similarity is integrated to determine the transmission priority value between MDs, and finally, the transmission priority between MDs is compared to make transmission decision. Through simulation experiment and comparison with other algorithms, the correctness of the theoretical analysis and the efficiency of the FRRF algorithm in energy consumption, delay, and transmission efficiency are verified.

INDEX TERMS Opportunistic mobile social networks, mobile edge computing, routing-forwarding algorithm, mobile device similarity, fuzzy reasoning system.

I. INTRODUCTION

With the advent of 5G, in order to satisfy the massive data demand, the energy consumption of wireless communication network has also increased sharply when paying attention to the improvement on data transmission rate [1]. By 2020, there will be 50 billion connected devices in the world [2]. In addition, FIGURE 1 shows cisco's average growth forecast for mobile data traffic around the world. As we can see from FIGURE 1, mobile data traffic will increase sevenfold from 2016 to 2021, reaching 48270 PB per month [3]. However, the explosive growth of data demand forced the increase in data service rate, and making energy consumption one of the most concerned points in the wireless communication network in the near future. It is conceivable that high energy consumption will leave the entire network in a low energy state, which in turn increase delay and decrease transmission efficiency. So energy efficiency has become one of the most important performance markers in the next generation 5G heterogeneous network [4], [5].

Fortunately, MDs carried by users have different similarity factors, such as residence, work place and interest. We can

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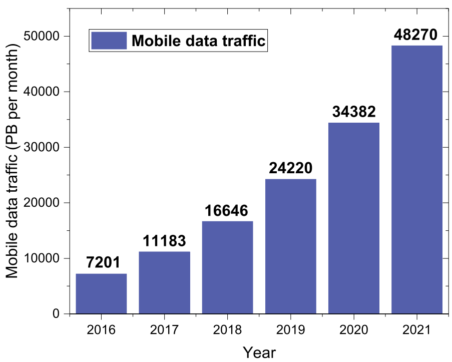

FIGURE 1. Mobile data traffic from 2016 to 2021.

use the similarity factor between MD to complete effective data transmission to improve energy efficiency. However, the physical size of MDs tends to be small in order to meet the compactness and portability of MDs, so the battery capacity and processor performance of MDs in wireless communication networks are limited [6]. However, with the rapid growth of mobile data traffic in wireless communication networks, the number of data transmission and the data volume per transmission in a network are also greatly improved, but MDs do not have enough capacity to transmit a large amount of data due to limited battery capacity and processor performance. Also, MDs need not only to transmit data, but also to calculate some tasks, so MDs use more energy. And at present, many compute-intensive mobile applications are deployed on MDs, so the time for MDs to enter the sleep state is faster because of low energy [7]. As a result, the issue of energy efficiency becomes more serious and challenging in wireless communication networks. Fortunately, Gartner predicts that more than 250 million smart cars will be connected to high-tech networks by 2020. At the same time, a Nvidia px2 self-driving car has the same computing power as 150 MacBook pro's. If vehicles can be utilized, not only the idle vehicle resources can be used reasonably, but also the cost of physical infrastructure can be greatly reduced [8], [9]. In a word, to improve energy efficiency, we start from reducing energy consumption of MDs. Especially, in order to reduce the energy consumption of MDs in wireless communication networks, we mainly study from the following two aspects.

On the one hand, we propose the MEC-based OMSNs. OMSNs derive from the end-to-end communication of mobile devices carried by people based on the encounter opportunity [10], [11]. When the transmission domain between users cannot be reached, OMSN usually adopt the store-and-forward method to complete the data transmission process [12], [13], and the message carrying MD forwards the message to a certain relay MD or the destination MD by means of the encounter opportunity caused by movement to forward. In wireless networks, MDs in an unpredictable geographical location need to communicate with each other at unpredictable geographical intervals. Therefore, as a multi-hop wireless technology, OMSN proposes that end-to-end data transmission can be achieved through "opportunistic communication". Such communication relies on the movement of MDs and the effective routing-forwarding algorithm, so as to give a MD the opportunity to act as a relay MD in some end-to-end data transmission. In addition, an effective routing-forwarding algorithm is to select reliable relay MDs for efficient data transmission [14]. Compare to other routing-forwarding algorithms, an effective routing-forwarding algorithm have the fewer number of hops in all successful message forwarding processes, and then the less energy and delay that MDs spend in the forwarding processes. Therefore, how to select reliable relay MDs is a pretty important problem in a routing-forwarding algorithm?

On the other hand, besides the effective routing-forwarding algorithm, we innovatively apply MEC to 5G OMSNs. MEC is a promising technology that allows users to access the computing services of small servers distributed close to users, which are defined as edge clouds in MEC [6], [18]. Moreover, MEC differs from cloud computing in that its computing resources are distributed around the network and are close to the end users. As a result, the energy consumption and delay during communication are reduced when MDs carried by users use the computing resources of edge cloud [19]. Generally, edge cloud provides computing and caching services for MDs in the network. Hence, MDs with limited performance offload some computationally intensive tasks to edge cloud and use the strong computing power of edge cloud relative to MDs to process tasks. Alternatively, MDs directly cache tasks that need to be processed in MDs frequently into edge cloud [20]. In wireless communication networks, the forwarding of messages between MDs is extremely frequent. Therefore, it is the best choice to cache the routing-forwarding algorithm directly on the edge cloud compared with offloading a task before each next hop optimal relay MD is selected.

To sum up, in order to solve the problem of delay, especially high energy consumption in 5G network, and improve transmission efficiency and energy efficiency of the whole network, this paper proposes the FRRF algorithm based on MDs similarity in a MEC-based OMSN. The FRRF algorithm uses the historical movement information and social attributes of MDs to determine the similarity between MDs. Based on fuzzy reasoning system and information entropy, the transmission priority value is calculated to comprehensively evaluate the movement and social similarity between MDs and destination MDs. By comparing the transmission priority value obtained, the message carrying MD can forward the message to the MD with higher transmission priority value, that is, the message carrying MD provides the opportunity for a MD with higher transmission priority value to act as a relay MD. The main contributions of this paper are as follows:

- We innovatively apply MEC to the OMSNs in 5G to relieve the computing pressure of MDs in the process of routing and forwarding [18], [21]. Moreover, we proposed the FRRF algorithm in the MEC-based OMSN. For the FRRF algorithm, based on fuzzy reasoning system and information entropy, the car takes both the MD movement and social similarity into account to determines the transmission priority value between MDs, and compares the transmission priority value between MDs in the network to select the next hop optimal relay MD.

- In order to accurately determine the transmission relationship between MDs in the MEC-based system, the following operations within the system will be performed. First, MDs collect and update their respective status information by means of the encounter between two MDs, and then offload their respective status information to the corresponding nearest car, so that the car can use the FRRF algorithm to accurately calculate the comprehensive similarity between MDs to determine the special transmission relationship between MDs.
- Simulation experiments simulate the MEC-based OMSN. The simulation results show the effectiveness of the proposed FRRF algorithm. More specifically, the simulation results show that the FRRF algorithm improves the delivery ratio of the entire wireless network, and reduces overhead on average, average end-to-end delay and energy consumption of the entire wireless network.

II. RELATED WORKS

In recent years, the academic has done a lot of research around the routing-forwarding algorithm in OMSNs [11], [16], [22]–[24], and proposed different effective methods under different application scenarios. In OMSNs, routing-forwarding algorithms are usually divided into two types: context-aware routing-forwarding algorithms and non-context-aware routing-forwarding algorithms. Context-aware routing-forwarding algorithm based on the similarity of nodes to select relay nodes through the social relations between nodes and the contextual information related to nodes [16], [22]. In addition, although context-aware routing-forwarding algorithms can improve the transmission environment and improve transmission efficiency, these algorithms usually need to manage a large amount of information and perform heavy computing tasks, thus bringing additional delay and energy consumption to the network. However, non-context-aware routing-forwarding algorithms perform flooding transmission, which brings many redundant message group copies to the network, and eventually leads to extremely high forwarding delay and energy consumption of the network [11], [23], [24]. It can be seen that both the context-aware routing-forwarding algorithm and the non-context-aware routing-forwarding algorithm will bring some extra delay and energy consumption to the entire wireless network, especially the non-context-aware routing-forwarding algorithm. Therefore, edge cloud is applied to OMSN to reduce the delay and energy consumption of nodes in the network. In this paper, we mainly studies the context-aware routing-forwarding algorithm based on node similarity in the MEC-based OMSN. Next, we will discuss some of the newer context-aware routing-forwarding algorithms, some of the context-aware routing-forwarding algorithms that involve mathematical methods, and the latest research in MEC.

In context-aware routing-forwarding algorithms, many studies calculate the similar level between nodes to define the relationship between nodes, such as the possibility of a future encounter between nodes, the moving trajectory of nodes, and community partitioning of nodes. Wang *et al.* [25] innovatively extracted social identity from messages generated by mobile nodes, and proposed the SlaOR algorithm that takes into account the multiple social identities of mobile nodes and their corresponding social influences. By the final simulation results, the performance of data transmission can be improved by taking social identity into account. However, the SlaOR algorithm does not consider a variety of social attributes. Wu *et al.* [26] proposed the SRBRA algorithm, which is based on social relations. Firstly, real-time data generated by nodes are analyzed and summarized, and then specific factors affecting social relations between nodes are extracted to calculate the value of social relations between nodes. Finally, according to the social relation value between nodes, the social relation value between the neighbor node and the destination node is sorted to select the optimal next-hop relay node to complete the transmission of messages. However, the SRBRA algorithm does not take the mobility of nodes into consideration. Besides, Mayer *et al.* [27] studied a framework that takes individual context, society and relationships as matching opportunity predictors. The proposed algorithm based on a series of studies can predict the cooperation opportunities of data transmission between nodes, and then determine the end-to-end communication between nodes in the network according to the cooperation opportunities between nodes.

Some mathematical methods and models are usually used in context-aware routing-forwarding algorithms, such as markov decision model, set theory and graph theory. Two of the next three papers use game theory and one uses graph theory. Nguyen and Nahrstedt [28] proposed a new context routing protocol (GT-ACR) based on game theory to select the most appropriate relay node to forward packets. Through the non-zero cooperation times of two nodes, the GT-ACR protocol builds the game depends on the context information, the distance between the corresponding node and the target node, and the encounter index. In [29], in order to determine the cost to achieve efficient data transmission, Talipov *et al.* designed a model based on user context replication and the graph theory, which is an online backpack problem. The scheme learns and predicts the context information of each node in order to calculate the data delivery probability of each node, and the number of copied messages is adjusted based on the given delivery threshold. However, the scheme only considers the data information in the process of node transmission, which means the decision accuracy of message transmission needs to be improved in the process of transmission. Besides, in [30], in order to find the vertex cover suitable for the perceptive tasks in the group, Phuong Nguyen and Klara Nahrstedt designed a new context-aware approximation algorithm. At the same time, in order to assign the sensor task to a more "socialized" device for better sensor coverage, a human-centered guidance strategy for initial assignment of the sensor device based on participants' meta information was also designed. And the node of this algorithm completes the individual coverage of a social vertex with the human-centered information.

MEC has many research points, such as resource management on MEC, security and privacy issues in MEC, caching issues on MEC server, mobility management, deployment of MEC server, and green energy MEC. Some of the existing work uses MEC computing resources to relieve their own computing pressure [31]–[35]. In [31], in order to study the video collaborative processing scheme, Long C *et al.* proposed an edge computing framework for collaborative processing of delay-sensitive video tasks on MDs. The framework takes both video group matching and group information into consideration to maximize the detection accuracy of people in the video task deadline. In addition, both the execution delay of tasks on the camera and the delay of data offloaded to the edge server is reduced. In [32], under the application scenarios of augmented reality and other compute-intensive time-delay sensitive tasks, Chen M *et al.* proposed the architecture of the software defined super-dense network (SD-UDN). The devices under this architecture can offload tasks to the edge cloud. The main purpose of the paper is to solve the task offloading problem to minimize delay. Especially, the task offloading problem is a NP hard and mixed integer nonlinear programming problem, which is composed of task assignment sub-problem and resource allocation sub-problem. Li *et al.* [33] proposed new vehicle network structure in the smart city scenario, and combined optimization of cache, network and computing resources to alleviate congestion in the network. In addition, this structure introduces the programmable control principle of software-defined network. And after modeling the service, vehicle mobility and system state, the paper proposes the joint resource management scheme to minimize the system cost, namely the task execution time and network overhead, in which this scheme is a partially observable Markov decision-making process.

The rest of the paper is as follows: Section III shows the modeling process of the FRRF algorithm. Section IV shows the FRRF algorithm in detail and analyzes its performance. Section V provides simulation experiments to verify the theoretical analysis of the FRRF algorithm and its effectiveness. Finally, Section VI gives the conclusion of this paper. Some key mathematical notations are explained in Table 1.

III. SYSTEM MODEL DESIGN

As shown in FIGURE 2, we consider a system of MEC-based OMSN, which consists of x MDs and s cars that have strong computing power and cached the FRRF algorithm. FIGURE 2 depicts the process of a message being forwarded exactly from the start MD (MD 1) to the destination MD (MD x). Since the MDs do not have strong computing power, the cars with strong computing power are used to assist the MDs in computing some tasks, which mainly refers to some algorithms. To better understand a complete message forward process, we clearly list the five steps involved in a specific transmission process during message forwarding. A message transmission process between two MDs involves three steps of communication between the message carrying MD and the car closest to the message carrying MD. In order to leveraging the computing power of cars, all MDs except for the destination MD in any message forwarding process have to communicate with a car. The five stages in the process of transfer a message to the next hop are shown below in chronological order.

- In the first stage, MDs in the network share network status information by encountering each other, so as to achieve the purpose of collecting as much MD information about the network as possible. The MD information here mainly refers to the movement and social preferences information of the MD.
- In the second stage, message carrying MD offloads some information about the message (destination MD number) and MD information in the network collected by the MD itself to its nearest car through the uplink.
- In the third stage, after receiving the information offloaded by the message carrying MD in the two stage, the car will take both the destination MD number of the message and MD information in the network as input to the FRRF algorithm. Then the car closest to the message carrying MD executes the FRRF algorithm based on the input data information. Finally, the optimal next hop MD number is obtained.
- The fourth stage is that the car closest to the message carrying MD returns the execution result (the optimal next-hop MD number) of the FRRF algorithm to the message carrying MD by downlink.
- In the fifth stage, the message carrying MD transfers the message according to the optimal next hop MD number received from the car.

Similarly, loop through these five steps until the message is forwarded to the destination MD x, which means that the forwarding process of the message is completed.

In this section, we consider some steps of the process of message forwarding. The second, fourth and fifth stages mentioned above is beyond the scope of our research, and we mainly study the first stage and the FRRF algorithm involved in the third stage. Next, we mainly discuss how do MDs collect the network information and how do cars select the optimal next hop delay MD by the FRRF algorithm, that is car chooses a MD according to the FRRF algorithm and gives the MD the opportunity to act as a relay MD in the process of message forwarding. To avoid confusion and ease of understanding, the whole process of the message

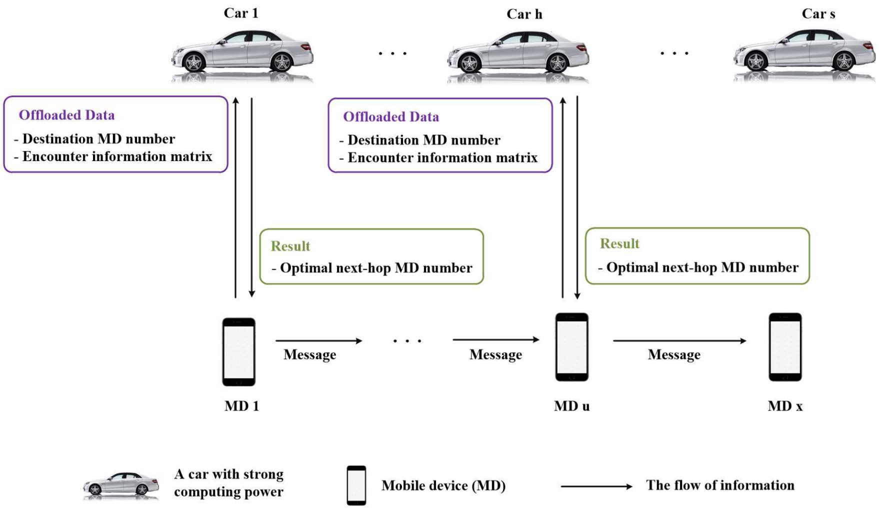

FIGURE 2. A simple and successful message forwarding process in the mobile edge computing-based opportunistic mobile social networks.

TABLE 1. Definition of key mathematical notations.

Symbol	Defination
x	The number of MDs in the MEC-based OMSN
s	The number of cars that have strong computing power in the MEC-based OMSN
t_{prep}	The length of the preparatory period
$State_{n1}$	The state of MD $n1$
Dis_{n1}	The moving distribution of MD $n1$
α_{n1}	The eigenvector of MD $n1$ containing different social attributes
$List_{n1}$	The state sequence of MD $n1$ established by MD n1 meeting with other MDs during a preparation period
$EState^{1}_{n1}$	The first encounter information of MD $n1$ established during a preparation time
ES_{n1}	The all encounter information of MD $n1$ established during a preparation time.
$MS_{n1,n2}$	The moving similarity between MD $n1$ and MD $n2$
$SS_{n1,n2}$	The social similarity between MD $n1$ and MD $n2$
LS	The position set of the all communication area in the network
J_{n1}	The total number of message transmission that takes place between MD $n1$ and other MDs
t^{j}_{n1}	The time point of MD $n1$ when $j-th$ message transmission between MD $n1$ and other MDs
p^{j}_{n1}	The communication area position of MD $n1$ when $j-th$ message transmission between MD $n1$ and other MDs
A_{n1}	The interest sub-vector of MD $n1$
$sim^{A}_{n1,n2}$	The similarity of interest sub-vector between MD $n1$ and MD $n2$
M	The weight decision matrix of the network
z_{uv}	The $v-th$ sub-vector of MD u
C_{uv}	The contribution level of the $v-th$ social attribute value of MD u
TC_{v}	The contribution level of the $v-th$ social attribute value of all MDs
g_{v}	The contribution consistency level of each MD on the $v-th$ social attribute
w_{v}	The weight of the $v-th$ sub-vector similarity
w^{*}_{v}	The adjusted weight of the $v-th$ sub-vector similarity
β_{v}	The subjective assess weight
$F_{\mu}(b)$	The normal distribution membership function
$TPV_{n1,n2}$	The transmission priority value between MD $n1$ and MD $n2$

being transmitted from the start MD to the destination MD is defined as forwarding, in which the message transmission between MDs is briefly described as transmission.

A. COLLECT AND AFFLOAD NETWORK STATUS INFORMATION

In order to get the network status information of MDs, there exists a special preparatory period t_{prep} where MDs collect and update sufficient and accurate information about the movement and social preferences of MDs in the network. The length of the preparatory period t_{prep} usually set based on the activity cycle of the MDs in the network [27]. After collecting the network status information based on the encounter between MDs , MDs offload the network status information to the nearest car through the uplink.

Firstly, we quantify the process of collecting and updating MD movement and social habits during the preparatory period. We define a triple to denote the state of MD $n1$ collected during a preparation period, as shown below

$$State_{n1} = (Dis_{n1}, \alpha_{n1}, List_{n1}), \tag{1}$$

where Dis_{n1} and α_{n1} are the moving distribution of MD $n1$ and the eigenvector of MD $n1$ containing different social attributes, respectively. $List_{n1}$ is the state sequence established by MD $n1$ during a preparation period t_{prep}, and $List_{n1}$ is defined as follows

$$List_{n1} =< State_{a}, State_{b}, \ldots, State_{m} >, \tag{2}$$

where $State_a$, $State_b$, $State_m$ are the states of MD a, MD b and MD m when they encounter MD $n1$ during the preparation period t_{prep}, respectively. It must be said that unlike the social attributes of MDs, the moving distribution of MDs changes with time, so updating the movement information of MDs in time is beneficial to the timeliness of the collected data.

Meanwhile, during the preparation time t_{prep}, once MDs encounter, there will establish a five-tuple that contains all the information of the two MD encounters, where the fifth item of the five-tuple is the union of the two-MD state sequence. Moreover, the exchange of information can be done through the cooperation of multiple MDs in the network. So we use five-tuples $EState^1_{n1}$ to represent the encounter information established when MD $n1$ encounters other MD (such as MD $n2$) for the first time during the preparation time. Also, in order to establish a data set about MD similarity, the encounter information matrix will be established during the preparation time. So we assume that MD $n1$ encounters k MDs, and we establish matrix ES_{n1} that denote the k encounter information of MD $n1$ during the preparation time. $EState^1_{n1}$ and ES_{n1} are represented by equations (3) and (4) as follows, respectively.

$$\begin{aligned} EState^1_{n1} &= State_{n1} \bigcup State_{n2} \\ &= (Dis_{n1}, \alpha_{n1}, Dis_{n2}, \alpha_{n2}, List_{n1,n2}), \end{aligned} \tag{3}$$

$$ES_{n1} = (EState^1_{n1}, EState^2_{n1}, \ldots, EState^k_{n1}). \tag{4}$$

Secondly, we describe the process by which MD $n1$ offloads the encounter information matrix ES_{n1} to the nearest car through the uplink. The wireless channels in the system all follow the Small-scale Rayleigh fading, so the states of wireless channels are independent. Moreover, the transmission rate between MD $n1$ and the nearest car to MD $n1$ is given as follows:

$$r_{n1} = B_{n1} log_2(1 + \frac{P_{n1} h_{n1}}{w_0}), \tag{5}$$

where B_{n1} is the channel bandwidth of MD $n1$ in the offloading process. P_{n1} is the transmission power of MD $n1$. While h_{n1} and w_0 represent the channel gain and white noise power level of MD $n1$ in the offloading process, respectively.

After the message carrying MD (MD $n1$) establishing the encounter information matrix ES_{n1} through collecting the information of the MDs in the network during the preparation period and offloading the encounter information matrix ES_{n1} to the nearest car, the car determines the optimal message transmission decision of MD $n1$ through fuzzy evaluation of the movement and social similarity of the MDs in the network and then return the optimal message transmission decision to the message carrying MD (MD $n1$) by downlink. In this paper, we do not consider the delay and energy consumption in the downlink. This is because the amount of data returned through the downlink is small, and the downlink transmission rate is much higher than that of the uplink.

Next, we will model the FRRF algorithm in the following two subsections.

B. PHASE 1 OF THE FRRF ALGORITHM: ASSESS MD SIMILARITY

Based on the collected information, the car in the MEC-based OMSN system will assess the movement and social similarity between MDs. We first assess the movement similarity between MDs.

In general, the more similar the moving trajectories between MDs, the greater the likelihood that the message will be forwarded successfully between MDs. Therefore, we use the moving trajectories between MDs to describe the movement similarity between MDs. Moreover, the moving trajectory of a MD based on spatial and temporal information of the MD, so the joint time point and communication area in the FRRF algorithm are used to describe the moving trajectories of MDs in the MEC-based OMSN system, such as $(t^1_{n1}, p^1_{n1}), (t^2_{n1}, p^2_{n1}), \ldots, (t^i_{n1}, p^i_{n1}), \ldots, (t^j_{n1}, p^j_{n1}), \ldots, (t^{J_{n1}}_{n1}, p^{J_{n1}}_{n1})$, where t^j_{n1} and p^j_{n1} indicate the time point and the communication area position of MD $n1$ when $j-th$ message transmission between MD $n1$ and other MDs, respectively. And J_{n1} is the total number of message transmission that takes place between MD $n1$ and other MDs. Now, in the position set LS of the all communication area in the network, we can calculate the moving distribution Dis_{n1} of MD $n1$ by the following formula:

$$Dis_{n1} = \sum_{j=1}^{J_{n1}} \frac{h(LS, p^j_{n1})}{J_{n1}}. \tag{6}$$

In equation (6), if $p^j_{n1} \in LS$, then $h(LS, p^j_{n1}) = 1$; otherwise, $h(LS, p^j_{n1}) = 0$. This is because MD $n1$ can communicate with other MDs in the same position set of communication area LS, $h(LS, p^j_{n1}) = 1$.

In addition, we set different weights θ for different periods based on the large difference in user's geographic location between working and non-working periods. In detail, every day during work, each user repeats almost exactly the same moving trajectory, such as from a user's residence to the user's work place, so the weight value θ of the period will be higher than non-working period. In contrast, users are unrestricted in their activity during non-working period and are therefore more likely to move randomly throughout the entire communication area. In order to reduce the impact of the non-working period, we give a smaller weight value θ for the non-working period than for the working period. Therefore, the moving similarity $MS_{n1,n2}$ between MD $n1$ and $n2$ is given in formula (7), which is show as follows:

$$MS_{n1,n2} = \frac{\sum_{j=1}^{J_{n1}} \sum_{i=1}^{J_{n2}} \theta(\Delta t - |t^j_{n1} - t^i_{n2}|) h(p^j_{n1}, p^i_{n2})}{\sum_{j=1}^{J_{n1}} \sum_{i=1}^{J_{n2}} \theta(\Delta t - |t^j_{n1} - t^i_{n2}|)}. \tag{7}$$

$|t^j_{n1} - t^i_{n2}|$ denotes the time interval between the $j-th$ message transmission of MD $n1$ and the $i-th$ message transmission of MD $n2$. And Δt is the time precision that denote the ratio of all MDs in the same geographic location at the same time. As for $h(p^j_{n1}, p^i_{n2})$, which is the position similarity between the $j-th$ message transmission of MD $n1$ and the $i-th$ message transmission of MD $n2$.

Secondly, the social similarity between MDs is evaluated by studying the relationship between the social attributes of MDs in the network. The social attribute eigenvector of MD $n1$ is defined as follows:

$$\alpha_{n1} = (A_{n1}, B_{n1}, \ldots, Y_{n1}), \tag{8}$$

where $A_{n1}, B_{n1}, \ldots, Y_{n1}$ represent the different social attribute sub-vectors of MD $n1$, and each MD in the system has y social attribute sub-vectors. For example, $A_{n1} = (a_1, a_2, a_3, a_4)$ is the interest sub-vector, in which a_1, a_2, a_3 and a_4 represent the different characteristic words of the interest sub-vector, which are expressed as table tennis, movies, music and climbing, respectively. If MD $n1$ only likes to play table tennis, then MD $n1$ only has one characteristic word in the interest sub-vector A_{n1}, i.e., table tennis, so $A_{n1} = (1, 0, 0, 0)$. Besides, we assume that MD $n1$ encounters k MDs, and we establish matrix ES_{n1} that denote the k encounter information of MD $n1$. For the interest sub-vectors of MD $n1$ and MD $n2$, the similarity of interest sub-vector between the two MDs is given in formula (9).

$$\begin{aligned} sim^{A}_{n1,n2} &= \frac{A_{n1}A_{n2} + \varphi}{max(\|A_{n1}\|^2, \|A_{n2}\|^2) + \varphi} \\ &\quad + \frac{min(\|A_{n1}\|^2, \|A_{n2}\|^2) - A_{n1}A_{n2}}{\|A_{max}\|^2},\ (n1 \neq n2), \end{aligned} \tag{9}$$

where $\|A_{n1}\|$ and $\|A_{n2}\|$ are interest sub-vector models of eigenvectors of MD $n1$ and MD $n2$, respectively. A_{max} means that all the characteristic words contained in the interest sub-vector are 1, i.e., $A_{max} = (1, 1, 1, 1)$, and φ represents the minimum sub-vector. Consequently, we can easily tell that $0 \leq sim^{A}_{n1,n2} \leq 1$.

In addition, by evaluating the similarity of all social attributes sub-vectors between MD $n1$ and MD $n2$, we can obtain the social similarity between MD $n1$ and MD $n2$, as shown below

$$\begin{aligned} SS_{n1,n2} &= w_1 sim^{A}_{n1,n2} + w_2 sim^{B}_{n1,n2} +, \ldots, + w_y sim^{Y}_{n1,n2}, \\ &\quad (n1 \neq n2), \end{aligned} \tag{10}$$

where $w_1, w_2, \ldots, w_v, \ldots, w_y$ are the weights of similarity of different sub-vector between MD $n1$ and MD $n2$. We use an improved entropy evaluation method to calculate the weights of similarity of different sub-vector between MDs and give the weight decision matrix M, which is shown below

$$M = \begin{pmatrix} z_{11} & \cdots & z_{1v} & \cdots & z_{1y} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{u1} & \cdots & z_{uv} & \cdots & z_{uy} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{x1} & \cdots & z_{xv} & \cdots & z_{xy} \end{pmatrix} \tag{11}$$

where z_{uv} is the $v-th$ sub-vector of MD u, that is the $v-th$ social attribute value of MD u. Besides, the contribution level of the $v-th$ social attribute value of MD u is quantified as

$$C_{uv} = \frac{z_{uv}}{\sum_{u=1}^{x} z_{uv}}. \tag{12}$$

And the contribution level of the $v-th$ social attribute value of all MD is as follows

$$TC_v = -\frac{1}{lnx} \sum_{u=1}^{x} C_{uv} ln(C_{uv}). \tag{13}$$

TC_v ranges from 0 to 1. If the contribution level of $v-th$ social attribute value of each MD approaches to be equal, then $TC_v = 1$.

Thus, the weight of a sub-vector can be determined according to the corresponding contribution level. We now define the contribution consistency level of each MD on $v-th$ social attribute, i.e., $g_v = 1 - TC_v$. Then, the weight w_v of $v-th$ sub-vector similarity is given in the equation (14). In particular, the adjusted weight w^{*}_{v} is given in the equation (15) when the message carry MD can also give the subjective assess weight β_v according to its historical experience.

$$w_v = \frac{g_v}{\sum_{v=1}^{y} g_v}. \tag{14}$$

$$w^{*}_{v} = \frac{\beta_v g_v}{\sum_{v=1}^{y} \beta_v g_v}. \tag{15}$$

In conclusion, based on the above research on the social similarity of MDs, the MDs in the MEC-based OMSN system can be divided into different communication communities. By taking advantage of the fact that MDs belonging to the same communication community have more opportunities to transmit data to each other, the success rate of message forwarding between MDs can be greatly improved.

Next, according to the fuzzy reasoning system, we will evaluate the transmission priority of MDs by combining the movement similarity and social similarity of MDs.

C. PHASE 2 OF THE FRRF ALGORITHM: COMPUTE TRANSMISSION PRIORITY BY THE FUZZY REASONING SYSTEM

In the FRRF algorithm, we use the fuzzy reasoning system to determine the movement similarity degree and social similarity degree between MDs, and then calculate the transmission priority between MDs. In fact, the special relationship between MDs can be determined by the similarity between MDs. However, some unstable factors between MDs affect the similarity between them. If the data transmission between MDs is determined based on the affected similarity, it will cause the MDs in the system to collect inaccurate network state information. Therefore, we do not directly use similarity between MDs to determine the data transmission between MDs. We first use similarity between MDs to obtain a transmission metric, which representing the fuzzy degree of message forwarding between MDs and can effectively avoid the disadvantages of the affected similarity between MDs. Moreover, because of the extensive applicability of Mamdani fuzzy system, we use Mamdani fuzzy system as the fuzzy reasoning system in our paper. The fuzzy reasoning system is composed of the fuzzifier, the fuzzy inference, and the defuzzifier, respectively. Next, we will describe the three components of the fuzzy reasoning system in detail.

Firstly, fuzzifier is used to compute the membership level of fuzzy sets in fuzzy reasoning systems. For the fuzzifier in our paper, movement similarity and social similarity are taken as two input variables, and three fuzzy sets are defined for both input variables, i.e., low, medium and high. Membership

TABLE 2. Nine different situation for our proposed fuzzy reasoning system.

Rule No.	$MS_{n1,n2} + SS_{n1,n2}$	Transmission Priority
1	high + high	level 1
2	high + medium	level 2
3	high + low	level 3
4	medium + high	level 4
5	medium + medium	level 5
6	medium + low	level 6
7	low + high	level 7
8	low + medium	level 8
9	low + low	level 9

level of each fuzzy set can be calculated by corresponding membership function. Therefore, we define three different membership functions for the three fuzzy sets. In general, different membership functions are defined according to different scenarios, like triangular and trapezoidal. Since the movement of MDs in the system follows a normal distribution, we define a normal distribution membership function to evaluate the membership level of these two input variables in our fuzzy reasoning system, as shown below

$$F_{\mu}(b) = \frac{1}{\sqrt{2\pi}\sigma} exp(-\frac{(b-\mu)^2}{2\sigma^2}), \tag{16}$$

where μ is the type of fuzzy set, and b is the specific value of similarity between MDs. Besides, σ^2 is the variance of the random variable. Therefore, we can get three normal distribution membership functions and the three different membership levels of fuzzy set according to the similarity between MDs.

Secondly, we do fuzzy reasoning. In the Mamdani fuzzy system, two input variables (movement similarity and social similarity) correspond to three different fuzzy sets, so the combination of the two input variables corresponds to nine different fuzzy sets, which is shown in Table 2. Based on the FRRF algorithm, we comprehensively consider the MS_{n_1,n_2} and SS_{n_1,n_2} between the MDs to evaluate the message transmission priority, and then, according to the optimal next-hop delay MD number returned by the corresponding car, the message carrying MD can forward the message to a delay MD. Also, the nine message transmission priorities for these nine different situations are given in Table 2, where level 1 has the highest transmission priority, and the priority of level 1 to level 9 decreases step by step. It is easy to analyze from Table 2 that the movement similarity between MDs has a deeper impact on message forwarding than the social similarity between MDs. On the one hand, the reason is that the movement similarity reflects the similarity of the moving trajectories between MDs. Furthermore, the higher the movement similarity between MDs makes the two MDs more likely to meet, the greater the possibility of message transmission between MDs. On the other hand, social similarity divides MDs into different communities according to their social attributes. In detail, MDs with similar social attributes will be divided into the same communities. And the higher the possibility of transmitting messages between MDs belonging to the same community.

Finally, we show the third part of the fuzzy reasoning system after fuzzy reasoning, which is defuzzifier. Based on the Mamdani fuzzy system, the FRRF algorithm uses OR operation and AND operation to determine the transmission priority between MDs. In detail, the OR operation is first used to maximize the values of all fuzzy sets, followed by the AND operation to compute the minimum combination of the values of these fuzzy sets. In other words, the maximum shadow region of the value of each fuzzy set is obtained through the OR operation, and the minimum overlapping shadow region of the six largest shadows of the two input variables is obtained through the AND operation. Moreover, the maximum shadow region of the value of each fuzzy set represents the control result of each membership function. And data transmission priority can be obtained through the minimum overlapping shadow region of the six largest shadows of the two input variables, which is the data transmission recommendation results obtained by fuzzy reasoning based on movement similarity and social similarity. As for the final transmission priority value, the movement of the MDs in the system follows the normal distribution, so we use equation (17) to calculate the centroid of the overlapping shadow region and creatively use it as the transmission priority value.

$$TPV_{n1,n2} = \frac{\sum_{l=1}^{L} F_l \cdot s_l}{\sum_{l=1}^{L} F_l}, \tag{17}$$

where s_l is the MD similarity between MD $n1$ and MD $n2$, and F_l is the membership level of the MD similarity between MD $n1$ and MD $n2$. Moreover, L is the number of coordinates at the boundary of the minimum overlapping shadow region.

For the sake of understanding, we take an example and assume that the start MD (MD $n1$) needs to forward a message it carries to the destination MD (MD $n6$). After the preparatory period, each MD in the network has collected detailed information of the network state. First, the start MD (MD $n1$) offloads the collected encounter information ES_{n1} and the destination MD number of the message to the nearest car. Then the nearest car computes and compares the transmission priority values according to the FRRF algorithm, and returns the optimal next-hop delay MD number to the start MD (MD $n1$). This is because the highest transmission priority value is between the optimal next-hop delay MD and the destination MD (MD $n6$). According to the received optimal next-hop relay MD number, the start MD (MD $n1$) will forward the carried message to the optimal next-hop relay MD. Moreover, FIGURE 3 shows the whole process. It can be known from FIGURE 3 that MD $n2$, $n3$ and $n4$ are neighbors of the start MD (MD $n1$), and MD $n5$ and $n7$ are neighbors of MD $n3$. In order to make the message smoothly and efficiently forwarded from MD $n1$ to MD $n6$, the nearest car uses both the FRRF algorithm and the encounter information to calculate and compare the transmission priority values between the MDs and the destination MD. Since $TPV_{n3,n6}$ and $TPV_{n5,n6}$ are respectively the maximum transmission priority values in the communication domain of $n1$ and $n3$, the start MD $n1$ will first transmit the message to its neighbor

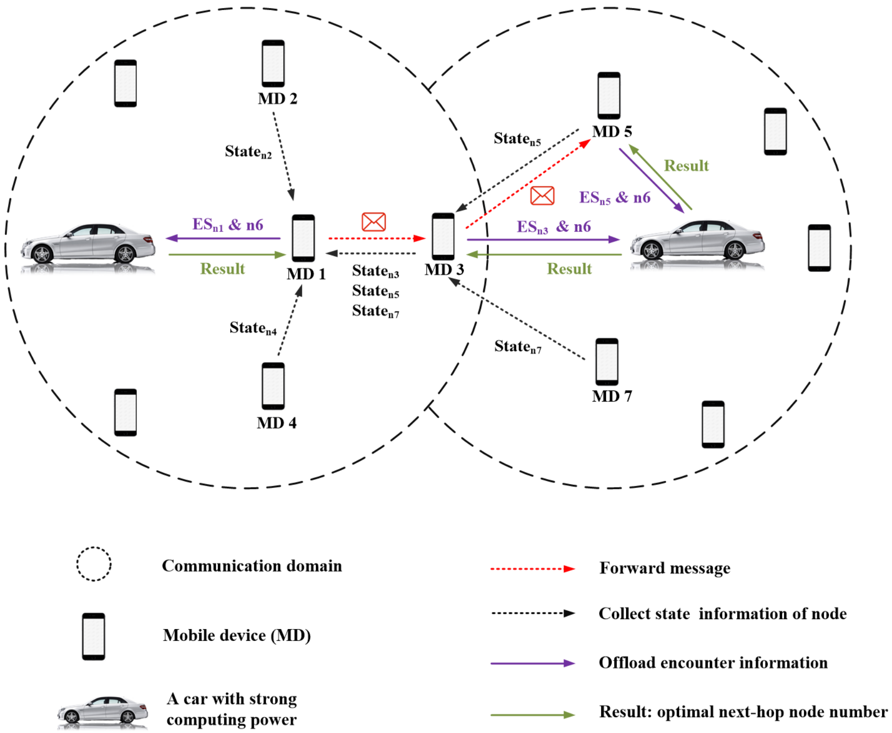

FIGURE 3. The detailed process by which a message is forwarded from the start MD (MD $n1$) to the destination MD (MD $n6$).

MD $n3$, and then MD $n3$ transmit the message to its neighbor MD $n5$. Finally, MD $n5$ transmit the message to destination MD (MD $n6$) to complete the whole message forwarding process.

D. THE FRRF ALGORITHM

In a word, the FRRF algorithm is a routing-forwarding algorithm based on fuzzy reasoning system to study the similarity between MDs in the MEC-based OMSNs system. The biggest difference from other routing-forwarding algorithms is that the FRRF algorithm is cached on cars with strong computing power in advance and executed on the cars. So using the computing power of the cars can save a lot of power for the MDs in the system. In order to better understand the FRRF algorithm, we have listed the detailed steps of the FRRF algorithm.

- In the preparatory stage, each MD in the system collects movement and social attribute information, and builds its own state triple. In addition, each MD will share its own state triple and at the same time establish and improve its own encounter information matrix by the encounters between MDs.
- The message carrying MD offloads the established encounter information matrix and the destination MD number of the carried message to the nearest car. According to the offloaded information, the car find the optimal next-hop delay MD, which has the highest movement or social similarity with the destination MD of the carried message. Because there is the highest movement or social similarity between the optimal next-hop relay MD and the destination MD, the optimal next-hop relay MD is more likely to be the relatives or friends of the destination MD, or have a highly similar movement trajectory to the destination MD. By selecting the optimal next-hop relay MDs in this way, the message can be successfully and efficiently forwarded from the start MD to the destination MD.
- Based on the Mamdani reasoning system, the car computes the membership level of similarity between MDs. Also, the car determines the transmission priority level of these MDs versus the destination MD, and finally computes the transmission priority values between these MDs and destination MD.
- The car determines the optimal transmission decision by comparing the calculated transmission priority values. And then the message carrying MD can transfer the message to the MD with the highest transmission priority value. By repeating the same four steps, the message can eventually be transmitted from the start MD to the destination MD.

In order to describe the FRRF algorithm more intuitively, the detailed flow of the FRRF algorithm is given in Algorithm 1.

More specifically, in the preparatory stage, the meeting MDs in the network share state sequences with each other to constantly update their encounter information matrix, hence the time complexity of this stage is $O(\log_2 n)$. And then, the time complexity of this process of calculating the transmission priority values of MDs based on the fuzzy reasoning system is $O(n)$. Finally, cars compares the calculated transmission priority value and determines the optimal message transmission decision, so the time complexity of this process is $O(\log n)$. In conclusion, the overall time complexity of the proposed FRRF algorithm can be expressed as $O(\log_2 n + n + \log n) = O(n)$. Compared with Spray and Wait algorithm with time complexity $O(n \log n)$, the FRRF algorithm has advantages. Although the Epidemic algorithm and the FRRF algorithm have the same time complexity $O(n)$, MDs in the network can save a lot of energy under the FRRF algorithm, this is because a large part of the computation is offloaded to the car under the FRRF algorithm.

Algorithm 1 The Proposed FRRF Algorithm

Input: MD $n1$, MD $n2$, MD $n3$ and destination MD $n4$
Output: $TPV_{n1,n4}$, $TPV_{n2,n4}$ and $TPV_{n3,n4}$

/*The computation of transmission priority*/
MDs in the network collect information about all encounter MDs;
if ($n1.isMessageCarrier()$) **then**
  Give different weight for each sub-vector of the social attribute eigenvector;
  Compute MS and SS between each MD and the destination MD of the message;
  for each membership function of the fuzzifier component **do**
    Compute the membership degrees of movement and social similarities;
  end for
  Determine the transmission priority degree of MDs;
  $TPV = fuzzy(MS, SS)$;
  Output TPV;
end if
/* Forwarding messages */
if ($n2.isNeighbor(n1) \wedge n3.isNeighbor(n1)$) **then**
  if ($TPV_{n2,n4} > TPV_{n1,n4} \wedge TPV_{n3,n4} > TPV_{n2,n4}$) **then**
    MD $n1$ transfers the message to MD $n3$;
  end if
end if

IV. SIMULATION

A. PARAMETERS SETTING IN SIMULATION

The simulation uses Matlab R2016a to simulate real scenario and evaluate the performance of the FRRF algorithm. In order to clearly show the advantages of the FRRF algorithm, we compare the FRRF algorithm with Epidemic [36], Spray and Wait [37], EIMST (Effective Information Transmission Based on Socialization Nodes) [38] and ICMT (Information Cache Management and Data Transmission Algorithm) [11], in which EIMST and ICMT are two new routing-forwarding algorithms, while Epidemic and Spray and Wait are two typical traditional routing-forwarding algorithms. In the simulation experiment, we set the relevant parameters as follows:

TABLE 3. Detailed parameter settings in the simulation environment.

Name of Simulation Parameter	Value
Simulation tool	Matlab R2016a
Mobility model	HCMM (Health Capability Maturity Model)
Communication area (m^2)	$4500 * 4500$
Geographic area (m^2)	$900 * 900$
Number of MDs	550
Total simulation time (h)	12
Preparation time (min)	25, 30, 35, 40, 45, 50, 55
Storage capacity of a MD (Mb)	10, 15, 20, 25, 30, 35, 40
Speech range of a MD (m/s)	1–9
Initial energy of battery for a MD (J)	20
Number of sub-vectors	5
Number of feature words	25

The communication domain is a quare with $4500m * 4500m$. And the communication domain is divided into 25 equal geographic regions, each with a square range of $900m*900m$. The total number of MDs in the simulation are 550 and each MD has an initial energy of 133200 J. The HCMM (Health Capability Maturity Model) movement model [39] is applied to the MDs in the communication domain in the MEC-based OMSNs system, and the HCMM is based on community division. Also, MDs in the same community communicate more frequently, and the weight θ can be set as 0.8 [27], [40]. The total simulation time is 12 hours. Moreover, the preparation time t_{prep} is set to 25, 30, 35, 40, 45, 50 and 55 min, respectively, where 25 min is the initial value. In predicting the user's coincidence degree in time and geography, we set the time accuracy Δt to 1 h. The storage capacity of the MD is set to 10, 15, 20, 25, 30, 35 and 40 Mb, respectively, where 10 M is the initial value. Besides, the initial battery capacity of each MD in the system is full and initial energy of battery for each MD is 100 J. More specifically, each MD consumes 0.25 J for every 10 packets transmitted. The speed range of the MDs is set to 1 to 9 m/s to match the normal movement speed of humans, animals and vehicles. Interest, place of work, occupation, residence, and physical characteristics are all social attributes of each MD. Besides, each social attribute contains five different characteristic words. For example, interest as a social attribute contains five characteristic words: table tennis, movies, music, climbing and reading. Therefore, each MD in the system has 5 different sub-vectors, and the total of 25 characteristic words of the 5 sub-vectors are randomly assigned to each MD. In order to make the setting of simulation parameters clearer, the following Table 3 is established to describe the simulation environment.

In addition to comparing the FRRF algorithm with the other four algorithms, the simulation focuses on four aspects, namely delivery ratio, overhead on average, average end-to-end delay and average remaining energy.

Delivery ratio: The parameter denotes the probability of choosing an optimal next-hop relay MD during the message transport phase. We define R as the delivery ratio throughout the network, which can be calculated by the following equation.

$$R = \frac{N^{rec}}{N^{sen}}, \tag{18}$$

where N^{rec} and N^{sen} represent the number of messages received by the neighbors around MDs and the number of messages transmitted by MDs, respectively.

Overhead on average: The parameter denotes the network overhead of successfully transmitting a message between MDs. We define O as the overhead on average, which can be calculated by the following equation.

$$O = \frac{T^{tot} - T^{suc}}{T^{tot}}, \tag{19}$$

where T^{tot} is the total time consumption of the all message transmitting process, and T^{suc} is the total time consumption of successfully transmitting message between MDs.

Average end-to-end delay: The parameter consists of three parts, that is the delay of select the optimal next-hop delay MD, the delay of relay MD waiting for the message, and the delay of message forwarding. We define D^{ave} as the average end-to-end delay, which can be calculated by the following equation.

$$D^{ave} = \frac{D^{sum}}{\chi^{suc}}, \tag{20}$$

where D^{sum} is the sum of the total delay of each MD, and χ^{suc} is the total number of MDs that successfully received the message.

Average remaining energy: The parameter denotes the average remaining energy of all MDs in the network at the end of the simulation experiment. Moreover, the energy consumption of the MD is composed of parts, that is energy consumption of basic operation when there is no computing task (including collect network status information), energy consumption of offloading encounter information and energy consumption of transmitting message. We define E^{ave} as the average remaining energy, which can be calculated by the following equation.

$$E^{ave} = \frac{E^{sum}}{\chi}, \tag{21}$$

where E^{sum} is the total energy of each MD in the network at the end of the simulation experiment, and χ is the total number of MDs in the network.

B. SIMULATION CASE ANALYSIS

According to equation (16), for the low, medium and high fuzzy sets defined in our paper, we have three normal membership functions, i.e., $F_1(b)$, $F_2(b)$ and $F_3(b)$, respectively.

$$F_1(b) = \frac{1}{\sqrt{2\pi}\sigma_1} exp(-\frac{(b-\mu_1)^2}{2\sigma_1^2}), \tag{22}$$

$$F_2(b) = \frac{1}{\sqrt{2\pi}\sigma_2} exp(-\frac{(b-\mu_2)^2}{2\sigma_2^2}), \tag{23}$$

$$F_3(b) = \frac{1}{\sqrt{2\pi}\sigma_3} exp(-\frac{(b-\mu_3)^2}{2\sigma_3^2}). \tag{24}$$

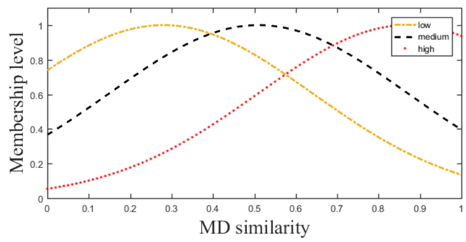

FIGURE 4. In normal distribution, three membership functions corresponding to three fuzzy sets, i.e., low, medium and high fuzzy set.

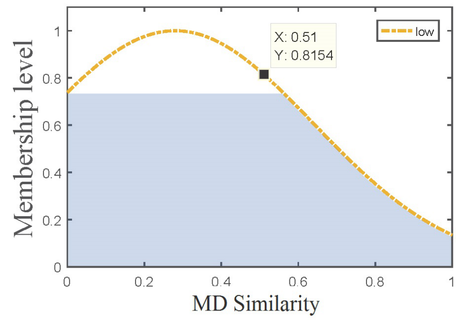

FIGURE 5. The maximum shadow region of low membership function when $MS_{n1,n2} = 0.51$.

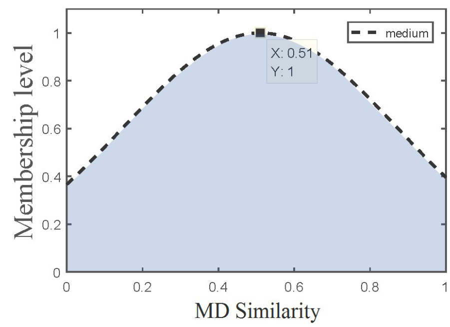

FIGURE 6. The maximum shadow region of medium membership function when $MS_{n1,n2} = 0.51$.

By adjusting parameters through experiments, we finally get $\mu_1 = 0.28, \sigma_1^2 = 0.36^2$, $\mu_2 = 0.51, \sigma_2^2 = 0.36^2$ and $\mu_3 = 0.87, \sigma_3^2 = 0.36^2$. And the geometry of the final transformation is shown in FIGURE 4.

For example, when $MS_{n_1,n_2} = 0.51$, $F_1(0.51) = 0.8154$, $F_2(0.51) = 1$, $F_3(0.51) = 0.6065$. After OR operation, FIGURE 5, 6 and 7 can respectively correspond to the maximum shadow region of the low, medium and high membership functions. Considering further, when combining $MS_{n_1,n_2} = 0.51$ and $SS_{n1,n2} = 0.51$, the minimum overlapping shadow region of the six largest shadows of the two input variables is shown in FIGURE 8 after the AND operation.

C. RESULT ANALYSIS

Firstly, we show the performance of the FRRF algorithm versus the preparatory period t_{prep} through FIGURE 9, 10, 11 and 12. Except that the MDs in the same

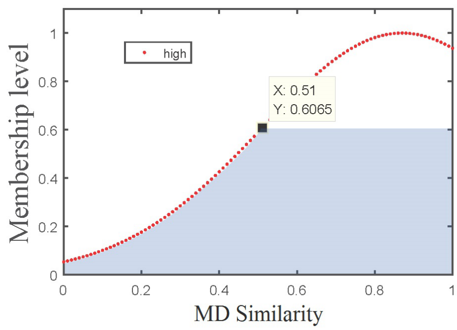

FIGURE 7. The maximum shadow region of high membership function when $MS_{n1,n2} = 0.51$.

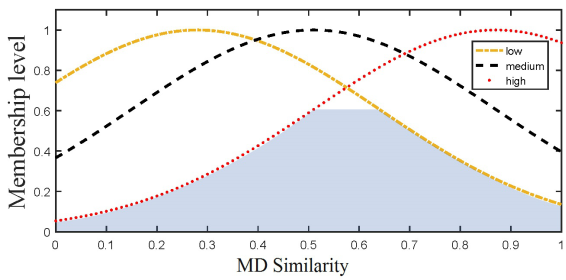

FIGURE 8. The minimum overlapping shadow region of low, medium and high membership functions when $MS_{n1,n2} = 0.51$ and $SS_{n1,n2} = 0.51$.

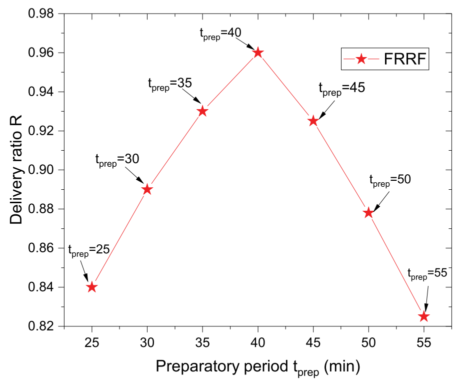

FIGURE 9. The delivery ratio R versus the preparatory period t_{prep}.

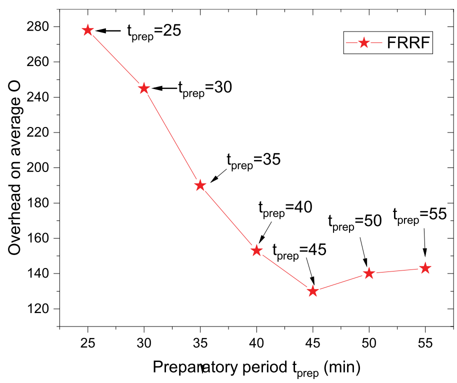

FIGURE 10. The overhead on average O versus the preparatory period t_{prep}.

community can share the state sequence information with each other, the MDs moving randomly in the communication domain will share the state sequence information once they meet in the preparation period. Therefore, the length of the preparatory period will affect the comprehensiveness of the MD to the network status collection, and further affect the performance of the FRRF algorithm. Based on the simulation results, it can be known that when the simulation time is 12 h and the preparatory period t_{prep} is $35 - 45$ min, the FRRF algorithm can show the best performance.

FIGURE 9 shows the delivery ratio R versus the preparatory period t_{prep} ranging from 25 to 55. It can be seen from FIGURE 9, with the increase of the preparation period, the value of delivery ratio increases rapidly first, followed by the value of delivery ratio rapidly decline. In detail, the delivery ratio achieved the maximum value 0.96 when the preparation period is 40 min. The reason is that, on the one hand, with the increase of the preparation period, MDs can collect more network status information, and then cars can calculate more accurate similarities between MDs and select the optimal relay MD by comparing the similarities between MDs. On the other hand, too long preparation period makes the MDs in the network carry and share information too frequently, and even deal with some irrelevant information in the process of sharing. As a result, MDs consume a large amount of energy, and then move slowly or stop due to the low energy of MDs. In addition, the collection, offloading, and transmitting of network status information all require the storage space of the MDs and consume the energy of the MDs. Therefore, if the preparation period is too long, MDs in the network will consume a lot of resources, and the delivery rate of the network will go down.

FIGURE 10 shows the overhead on average O versus the preparatory period t_{prep} ranging from 25 to 55. It can be seen that the maximum overhead on average is no more than 278. With the increase of the preparatory period, the corresponding overhead on average keeps decreasing. The longer the preparatory period, the deeper the MD's understanding of the network. At the same time, more MDs are involved in information collection and message forwarding. Therefore, the data transmission between MDs is more efficient and stable, and the number of hops during the successful message forwarding is also significantly reduced. In a word, the time and distance costs of successfully forwarding a message between MDs are reduced, so that the cache space and computing resources of MDs can be effectively utilized. It is obvious from FIGURE 10 that the overhead on average in the whole network is continuously reduced from 278 to 145.

FIGURE 11 shows the average end-to-end delay D^{ave} versus the preparatory period t_{prep} ranging from 25 to 55. It can be seen from FIGURE 11, with the increase of the preparation period, the average end-to-end delay first drops sharply and then rises. In detail, when the preparatory period is 35 min, the FRRF algorithm can achieve the minimum

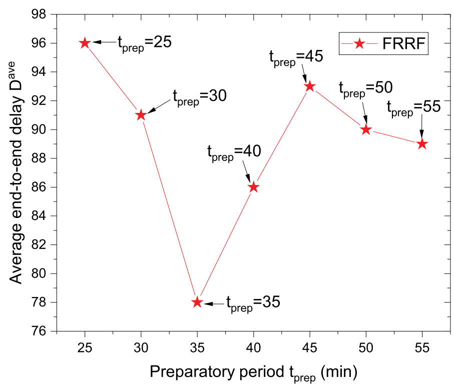

FIGURE 11. **The average end-to-end delay D^{ave} versus the preparatory period t_{prep}.**

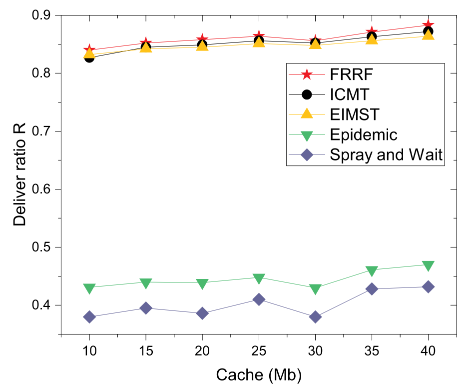

FIGURE 13. **The delivery ratio R of five algorithms versus the buffer space size.**

average end-to-end delay, namely 78. Appropriately prolonging the preparation period increases the frequency of information exchange between MDs, and then sufficient statistics of the social attributes between MDs. Furthermore, the car computing the similarity between MDs and compare the similarity to select the optimal next-hop relay MD, which finally enabled the data to be successfully forwarded, thus reducing the extra time spent in the process of data forwarding due to the selection of bad relay MD. However, the too long preparation time makes the MDs in the system carry some additional information, which may lead to the lack of energy and memory of the MDs, thus making it take more time for the MDs to collect information and transmit messages, and finally causing the average end-to-end delay to increase.

FIGURE 12 shows average remaining energy E^{ave} versus the preparatory period t_{prep} ranging from 25 to 55. It can be seen that the average remaining energy decreases slowly with the increase of the length of preparation period. On the one hand, the longer the preparation period, the more energy the MDs need to spend to understand the whole network. In other words, the MDs in the network can collect more MD data information by encountering each other. In addition, the more network information the MD collects, the more data the MD needs to offload to the nearest car. As a result, MDs consume more energy and thus have less energy left over. On the other hand, as the knowledge of the network is more comprehensive and deeper, the car can select a better next hop delay MD on the basis of the network state. Then the number of hops during the successfully message forwarding will be effectively reduced, which means that the energy consumption of MDs in the process of message forwarding will also be effectively reduced. As a whole, the average remaining energy of MDs decreases with the increase of the preparatory period.

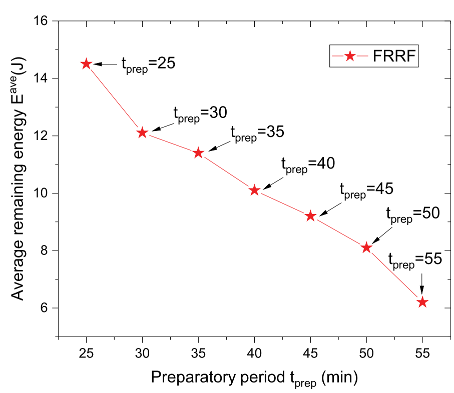

FIGURE 12. **The average remaining energy E^{ave} versus the preparatory period t_{prep}.**

Secondly, we compare and analyze the FRRF algorithm with the other four algorithms. Since some algorithms in the OMSN are based on contextual information, MDs in the system need to carry, transmit and forward some text information about the network state. However, the limited cache space of MDs limits data transfer. Based on this, we set the buffer space size of the MD as a variable in the simulation experiment to study the transmission capacity of these algorithms. The experimental results show that compared with the other four algorithms, the FRRF algorithm performs better in delivery ratio, average end-to-end delay, network overhead and average remaining energy. Below, we compare the performance of the five algorithms in terms of delivery ratio, average end-to-end delay, network overhead and average remaining energy in detail according to FIGURE 13, 14, 15 and 16, respectively.

FIGURE 13 shows the delivery ratio R of five algorithms versus the buffer space size from 10 Mb to 40 Mb. On the whole, the delivery ratio of the five algorithms increases with the increase of the size of cache space. The reason is that the MDs in the system have enough cache space to carry more information and handle more complex computing tasks. Besides, the delivery ratio under the FRRF algorithm is always higher than that under other four algorithms. In the FRRF algorithm, because the successful forwarding of messages is achieved through context information and MD similarity. By the FRRF algorithm, the MDs in the system are divided into different communities according to their social similarities. Moreover, the MDs with higher movement similarity within the same community will communicate more

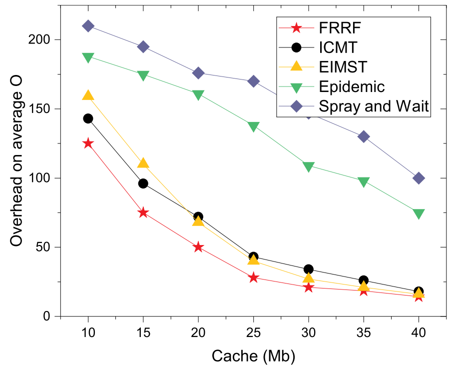

FIGURE 14. The overhead on average *O* of five algorithms versus the buffer space size.

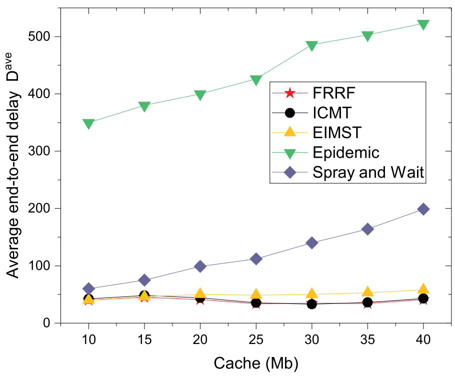

FIGURE 15. The average end-to-end delay D^{ave} of five algorithms versus the buffer space size.

frequently because there are more opportunities to meet. At the same time, car comprehensively considers MD movement and social similarity to determine the optimal next-hop relay MD, so the delivery ratio of the FRRF algorithm is always the highest. For the Spray and Wait algorithm and the Epidemic algorithm, because these two algorithms are typical flooding algorithms, many message group copies will lead to poor transmission efficiency in the network, and then the delivery ratio of these two algorithms is also correspondingly low. Besides, the ICMT algorithm and EIMST algorithm realize message forwarding based on the mutual cooperation of multiple MDs, but the disadvantage is that the limited buffer space of MDs will affect the transmission efficiency. Therefore, these two algorithms are not an effective transmission strategy.

FIGURE 14 shows the overhead on average O of five algorithms versus the buffer space size from 10 Mb to 40 Mb. In general, as the buffer space of the MD increases, the MD will have more space to store network state information and perform computing tasks, so the average overhead of these five algorithms is significantly reduced. In addition, because the FRRF algorithm uses the similarity of MDs to determine the optimal process of message forwarding, the average overhead of the FRRF algorithm is always smaller than the other four algorithms. Specifically, due to the FRRF algorithm comprehensively takes movement and social similarity into consideration to evaluate the social relations between MDs, the probability of successful message forwarding of two MDs with close relation is higher. Therefore, based on the FRRF algorithm, when messages are forwarded from the start MD to the destination MD, there are relatively few relay MDs need to rely on. Furthermore, the routing and forwarding process of messages only costs less time and resources, and the overhead on average of the entire data transfer process is significantly reduced. For the Epidemic algorithm and the Spray and Wait algorithm, the average overhead is naturally higher than other algorithms because a large number of message group copies will lead to a large delay and consume a large amount of resources. For the ICMT algorithm and the EIMST algorithm, they can effectively manage MD information and buffer space, which can reasonably allocate resources and control transmission time, so the overhead on average of these two algorithms basically remains at the medium level of these five algorithms. In a word, compared with the other four algorithms, the FRRF algorithm is the best at the overhead on average.

FIGURE 15 shows the average end-to-end delay D^{ave} of five algorithms versus the buffer space size from 10 Mb to 40 Mb. On the whole, the average end-to-end delay of the five algorithms increases as the buffer space of the MDs increases. It is worth mentioning that the average end-to-end delay of the FRRF algorithm is always lower than other algorithms, and the average end-to-end delay of the FRRF algorithm fluctuates less and remains relatively stable when the buffer space grows from 10 Mb to 40 Mb. The reason is that the FRRF algorithm determines the optimal next-hop relay MD based on the calculation and comparison of MD similarity, and the whole message forwarding process can be determined by the optimal next-hop relay MD each time. However, the movement and social attribute information of the MD are not greatly affected by the buffer space of the MD, so the change of the buffer space size has little impact on the delay, including the delay of selection of the optimal relay MD, the delay of the relay MD waiting for messages, and the delay of message forwarding. Obviously, the average end-to-end delay of the Epidemic algorithm is very high, because Epidemic algorithm produces many copies of message groups, which increases the delay of selecting the optimal next-hop delay MD and the delay of forwarding the message. However, the average end-to-end delay of the Spray and Wait is lower than that of the Epidemic algorithm in the corresponding cache space, due to the number of message copies is effectively controlled. As for the EIMST algorithm and the ICMT algorithm, the average end-to-end delay is much lower than the two traditional algorithms. This is because community partitioning and information management are applied in the EIMST algorithm, while the ICMT algorithm uses a cooperative mechanism for effective utilization of MD buffer space. In conclusion, compared with the other four algorithms, the FRRF algorithm performs best on average end-to-end delay.

FIGURE 16 shows the average remaining energy E^{ave} of five algorithms versus the buffer space size from 10 Mb to

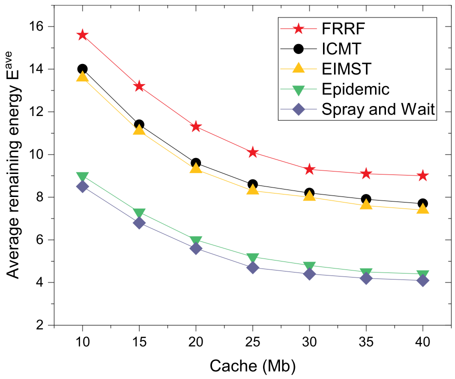

FIGURE 16. The average remaining energy E^{ave} of five algorithms versus the buffer space size.

40 Mb. Overall, as the buffer space of the MDs increases, the average remaining energy of MDs in the five algorithms decreases and eventually levels off. This is because once the buffer space increases, the MD will have more space to carry more messages and collect more MD encounter information, which will increase the number of times the MD transmits data and eventually cause more energy consumption. It is worth mentioning that the average remaining energy of the MDs under the FRRF algorithm is always higher than the other four algorithms. The main reason is that the FRRF algorithm is cached in the car and executed by the car, while the MD only needs to collect the network status information and offload the network status information to the nearest car. Compared to routing algorithm performed by the MD itself, the MD will save a lot of energy. In addition, data transmission between MDs is more efficient under the FRRF algorithm, which means that the number of hops in successful message forwarding is less, so MDs consume less energy and has more energy left over. It is obvious that the average remaining energy of the MDs under Epidemic algorithm and Spray and Wait algorithm is the lowest in the five algorithms. Since both Epidemic algorithm and Spray and Wait algorithm produce many copies of message groups, the number of information transmission increases, then resulting in more energy consumption of MDs. The average remaining energy of MDs under ICMT algorithm and EIMST algorithm is higher than that of two traditional algorithms. The reason is that ICMT algorithm effectively utilizes the buffer space of the MDs through a cooperative mechanism, while EIMT algorithm applies community segmentation and information management in the routing algorithm.

V. CONCLUSION

In this paper, we apply MEC to OMSNs innovatively. In order to effectively reduce the energy consumption and delay of MDs in wireless network, we proposed the FRRF algorithm in the MEC-based OMSNs. The FRRF algorithm comprehensively considers the movement and social similarity between MDs to determine the transmission priority value between MDs, and finally make the optimal transmission decision by comparing the calculated transmission priority value between MDs. More specifically, the calculation of similarity between MDs is based on fuzzy reasoning system and information entropy. Further, the complexity analysis in the FRRF algorithm part shows the low complexity and high efficiency of the FRRF algorithm. Finally, the correctness of the theoretical analysis, the efficiency in reducing energy consumption and delay, and advantages over other algorithms are verified by the simulation results.

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