

Retraction

Retracted: Load Balancing Selection Method and Simulation in Network Communication Based on AHP-DS Heterogeneous Network Selection Algorithm

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] W. Xiao, "Load Balancing Selection Method and Simulation in Network Communication Based on AHP-DS Heterogeneous Network Selection Algorithm," *Complexity*, vol. 2021, Article ID 4239750, 12 pages, 2021.

Research Article

Load Balancing Selection Method and Simulation in Network Communication Based on AHP-DS Heterogeneous Network Selection Algorithm

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This article proposes an Analytic Hierarchy Process Dempster-Shafer (AHP-DS) and similarity-based network selection algorithm for the scenario of dynamic changes in user requirements and network environment; combines machine learning with network selection and proposes a decision tree-based network selection algorithm; combines multiattribute decision-making and genetic algorithm to propose a weighted Gray Relation Analysis (GRA) and genetic algorithm-based network access decision algorithm. Firstly, the training data is obtained from the collaborative algorithm, and it is used as the training set, and the network attributes are used as the attribute set, and the continuous attributes are discretized by dichotomization, and the attribute that can make the greatest information gain is selected as the division feature, and a decision tree with strong generalization ability is finally obtained, which is used as the decision basis for network access selection. The simulation results show that the algorithm proposed in this thesis can effectively improve user service quality under three services, and the algorithm is simple and effective with low complexity. It first uses AHP-DS hierarchical analysis to establish a recursive hierarchy for the network selection problem and obtains the subjective weights of network attributes through the judgment matrix. Then, it uses a genetic algorithm to adjust the subjective weight, defines the fitness function in the genetic algorithm-based on gray correlation analysis, adjusts the weights of the selection operator, crossover operator, and variation operator in the genetic algorithm, and gets the network with the largest fitness as the target network, which can effectively improve the user service quality.

1. Introduction

With the rapid development of wireless network communication technology in recent years, wireless networks that comply with the new network communication standards of higher generation are continuously generated to meet the increasingly diverse needs of modern society in terms of available bandwidth, transmission rate, response latency, and usage price of the network. Also, due to the constraints of macrostrategic planning at the administrative level, the regional economic development level, and the input/output ratio of network replacement, network operators still choose to *maintain some older versions of their networks for a period before the new technology is fully rolled out. The strategy is to keep older versions of the network in operation

for a period until new technologies are fully rolled out. When in an area with multiple network coverage, users want to maintain optimal connectivity and seamless roaming at all times to achieve higher system performance and user satisfaction [1]. When users' business needs or geographic locations change, the performance of the network they access may change and they need to reevaluate whether the currently accessed network is still the best. If a better-performing network exists, the user may switch between networks [2]. When users are in an environment that incorporates different wireless networks, they need to choose the right network to access or switch to obtain better network resources based on the properties of each of these wireless networks and their own needs. Also, the network selection should reflect the "will" of the network side, which

should not only meet the network resource requirements of the accessing users as much as possible but also control their network load to avoid the pressure on network maintenance due to the excessive number of users admitted [3].

In heterogeneous networks, the network access selection mechanism plays a key role. On one hand, it determines the continuity and effectiveness of user network switching, helps users access the right network, and makes the network usage experience guaranteed. On the other hand, it helps network service providers to manage the reasonable allocation of network resources according to the unique properties of different networks, improve the efficiency of network resource utilization, and improve the service quality of users. Although many scholars have done a lot of research on network access selection algorithms, there are still many problems that need to be solved [4]. For example, some network access selection algorithms lack flexibility and cannot be combined with the real-time condition of network resources; how to do a good balance between the computational complexity and practical effectiveness of the algorithm; how to fully take into account the quality of service of users and the overall utilization of network resources [5]. With the development of heterogeneous networks, more wireless network technologies come into being and the performance of users' network terminals will continue to improve. To improve the overall effectiveness of the network and achieve efficient utilization, it is of positive significance to study the access selection mechanism of heterogeneous networks.

In our article, we reconstruct AHP with DS network for the first time and investigate its performance in all aspects, and we find that our results have strong reference value and practical value. In the more complex latter model, if the terminals still have uncontrolled decision-making power as in the above scenario of terminal-initiated network selection, it is inevitable that the network with good overall performance is used as the target access network too often (in the extreme case, all terminals select the same network), while the probability of the rest of the networks being selected is significantly smaller or even zero. The original network with better overall performance is overloaded with too many terminals, and the channel blocking rate increases accordingly, thus reducing the experience of the end-users connected to this type of network. The remaining networks with average performance have a high probability of being idle due to the low number of terminals connected to them, and the corresponding resources are wasted, which significantly reduces the overall system performance. Therefore, it is necessary to restrict the decision-making power of terminals to avoid the phenomenon of "overcooling and overheating" of the load of each network. This can be solved by using the so-called centralized network selection scheme.

2. Current Status of Research

Jiang et al. introduced a new normalization technique to eliminate the rank inversion of the utility function based on the original Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), making it simple to compute

both positive and negative ideal solutions [6]. Thanks to the theory of diminishing marginal utility and monotonic utility, each normalized attribute value of any network is calculated separately without considering the influence of other networks in the list. This is the main difference from the conventional normalization methods [7]. This normalization method can be applied to the corresponding processes of other multiattribute decision methods [8]. However, it requires the decision-maker to be familiar with each attribute and then normalize it using an appropriate formula. Joshi and Kumar investigated the integration of entropy and GRA to rank the overall performance of each alternative solution. In both solutions, the weights of the attributes are calculated by the entropy method, thus ignoring any user preferences [9]. As a result, their outputs may be too sensitive to the environment, leading to an increased number of vertical shifts and ping-pong effects. In [10], both proposed a combination of AHP and GRA to select the optimal network. AHP and GRA are used to assign weights to each attribute for the corresponding business class and to rank the alternatives separately. The main difference between these two methods is the difference in the GRA algorithm used. The former uses the standard GRA, while the latter is inspired by TOPSIS to improve the standard GRA [11]. Gray correlation coefficients and gray correlation degrees are calculated for each network with positive and negative ideal solutions. Finally, the combined evaluation value of each network is calculated by a formula like the one used in TOPSIS for calculating the relative closure coefficient.

Kunarakand Suleesathira mentioned a method that combines FAHP, standard deviation, and GRA. They used FAHP and standard deviation to calculate subjective and objective weight vectors [12]. Then, the two weight vectors are integrated into a combined weight vector by normalization of multiplicative synthesis. Finally, the ranking is completed using the original GRA algorithm. The scheme considers both the subjective experience of the decision-maker and the objective conditions of the network when calculating the integrated attribute weights. Therefore, it helps provide a high-quality weight vector for the GRA algorithm and obtain better ranking results [13]. Next, international ship and port facility security (ISPs) analyzes subscriber behavior to adjust service prices to maximize revenue [14]. The IoT fog computing scenario based on multiple service providers and multiple subscribing users combines a Stackelberg game and a many-to-many matching algorithm to solve the pricing problem of service providers and the resource purchase problem of subscribing users, where all game participants can obtain optimal benefits and achieve an equilibrium outcome [15]. Drone access to the network as a hotspot becomes a new way to expand the network. The different factors involved from individual drone decisions to the formation of the whole group decision and the different factors involved in it into the evolutionary game model were combined.

Such a macroscopic model consisting of microscopic foundations better reflects the diversity and complexity of actors. Applying the idea of a matching game to the

problem of resource allocation, participants are matched in the order of the matching list and can obtain a two-by-two stable convergence of matching results. This algorithm allows each applicant user's demand to be satisfied as much as possible and effectively reduces the load on the link and the delay experienced by the user's network switching. For network service providers, adjusting the price of network services is a common competitive tool. The game is based on Gounod's game and Starkburger's game. The game defines the network service provider as the leader and the wireless relay as the follower, and the two parties play around with the supply and demand of network resources.

3. Simulation Analysis of Load Balancing in Network Communication with AHP-DS Heterogeneous Network Selection Algorithm

3.1. AHP-DS Heterogeneous Network Selection Algorithm Ensemble Design. Nowadays, users are generally covered by multiple wireless networks in their locations, and these networks have different characteristics, such as high data transmission rate and limited coverage of wireless broadband technology, while cellular networks cover a wide range but high tariffs. Each of these networks has its strengths and weaknesses, no one network can meet all the needs of users, and no one can replace the other in a short period [16]. Therefore, how to design an efficient network access mechanism to provide high-quality services to users is the focus of research in wireless communication. The heterogeneous wireless network scenario studied in this article is shown in Figure 1, which consists of three wireless access technologies: Universal Mobile Telecommunications System (UMTS), Wireless Local Area Network (WLAN), and Worldwide Interoperability for Microwave Access (WiMAX), where UMTS has a wide coverage area but lower transmission rate, lower packet delay, and packet jitter but higher price; WLAN has a smaller coverage area but higher transmission rate than UMTS and is cheaper but WiMAX offers the same available rate as WLAN but at a higher cost compared to WLAN. Users are randomly distributed in the areas covered by these networks and need to choose the best network access according to their service characteristics.

According to the classification of service types by international standards organizations, there are session-based services, streaming services, interactive services, and background services, respectively. Different services have different requirements on network attributes. The session class is a real-time service and thus requires high packet delay and packet jitter and a less stringent packet loss rate. Streaming services have higher requirements for throughput, allow a certain packet loss rate, and have lower requirements for transmission delay. Interaction class services have high requirements for throughput and cost. The background class service also requires a very high

packet loss rate and has low requirements for transmission latency. Different types of services have different quality of service (QoS) requirements [17]. To enable users to select a suitable network according to their service characteristics, this chapter proposes a network selection algorithm based on AHP and similarity. In the first step, different judgment matrices are assigned to different service types, and the attribute weights are obtained by the AHP algorithm; in the second step, the similarity is calculated based on user requirements and network attributes; finally, the similarity between user requirements and network is weighted to obtain the similarity, and the one with the greatest similarity is selected as the target network.

After getting the attribute weights, the similarity between network attributes and user requirements is calculated in three cases (fixed value and fixed value; fixed value and interval; interval and interval), and finally, the total similarity between network and user requirements is weighted to get the total similarity between network and user requirements. AHP is a commonly used subjective decision method that can be used to deal with multi-attribute decision problems; it simplifies the problem and has specific solution steps for multiattribute decision problems. It specifically includes establishing the recursive hierarchy, the judgment matrix, weight calculation, and consistency test. After establishing the recursive hierarchy of the network selection problem, the judgment matrix required to calculate the attribute weights is determined separately according to the user requirements for different business types. When considering the weights of each attribute of the network, if we set them subjectively, it may not be comprehensive enough, and we need to adopt hierarchical analysis to solve the problem of setting weights. At the same time, users need to determine the attribute weights according to different business types. Therefore, the judgment matrix $A_{m \times n}$ under different business types is obtained based on the hierarchical analysis method.

$$A_{m \times n} = (a_{ij})_{m \times n} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix}, \quad (1)$$

where a_{ij} denotes the importance of attribute i relative to attribute a_{jm} under business k , and n is the number of attributes. Satyr proposed the number 1–9 and its reciprocal as the value of a_{ij} , and a larger a_{ij} indicates that attribute r_i is more important relative to attribute r_j and accounts for a larger weight. Subjective weights and consistency tests are calculated according to different business types. From the definition of the AHP judgment matrix, it is known that the elements in its judgment matrix are the ratio of a factor to another factor under the same criterion, so the matrix kA has the following form.

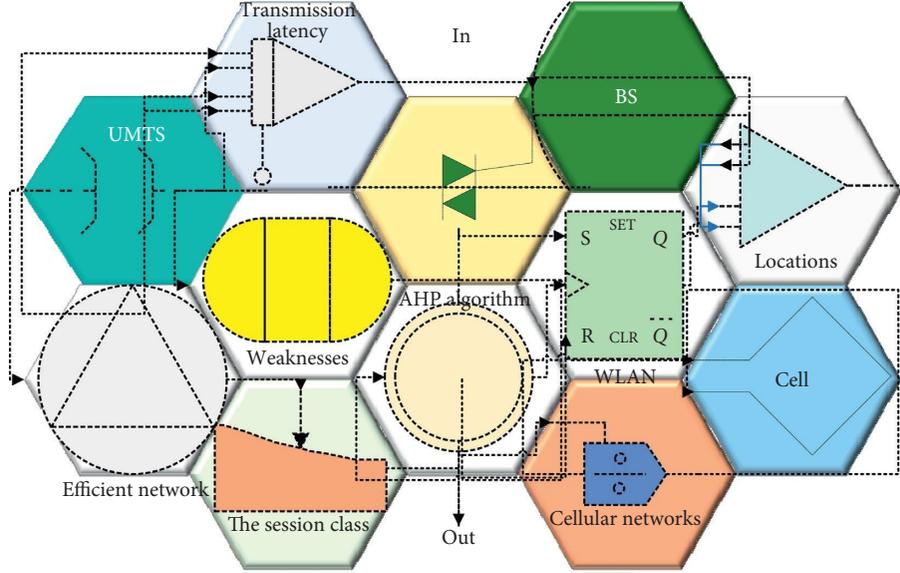


FIGURE 1: Heterogeneous wireless network system model.

$$A_{m \times n} = (a_{ij})_{m \times n} = \begin{bmatrix} \frac{w_{k1}}{w_{k1}} & \frac{w_{k1}}{w_{k2}} & \dots & \frac{w_{k1}}{w_{km}} \\ \frac{w_{k2}}{w_{k1}} & \frac{w_{k2}}{w_{k2}} & \dots & \frac{w_{k2}}{w_{km}} \\ \dots & \dots & \dots & \dots \\ \frac{w_{kn}}{w_{k1}} & \frac{w_{kn}}{w_{k2}} & \dots & \frac{w_{kn}}{w_{nm}} \end{bmatrix}, \quad (2)$$

w denotes the weight of attribute r , under business k , $1 \leq k \leq 3, 1 \leq i \leq 6$. The weight vector is denoted by $W = [w_1, w_2, \dots, w_m]$. The weight vectors of the attributes can be obtained by computing the nonzero eigenvectors of matrix A ; in practice, there are many ways to find the approximate eigenvectors of the matrix. The root-finding method is used to obtain the weight vector $W_R = [w_1, w_2, \dots, w_6]$ of the network attributes.

Similarity, as the name implies, refers to the degree of similarity between two objects. In this chapter, the similarity method is applied to the network selection algorithm by considering the network in the user's range as an object to be tested, which is a whole object consisting of available rate r_1 , peak transmission rate r_2 , packet delay r_3 , packet jitter r_4 , packet loss r_5 , and cost per bit r_6 . If one part of the attributes is good, but the rest is poor, it will also affect the overall network performance. At the same time, the user requirements for the network attributes r_1, r_2, r_3, r_4, r_5 , and r_6 constitute a standard object.

This chapter considers the network selection problem from the network and user perspectives and requires a model for calculating the similarity between the objects to be tested in the network and the standard objects of user requirements. The candidate network j is denoted by $r_j^N = [r_{j_1}^N, r_{j_2}^N, r_{j_3}^N, r_{j_4}^N, r_{j_5}^N, r_{j_6}^N]$ and r denotes the value of the i th attribute of network j . The user demand is denoted by $r_k^U =$

$[r_{k_1}^U, r_{k_2}^U, r_{k_3}^U, r_{k_4}^U, r_{k_5}^U, r_{k_6}^U]$ and r denotes the user's ideal value of the i th attribute under service k . The similarity between candidate networks and user requirements is obtained, and the network corresponding to the maximum similarity is selected as the best network, so how to quantify the similarity is critical. The nearest neighbor method (KNN), which calculates similarity by the case-based reasoning (CBR) method, is applied to the network selection and the calculation formula is as follows:

$$S_{kj}^{UN} = \frac{\sum_{i=1}^n w_{ki} \text{sim}(r_{ki}^U, r_{ji}^N)^2}{\sum_{i=1}^n w_{ki}^2}, \quad (3)$$

where n is the number of attributes, $\text{sim}(r_{ki}^U, r_{ji}^N)^2$ is the similarity between the i th attribute of network j under service k and the user demand for attribute i , and S_{kj}^{UN} is the total similarity between the candidate network r^N and the user demand r . Under service k , the network corresponding to the largest S_{mj} ($1 < j < 6$) is selected as the target network. Hamming distance is used to calculate the similarity between individual attributes, but it needs to know the maximum and minimum values of attributes, and in the process of network selection, users may not know the maximum and minimum values of attributes at a certain moment, so this article uses Canberra distance to calculate the similarity between individual attributes, and the formula is as follows:

$$\text{sim}(r_{ki}^U, r_{ki}^N)^2 = 1 + \frac{|r_{ki}^U - r_{ki}^N|^2}{r_{ki}^U + r_{ki}^N}. \quad (4)$$

Generally, a definite attribute value is required, but in the process of actual network selection, due to the complexity of the user's subjective thinking and the dynamic changes in the objective environment of the network, it is often inaccurate to describe the problem with only a definite attribute

value. For example, when users choose to access the network, for different types of services, their needs are usually not a fixed value, but an interval. Similarly, network attributes change from time to time, so it is more realistic to use intervals rather than fixed values to represent network attributes and requirements [18].

Consider first the simplest case, where the user's demand for network attributes $r_{k_i}^U$ under service k and the i th attribute value $r_{k_i}^N$ of network j are two fixed values; then, the following equation can directly express the attribute similarity calculation formula.

$$\text{sim}(r_{k_i}^U, r_{k_i}^N) = \sqrt{1 + \frac{|r_{k_i}^U - r_{k_i}^N|^2}{r_{k_i}^U + r_{k_i}^N}}. \quad (5)$$

The network corresponding to the maximum similarity is selected as the optimal network, which has the most compatible attribute parameters with the user's demand, and the network is selected to best improve the user's service quality. The flowchart of the network selection algorithm in this chapter is shown in Figure 2. The switching method of in-vehicle heterogeneous networks with maximum network utility (minimum network cost) is chosen alone and can be considered a classical game-based switching method. In this kind of switching, the participants are network terminals, the strategies are candidate networks, and the benefits are the utilities corresponding to the candidate networks. When the terminal performs network switching, it always selects the network with the maximum network utility, in the next switching cycle, updates the network utility, and reswitches. However, in the real scenario, the state of the wireless network system is determined by many random factors; i.e., the game environment is undetermined. Therefore, the classical game model cannot accurately describe the heterogeneous network system, and the classical game-based network switching methods cannot be used by terminals to achieve switching to optimize network performance in scenarios with varying network performance. Also, the simulation validation methods used in these classical game-based methods, i.e., specific network performance parameters given and used for testing, need to be improved.

It can be assumed that only P_i affects the switching decision of terminals in a relatively short period. Objectively, P_i is determined by the number of terminals in the network, signal-to-noise ratio, masking, and other conditions. In practical applications, network evaluation is often calculated quantitatively from measurable network performance parameters, such as transmission delay, packet loss rate, and delay jitter. Based on the above points, the following is obtained:

$$E_i = P_i = G(x_i) = F(s_i). \quad (6)$$

$G(x)$ is the equation to calculate the network performance evaluation metrics by network performance parameters; E_i is the vector composed of network environment conditions; $F(s_i)$ is the relationship between network environment conditions and network evaluation metrics. It

should be noted that $G(x_i)$ is an artificially defined function, while F is a relationship that does not depend on human will.

Based on the above analysis, it is found that this instability is caused by the fact that when too many terminals are switched from the degraded network to the better network, the performance of the better network decreases, and the network utility evaluation decreases so that it is lower than that of the degraded network, causing the system to be unstable and generating a continuous ping-pong effect. For this reason, an appropriate amount of network terminals needs to be selected to switch from the degraded network to the better network. For the above problem, assume that when s terminals are switched from network A to network B , for any terminal, then

$$\begin{aligned} E_A'' &= E_B'', \\ \Delta E &= f_A(g-s) + f_A(g) - f_B(h) + f_B(h+s). \end{aligned} \quad (7)$$

Here, g , h , and s all represent the number of terminals. The main reason for the above stability problems caused by existing methods is that the onboard heterogeneous network switching methods hope to achieve the stability of the network system through a single game. After the relevant methods are established, existing studies verify the simulation by using constants as the performance parameters of the network, leading to the above stability problems when these methods are applied to varying network performance [19]. To solve this problem, based on the construction of an in-vehicle heterogeneous network system structure oriented to varying network performance, the article proposes an in-vehicle heterogeneous network model under varying network performance conditions as a way to describe the in-vehicle heterogeneous network system environment and also as the simulation and restriction conditions of the algorithm, followed by the corresponding switching method to overcome the existing research that uses fixed network parameters for simulation to cause the potential system stability problems.

3.2. Load Balancing Simulation in Network Communication. A vehicular heterogeneous network is a wireless network system that provides vehicle-vehicle and vehicle-road communication services and Internet access services for Telematics applications through the combination of multiple wireless communication technologies. In the road traffic environment, there are multiple self-organized networks, including DSRC, and multiple wireless access networks, including LTE and Wi-Fi. The vehicle is equipped with a heterogeneous network vehicle terminal, and multiple networks are online at the same time. The terminal can choose to transmit information related to Telematics applications on different networks. Based on this hardware architecture, researchers have designed different network system architectures for different optimization purposes, including minimizing network access cost, load balancing, maximizing terminal performance, and maximizing system performance.

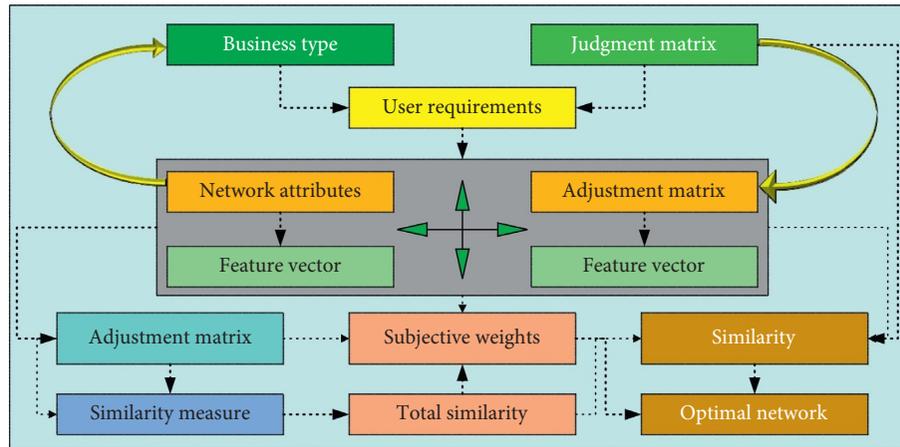


FIGURE 2: Algorithm flowchart.

The heterogeneous network system of the vehicle based on geographic location, considering the fading characteristics of the wireless signal and the access cost of different networks, makes the vehicle terminal preferably attached to a certain kind of network. The vehicle achieves network access through DSRC, and other areas are accessed through the LTE network. This system architecture is particularly suitable for vehicle-road communication applications and Internet access applications and can minimize the network connection cost. However, this system architecture lacks support for vehicle-to-vehicle communication. Some studies have used this network architecture to achieve vehicle-vehicle peer-to-peer communication by designing routing algorithms, but the vehicles are in operation with fast network topology changes, unstable routing tables, and high addressing and routing overhead [20]. The method also lacks research on the application of message broadcasting in vehicular networks, which makes it impossible to meet the real-time communication performance requirements under in-vehicle heterogeneous networks. For these reasons, this architecture is not suitable for the most important safety applications in Telematics.

At the bottom layer of the network structure, i.e., roadside devices and vehicle-mounted devices, the network structure is not adjusted. The network application sends the network transmission request to the heterogeneous network access terminal, and the terminal selects different wireless access technologies to provide network services for the Telematics application after making internal logical judgments. The IDE assists the Telematics terminal in making switching decisions and providing authentication, billing, resource management, and network switching management for the heterogeneous network application. For authentication, billing, and certification services of heterogeneous networks, IDE also needs to access the agents of the three candidate networks, unify maintenance data, and forward them to the attribution agents in the attribution networks for unified control and settlement work by servers, as shown in Figure 3.

Based on the above summary of the existing in-vehicle heterogeneous network system architecture, it is found that

the in-vehicle heterogeneous network system architecture determines the network performance and the applicable in-vehicle heterogeneous network applications to a certain extent. It is important to establish a network architecture that can meet the requirements of in-vehicle applications and structural needs. To maintain the in-vehicle heterogeneous network system and provide network parameters for network switching to the in-vehicle heterogeneous network terminals, the existing heterogeneous network system architecture requires additional network overhead. When the network traffic is small and the network capacity is sufficient, the additional network overhead will not have a significant impact on the heterogeneous network system; when the network traffic is large and the network capacity is insufficient, the additional network overhead will increase the congestion of the in-vehicle heterogeneous network system and reduce the utility of the heterogeneous network system [21]. For this reason, when designing the structure of an in-vehicle heterogeneous network system, it is necessary to utilize the data information available at the terminal as much as possible and avoid additional network overhead as much as possible. There are rich types of in-vehicle heterogeneous network applications, including traffic applications and nontraffic applications, among which traffic applications can be divided into traffic safety applications and traffic non-safety applications. Different applications need to achieve network communication through transparent transmission to simplify the application development process. The above system architecture is used by researchers for a specific network application scenario, resulting in a lack of compatibility for that scenario to achieve transparent transmission, as shown in Table 1.

Many studies on in-vehicle heterogeneous networks use a split-cluster structure to organize heterogeneous network systems. The cluster structure can pool the network resources of different vehicles, improve network channel utilization, and reduce possible network congestion [22–24]. However, the cluster structure is an unfair network structure, where there are always cluster heads in the clusters, resulting in structural inequity in the network system. This inequity can lead to threats to the information security of

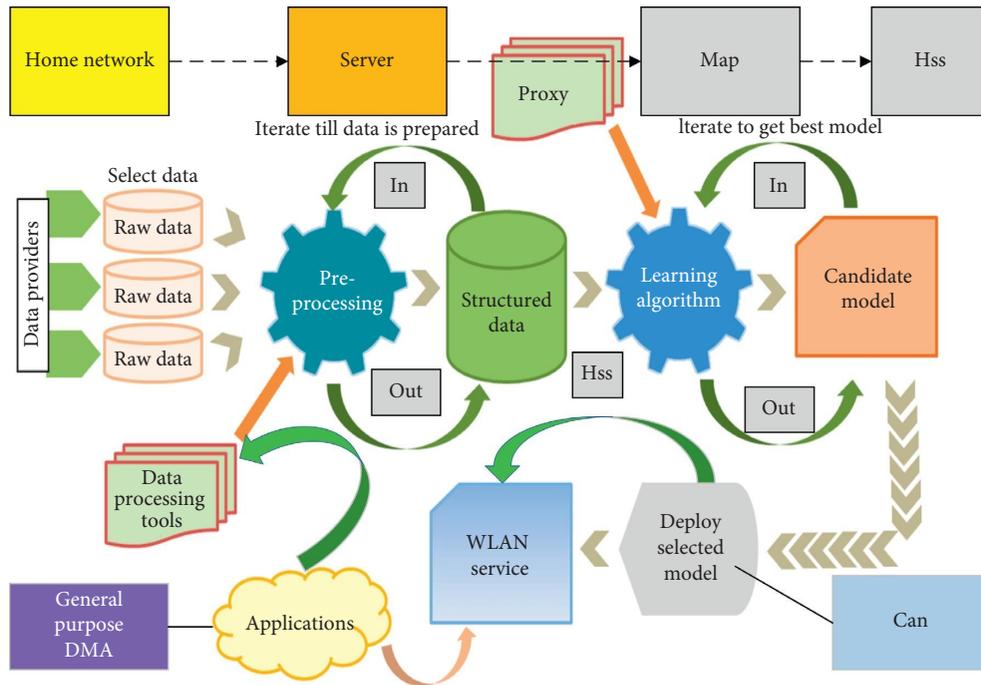


FIGURE 3: Hybrid intersystem structure.

TABLE 1: Abbreviated description table.

Abbreviations	Definition	Type
MN	Mobile node	Float
NB	Base station	Float
PCF	Packet control function	Int
PSDN	Packet-switched data networks	Int
RAN	Network controller	Float

other endpoints in the cluster by the cluster head with high authority or additional network overhead caused by the message forwarding task of the cluster head. This problem can seriously affect the application and diffusion of the clustered structure. In real traffic systems, the in-vehicle heterogeneous network system needs to rely on the traffic mechanical and electrical systems, including traffic signals, traffic networks, roadside base stations, and access points [25–27]. The feasibility of the in-vehicle heterogeneous network must be established on the basis that its structure can be implemented on real traffic mechanical and electrical systems. The related feasibility needs to be reflected in the economic feasibility, structural feasibility, and service feasibility of the network system.

4. Analysis of Results

4.1. Algorithm Performance Analysis. Figure 4 represents the changes in the number of vertical switches for each algorithm under four different service types: session class, stream class, interaction class, and context class, respectively. From Figure 4, as the number of decision points experienced by the terminal increases, the number of vertical switches of all algorithms increases, but the proposed algorithms grow at

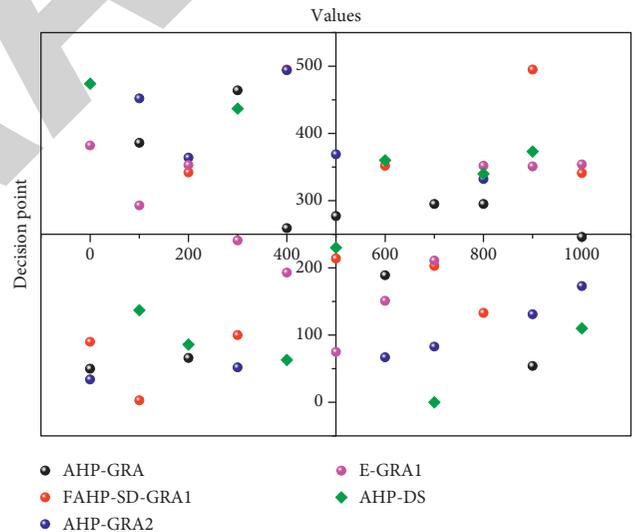


FIGURE 4: Number of vertical switches for each algorithm under different service types.

the slowest rate. After the 1000th decision point, the total number of vertical switches of the proposed algorithm for the four service types is 89, 87, 313, and 262, respectively. This indicates that the proposed algorithm has the highest performance in controlling the total number of vertical switches. Among them, it grows similarly and faster in the interaction and background classes than in the session and stream classes. This is a similar conclusion for the three algorithms AHP-GRA, FAHP-SD-GRA1, and AHP-GRA2. This is because all four algorithms use the same subjective attribute weights, so the trend of the number of vertical switching changes is relatively similar for the same sequence

of network conditions. For the E-GRA1 algorithm, the change in the number of vertical switches is the same for all four service types (up to 567 at the end). This is because the algorithm does not consider the subjective preferences of the decision-maker but simply relies on the DM data at a given moment to rank the network performance and select the best one for accessing the network. Similarly, the three algorithms, AHP-GRA, FAHP-SD-GRA1, and AHP-GRA2, increase the number of vertical switches in both the interaction and background classes slightly faster than E-GRA1, despite the combination of subjective user preferences and objective network conditions, indicating that the three algorithms are still overly sensitive to the perception of the environment compared to the proposed algorithms.

Given that only the proposed algorithm additionally uses the difference threshold control mechanism after completing the network performance ranking, to have a fair comparison of the performance differences of these five algorithms in controlling the number of vertical switches, Figure 5 shows the performance differences of each algorithm in controlling the number of unnecessary vertical switches assuming that the remaining four algorithms also use the same difference threshold control mechanism (all values of δ are 0.01). The difference in the performance of each algorithm in controlling the number of unnecessary vertical switches assuming that the remaining four algorithms also use the same difference threshold control mechanism (all values of δ are 0.01).

Figure 5 shows that with the same difference threshold mechanism, each algorithm can suppress some of the unnecessary vertical switches in each service type. For the session class, which has the lowest vertical switching urgency, the four compared algorithms can reduce the number of unnecessary vertical switches by 29, 79, 30, and 27, respectively, accounting for 10, 2837%, 35.2679%, 5.2910%, and 9.3103% of the total number of vertical switches. The FAHP-SD-GRA1 algorithm can reduce 81 unnecessary vertical switches in stream applications, accounting for 40.9091% of the total number of vertical switches, which is also the highest percentage of unnecessary vertical switches among the five algorithms. And this algorithm can control the highest 143 (21.6339% of the total number of unnecessary vertical switches) in the interaction class application. Of course, for the E-GRA1 algorithm, where the decision result is independent of the service type, it can reduce 30 unnecessary vertical switches, both of which account for 5.2910% of the total number. Therefore, it is possible to reduce the number of unnecessary vertical switches and thus the number of ping-pong effects by using threshold control techniques after the network has been sequenced. However, from the above analysis, even if all four algorithms add a differential threshold control mechanism, the proposed algorithm still outperforms the four comparison algorithms in suppressing unnecessary vertical switching, as shown in Figure 6.

In Figure 6, the direction of the dashed line is divided into horizontal and vertical. The former indicates that the terminal stays on the current network (adjacent decision points, the selected target network does not change), while

the latter indicates that the terminal makes a vertical switch (adjacent decision points, the selected target network is not the same). The longer the horizontal dash is, the longer the terminal stays in the corresponding network, and the fewer the number of switches it does. The denser the vertical line is, the more frequently the terminal switches vertically. If the dense state of the vertical folds is more concentrated, it means that a ping-pong effect occurs between these networks. The proposed algorithm has longer horizontal fold lengths and lower vertical fold densities for the graphs of these four service types. This situation is particularly evident for the session and stream-type applications. Figure 6 then details the network selection of each algorithm for each network after 1000 decision points for different service types and the number of ping-pong effects generated.

4.2. Analysis of Simulation Results. As shown in Figure 7, the controller out-of-connectivity cost represents the average response time of a controller to a flow request sent by a switch when a controller failure occurs in the network. As can be seen from the figure, the controller out-of-connection cost tends to decrease with time because all three mechanisms perform switch and controller remapping, which reduces the impact of controller failure on the network. However, in the SLC mechanism, due to the larger matching base from the switch perspective, the remapping time is longer, taking 42 s from failure to network stabilization. The GSC mechanism, considering from the controller perspective, can complete controller reselection within 26 s, but the granularity is coarse and the loss-of-connectivity cost after stabilization is still higher compared to the normal value.

The ASCMC mechanism, considering both switch and controller perspectives, takes about 10 s to complete. The ASCMC mechanism considers both the switch and the controller and requires about 10 s of network initialization search time. When the search is completed, the loss-of-connectivity cost decreases quickly, and the whole remapping process takes only 22 s, which improves the controller failure recovery efficiency by 23% compared with the other two mechanisms.

As shown in Figure 8, in the first 60 s, the controller load in both the outgoing and incoming domains of the switch roughly shows a significant downward trend. However, the controller load in the incoming domain increases to a certain extent because some switches with high load are migrated from the outgoing domain. However, after 60 s, the controller loads in both domains are basically in a balanced state. From the statistics, we can see that the initial load value of the migrated domain controller is set to 1400 Request/s, and the initial load value of the migrated domain controller is set to 800 Request/s. After migration, the load value of the migrated domain controller becomes 1133 Request/s, which is 19.1% lower than the initial value, while the load value of the migrated domain controller becomes 1041 Request/s. After migration, the load value of the migrated domain controller becomes 1133 Request/s, which is 19.1% lower than the initial value, while the load value of the migrated domain controller becomes 1041 Request/s, which is lower

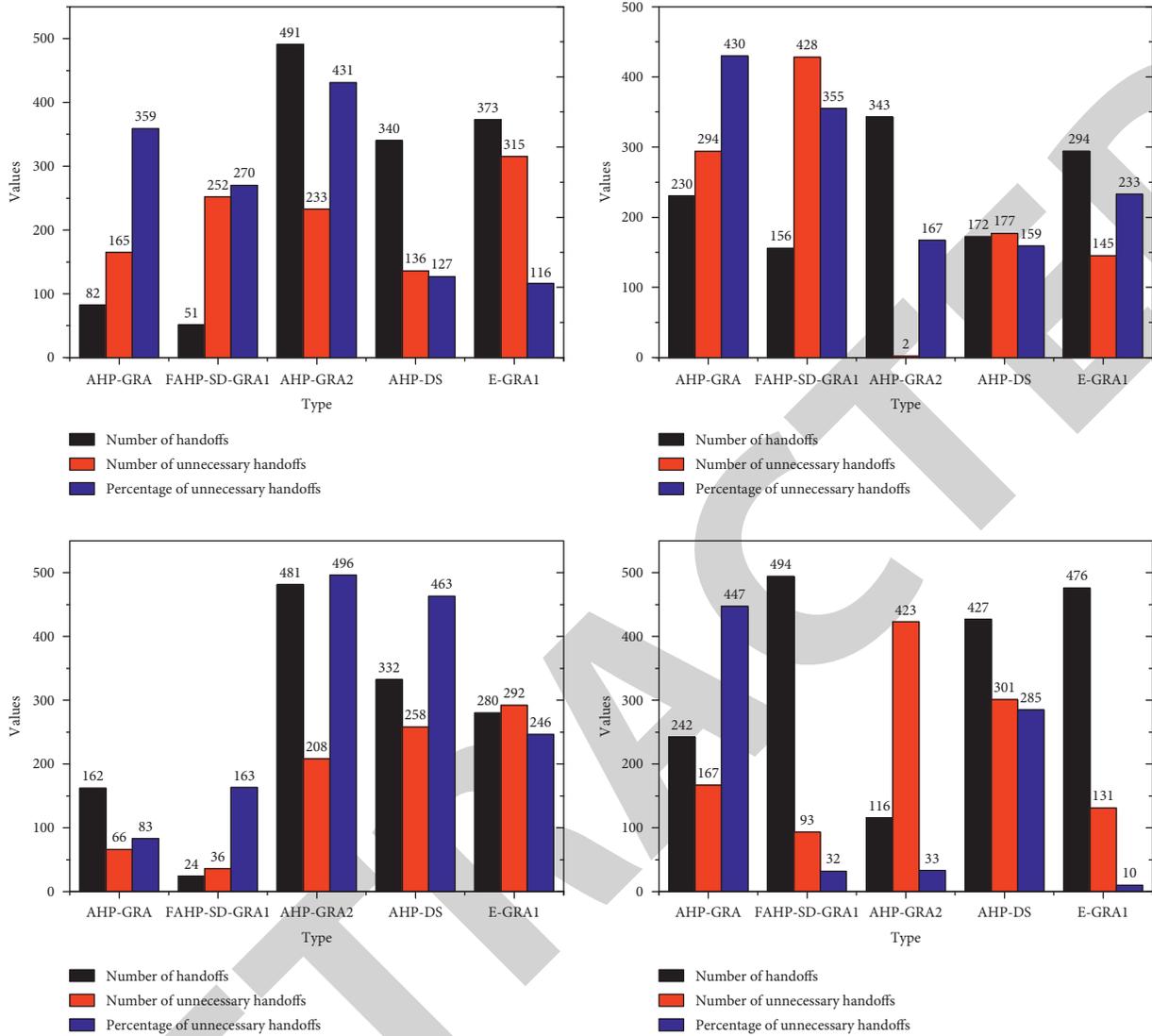


FIGURE 5: Number of unnecessary vertical switches assuming all algorithms use the same difference threshold.

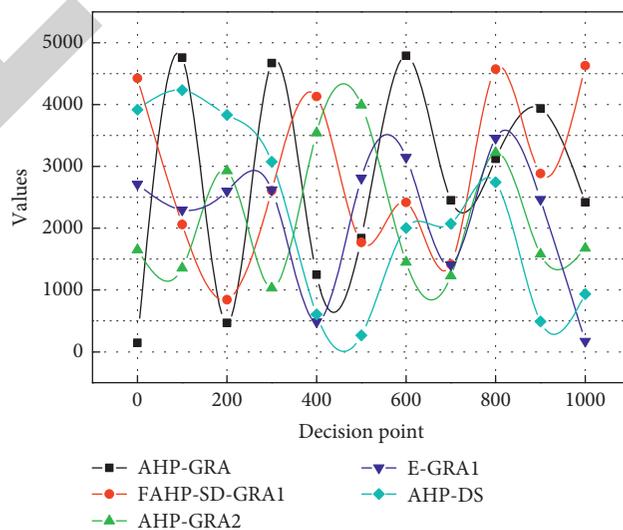


FIGURE 6: Network selection of each algorithm for different service types at each decision point.

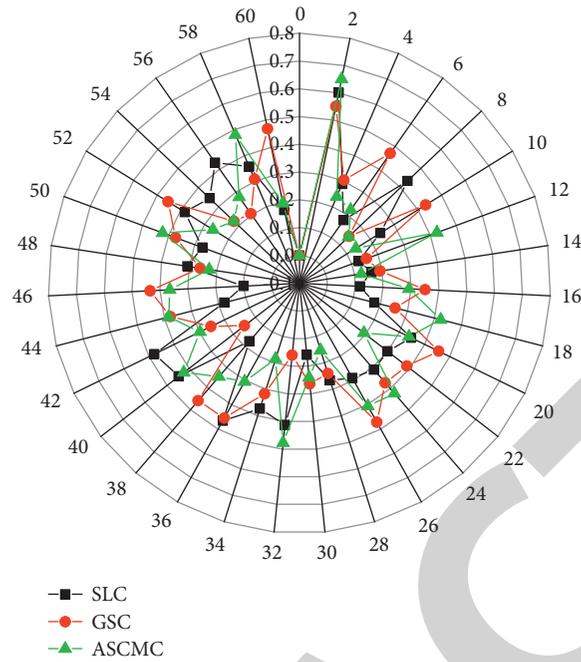


FIGURE 7: Comparison of the cost of controller disconnection.

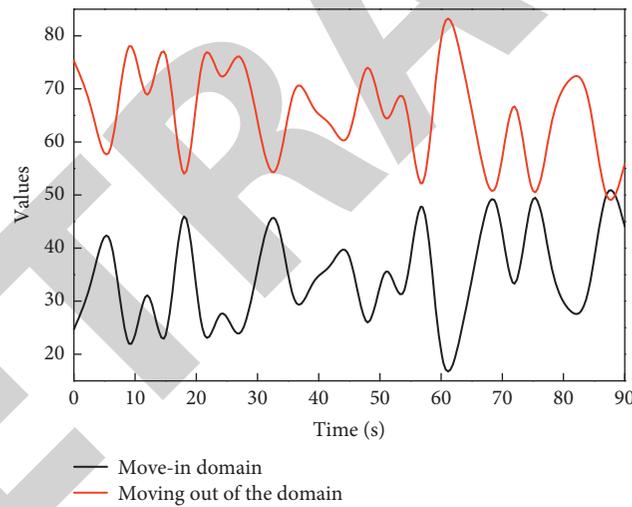


FIGURE 8: SDN subdomain controller load over time.

than the controller overload determination threshold of 1300, and the load of the migrated domain and the migrated domain is well balanced.

The strategy adds a collection and measurement module, an evaluation decision module, and a storage module for each subdomain controller, determines whether there is an overloaded controller by setting a dynamic threshold value, and designs an adaptive genetic algorithm-based migration to and from the domain selection strategy, and finally performs SDN multidomain migration for the switch using a survivorship and elimination mechanism. Simulation results show that this strategy improves the

migration efficiency by 19.7% compared with the existing switch migration algorithm and equalizes the load of each subdomain controller.

5. Conclusion

Considering users to establish network connections directly with ISPs, different IoT business applications are attached to user attributes, and the bias of different business applications to different network attributes is defined to enrich the factors considered by users in-network access selection. The algorithmic model consists of two dimensions: a Bertrand game

with price as a competitive means between different ISPs, and a matching game with priority for pairing between ISPs and subscribers. The utility function of ISPs is designed based on the Bertrand game theory, and the conditions and expressions for the existence of their equilibrium prices are derived. The utility functions of users are designed by combining several network attributes and user attributes, and the matching lists are constructed according to the magnitude of utility values. The simulation results show that the model maximizes the network benefits of the network service provider while ensuring the optimal matching results between the two parties. Considering wireless relays as the medium of connection between ISPs and subscribers, a Gounod game with competing network resource demands between wireless relays and a Stackelberg game between ISPs and wireless relays dominated by both network prices and network resource quantities are designed. Each equilibrium solution of the Gounod game is solved in turn to determine the optimal amount of network resources demanded. The simulation results are compared to derive the relationship between the speed of change of the network resource demand of wireless relays and the equilibrium speed and final revenue. The Starkberg game also reaches equilibrium with the equilibrium results of the Gounod game.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known conflicts of financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- [1] G. Araniti, P. Scopelliti, G. M. Muntean et al., "A hybrid unicast-multicast network selection for video deliveries in dense heterogeneous network environments," *IEEE Transactions on Broadcasting*, vol. 65, no. 1, pp. 83–93, 2018.
- [2] M. K. Hasan, A. F. Ismail, S. Islam, W. Hashim, M. M. Ahmed, and I. Memon, "A novel HGBBDSA-CTI approach for subcarrier allocation in heterogeneous network," *Telecommunication Systems*, vol. 70, no. 2, pp. 245–262, 2019.
- [3] Y. Zhong, H. Wang, and H. Lv, "A cognitive wireless networks access selection algorithm based on MADM," *Ad Hoc Networks*, vol. 109, no. 3, Article ID 102286, 2020.
- [4] T. M. Behera, S. K. Mohapatra, U. C. Samal et al., "I-SEP: an improved routing protocol for heterogeneous WSN for IoT-based environmental monitoring," *IEEE Internet of Things Journal*, vol. 7, no. 1, pp. 710–717, 2019.
- [5] D. D. Nguyen, H. X. Nguyen, and L. B. White, "Reinforcement learning with network-assisted feedback for heterogeneous RAT selection," *IEEE Transactions on Wireless Communications*, vol. 16, no. 9, pp. 6062–6076, 2017.
- [6] M. M. Hasan, S. Kwon, and S. Oh, "Frequent-handover mitigation in ultra-dense heterogeneous networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 1, pp. 1035–1040, 2018.
- [7] M. C. Chen, S. Q. Lu, and Q. L. Liu, "Uniqueness of weak solutions to a keller-segel-navier-stokes model with a logistic source," *Applications of Mathematics*, 2021.
- [8] F. Fang, J. Cheng, and Z. Ding, "Joint energy efficient sub-channel and power optimization for a downlink NOMA heterogeneous network," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 2, pp. 1351–1364, 2018.
- [9] R. Joshi and S. Kumar, "A dissimilarity Jensen-Shannon divergence measure for intuitionistic fuzzy sets," *International Journal of Intelligent Systems*, vol. 33, no. 11, pp. 2216–2235, 2018.
- [10] R. Priyadarshi, P. Rawat, and V. Nath, "Energy dependent cluster formation in heterogeneous wireless sensor network," *Microsystem Technologies*, vol. 25, no. 6, pp. 2313–2321, 2019.
- [11] A. Asheralieva, "Bayesian reinforcement learning-based coalition formation for distributed resource sharing by device-to-device users in heterogeneous cellular networks," *IEEE Transactions on Wireless Communications*, vol. 16, no. 8, pp. 5016–5032, 2017.
- [12] S. Kunarak and R. Suleesathira, "Multi-criteria vertical handoff decision algorithm for overlaid heterogeneous mobile IP networks," *Journal of the Franklin Institute*, vol. 357, no. 10, pp. 6321–6351, 2020.
- [13] D. Pickernell, P. Jones, and M. J. Beynon, "Innovation performance and the role of clustering at the local enterprise level: a fuzzy-set qualitative comparative analysis approach," *Entrepreneurship & Regional Development An International Journal*, vol. 31, no. 1-2, pp. 82–103, 2019.
- [14] A. Roy, P. Chaporkar, and A. Karandikar, "Optimal radio access technology selection algorithm for LTE-WiFi network," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 6446–6460, 2018.
- [15] E. Inga, S. Cespedes, R. Hincapie, and C. A. Cardenas, "Scalable route map for advanced metering infrastructure based on optimal routing of wireless heterogeneous networks," *IEEE Wireless Communications*, vol. 24, no. 2, pp. 26–33, 2017.
- [16] S. P. Wan, F. Wang, and J. Y. Dong, *Theory and Method of Intuitionistic Fuzzy Preference Relation Group Decision Making*, Science Press, Beijing, China, 2019.
- [17] T. D. Nguyen, J. Y. Khan, and D. T. Ngo, "A distributed energy-harvesting-aware routing algorithm for heterogeneous IoT networks," *IEEE Transactions on Green Communications and Networking*, vol. 2, no. 4, pp. 1115–1127, 2018.
- [18] M. Munjal and N. P. Singh, "Utility aware network selection in small cell," *Wireless Networks*, vol. 25, no. 5, pp. 2459–2472, 2019.
- [19] D. Lu, X. Huang, G. Zhang, X. Zheng, and H. Liu, "Trusted device-to-device based heterogeneous cellular networks: a new framework for connectivity optimization," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 11, pp. 11219–11233, 2018.
- [20] Z. Kuang, G. Liu, G. Li et al., "Energy efficient resource allocation algorithm in energy harvesting-based D2D heterogeneous networks," *IEEE Internet of Things Journal*, vol. 6, no. 1, pp. 557–567, 2018.

- [21] S. Dutt, S. Agrawal, and R. Vig, "Cluster-head restricted energy efficient protocol (CREEP) for routing in heterogeneous wireless sensor networks," *Wireless Personal Communications*, vol. 100, no. 4, pp. 1477–1497, 2018.
- [22] H. Zhang, F. Fang, J. Cheng, K. Long, W. Wang, and V. C. M. Leung, "Energy-efficient resource allocation in NOMA heterogeneous networks," *IEEE Wireless Communications*, vol. 25, no. 2, pp. 48–53, 2018.
- [23] J. Shi, Y. Lu, and J. Zhang, "Approximation attacks on strong PUFs," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, vol. 39, no. 10, pp. 2138–2151, 2019.
- [24] H. Xu, C. Zhang, H. Li, and J. Ou, "Real-time hybrid simulation approach for performance validation of structural active control systems: a linear motor actuator based active mass driver case study," *Structural Control and Health Monitoring*, vol. 21, no. 4, pp. 574–589, 2014.
- [25] B. Yang, X. Cheng, D. Dai, T. Olofsson, H. Li, and A. Meier, "Real-time and contactless measurements of thermal discomfort based on human poses for energy efficient control of buildings," *Building and Environment*, vol. 162, Article ID 106284, 2019.
- [26] W. Wang, Z. Gong, J. Ren et al., "Venue topic model-enhanced joint graph modelling for citation recommendation in scholarly big data," *ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP)*, vol. 20, no. 1, pp. 1–15, 2020.
- [27] W. Wei, Q. Ke, J. Nowak, M. Korytkowski, R. Scherer, and M. Woźniak, "Accurate and fast URL phishing detector: a convolutional neural network approach," *Computer Networks*, vol. 178, Article ID 107275, 2020.