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Adaptive Vertical Handover Mechanism using Back Propagation Algorithm for 5G Communications

CH. Srilakshmi Prasanna[1], Dr. S. Zahoor-ul-Huq[2], Dr. P. Chenna Reddy[3]

[1]Research Scholar, Jawaharlal Nehru Technological University Anantapur, India
[2]G. Pulla Reddy Engineering College, Kurnool, Affiliated to Jawaharlal Nehru Technological University Anantapur, India
[3]JNTUA College of Engineering, Ananthapuramu, Constituent college of Jawaharlal Nehru Technological University Anantapur, India
Email: sirikeshava9@gmail.com

The paper presents an algorithm that can be used in 5G networks to manage vertical handover. It uses neural networks and multi-attribute analysis to establish a framework that enables seamless transitions between various mobile networks. The various networks that are involved in the project build their own Back Propagation model. The performance metrics that are used are the packet loss rate, signal to noise ratio, error rate and maximum transmission rate. Metrics such as these play a important role in the development and training of the BP neural networks by serving as the input neurons' configuration. The algorithm also takes into account the wireless networks' download rate to evaluate their performance. Through its algorithm, the paper helps the users make informed decisions regarding the vertical handover process by selecting the best wireless network for their region. In a simulation environment, the system performed well and achieved a success rate of over 85%. This achievement shows the system's ability to handle various scenarios involving heterogeneous networks.

Keywords: Vertical handover, 5G Communication, SINR, Back Propagation.

1. Introduction

Due to the rapid evolution of wireless technology, there has been a wide variety of wireless networks that can be accessed simultaneously. Due to the nature of the wireless networks, they compete with each other. This has resulted in the coexistence of various kinds of networks. Because of the growing user base and the intricate nature of the networks, wireless networks have evolved into a multi-mode heterogeneous network. These include cellular and WLAN. Although WLAN networks offer relatively small cover-age and wide bandwidth, cellular series networks typically have narrow coverage areas and narrow bandwidth. This allows the two to complement each other and provide a more balanced and diverse wireless experience. The integration of 5G technology will also make the process more rapid [1]. The design of vertical handover algorithms should be considered with different candidate types and disturbing factors. In order to achieve a more accurate and efficient design, the paper uses neural network algorithms for machine learning.

There are various vertical handover algorithms that have their own disadvantages and advantages. For instance, the proposed algorithm for decision selection uses a light communication system. The proposed algorithm takes into account various attributes by using a two-person cooperative model and an analytic hierarchy. It also takes into account the traffic preferences and dynamic network parameters. Although the overall handover was reduced, the proposed algorithm took into account fewer factors [2].

Although it could reflect the user preferences and application requirements, the proposed algorithm did not take into account the 5G network [3]. The classification and review of the most significant multi-objective decision-making framework for next-generation wireless systems revealed its importance in addressing the various challenges associated with network selection. It also highlighted the research trend toward the use of multi-criteria selection in heterogeneous networks.

2. Literature Survey

In [4], the proposed algorithm for vertical handover recommends optimizing the utilization of the available resources by implementing more target networks during the handover. The proposed method also shows how the network parameters can be integrated into signal procedures to maintain connectivity. Unfortunately, the proposed vertical transmission algorithm neglected the transmission rate of the network.. Instead, it focused on improving the service quality by implementing a new composite rule based on the logarithm of the WLAN_UMTS network [5-7]. Although it achieved a high rate of success, it did not integrate the 5G and 4G networks. This strategy utilized multi-attribute decision making and fuzzy logic theory to select the optimal network for its vertical handover algorithm [8-10]. It also did not take into account the SINR attribute. A neural network-based vertical handover algorithm was proposed, but it only chose LTE and WLAN as its candidate networks. For the multi-homing load balancing algorithm, the recommended method used was a mixed integer model [9]. In [10], the authors proposed an algorithm for choosing the optimal wireless networks was based on a genetic algorithm, but it did not take into account the 5G network factors. In [11], The authors opted for a more heterogeneous approach to the selection of the candidate networks. They took into account the various attributes of each network and the user's preference. In [12], The authors created an intelligent algorithm that can be used for smooth vertical handover in mobile networks. The algorithm was implemented using a hybrid model, which combines the BBO and the Markov Chain. It was tested on various access technologies such as WiMAX, UMTS, and WiFi [11-13].

The development of vertical handover in wireless networks was not easy, as it involved taking into account various factors such as the design and implementation of 5G technology [14-15]. Although the reference mentioned the use of 5G, it did not successfully integrate the technology into heterogeneous networks. The reference also failed to take into account the environment factors when developing its algorithm for vertical handover. The literature used neural network theories in the development of this algorithm, but the efficiency of this method was improved. Despite the improvements, its operation process was still more complex.

The authors did not take into account environmental factors when developing the algorithms for vertical handover. Due to the upcoming popularity of 5G technology, the existing algorithms for vertical handover are expected to have an impact on the performance of the next generation wireless networks [16-17]. But, due to the lack of 5G network related factors, The majority of these algorithms may not have the capability to transition to the new technology when selecting the optimal network within the vicinity.

The existing vertical handover method is not ideal for addressing the complexity of 5G network systems and the running process. This paper introduces an innovative solution for addressing this problem by employing a neural network and a multi-attribute framework. The framework is built on a network environment that is set to allow us to switch between various types of networks. These include 4G, UMTS, WLAN, 5G, and GPRS [18-19].

Each of the networks build its own BP model, which is a three-layer structure that is designed to provide a high-speed transmission rate and minimize the noise and interference in the network. The various factors that can affect the network's performance are also taken into account to set the appropriate reference objects. These objects are used as the training and learning tools for the network. The paper aims to identify the best wireless network for vertical handover by evaluating the five different platforms. This method is carried out through a prediction target that is based on the download rate of the network. The selection process is then carried out using the different architecture of the networks [20-21].

In the context of relay selection among various networks, the neural network model defines the network characteristics. These characteristics are subsequently utilized to forecast the ideal download rate of the networks. The objective of this approach is to guarantee that the five existing networks are both resilient and efficient. The selection process for the final switch ensures that the users have a good experience. The new vertical handover algorithm that is presented in this paper is significantly different from the existing methods. It is able to perform the selection process using the 5G network and is designed with a multi-attribute framework that is designed to incorporating all the factors influencing the wireless network's performance [22].

3. Proposed Method

3.1 Configuration of Neural Network

The proposed approach introduces a vertical handover algorithm applicable to various mobile networks like UMTS, 4G, WLAN, and 5G, with each network building its unique three-layer BP model. The proposed model is formulated by considering the diverse factors influencing transmission rates and packet loss.. When a user enters the network environment, the terminal will automatically collect the various details about the network, such as its minimum delay and MTS. It will also input the values to the training neural network models. The terminal then chooses the optimal wireless network with the highest predicted download rate based on the various types of networks and their respective download rates. It uses the BP neural network framework to perform vertical handover. Figure 1 shows the proposed neural network model.

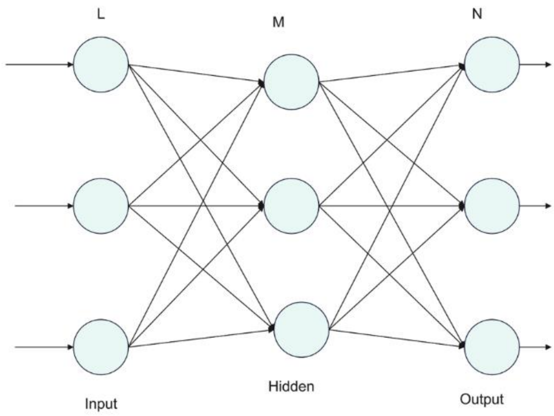

Figure 1: Proposed Neural Network model using Back Propogation

Where L, M and N denotes the input, hidden and output neurons. Eq. 1 shows the back propagation algorithm using the Log-sigmoid function.

$$f(x) = \frac{1}{1+e^{x}} \quad (1)$$

This study consists of two main elements: the error function which is shown in Eq. 2 and the error propagation algorithm. The latter is instrumental in adjusting the neural network's weights and aligning the error function's bias with the anticipated value.

$$Err = \frac{\sum_i (ex_i + Ot_i)^2}{2} \quad (2)$$

Where ex_i denotes the network parameter results expected values and Ot_i denotes the neural network output values. Furthermore, the associated neural network model must be solved to facilitate the algorithm's operation.

The Back Propagation model illustrates the operational details in Figure 1. The network’s weight parameters are denoted by X_j, Y_j, and Ot_j, and the error function is represented by Err. X_j, denotes the input jth node, Y_j denotes the hidden layer jth node and Ot_j represents the output layer jth node. The Back Propagation model's computational expressions are presented in detail. For instance, the input vector's value is X, and the corresponding weight parameters are shown as W. t represents the neuron threshold. Eq. 3 shows the output of the network.

$$y = f(\sum_{i=1}^{m} w_i x_i - t) \quad (3)$$

Eq. 4 shows the expression of the activation function f.

$$f(x) = \begin{cases} -1 & x < 0 \\ 1 & x \geq 0 \end{cases} \quad (4)$$

Eq. 5 shows the hidden layer node output.

$$y_i = f\left(\sum_j w_{ij} x_j - t_i\right) = f(net_i) \quad (5)$$

Eq. 6 shows the output layer node output.

$Ot_l = f\left(\sum_j T_{ij}\, x_j - t_l\right) = f(net_l)$ (6)

Eq.7 shows the output layer node error.

$Err = \frac{1}{2}\sum_l (t_l - ot_l)$ (7)

Hence, the primary objective of the network model during training and learning is to reduce the error Err. Consequently, there exists a proportional connection between the adjustment of the network's weights and the negative gradient of error Err, as stated in Eq.8.

$\frac{\partial Err}{\partial T_{li}} = \sum_{k=1}^{m} \frac{\partial Err}{\partial ot_k}\frac{\partial ot_k}{\partial T_{li}} = \frac{\partial Err}{\partial ot_l}\frac{\partial ot_l}{\partial T_{li}}$ (8)

Eq. 9 shows the hidden layer node gradient error function.

$\frac{\partial Err}{\partial w_{li}} = \sum_l \sum_i \frac{\partial Err}{\partial ot_l}\frac{\partial ot_l}{\partial y_i}\frac{\partial y_i}{\partial w_{li}}$ (9)

Eq. 10 shows the output layer node gradient error function.

$\frac{\partial Err}{\partial t_l} = \sum_{k=1}^{m} \frac{\partial Err}{\partial ot_k}\frac{\partial ot_k}{\partial t_l} = \frac{\partial Err}{\partial ot_l}\frac{\partial ot_l}{\partial t_l}$ (10)

The network model is a multi-layer structure that is designed to train using an error backpropagation algorithm. The first step in this process is to establish the network's connections with small values. The training sample is then selected, and its error gradient is computed. Gradient descent and mean square error techniques are then used to adjust the connection weights of the network. The process continues, and the network's bias and weight values are continuously modified. The goal is to gradually align the outputs of the network with the desired ones. The three-layer architecture of the network is presented in Figure 2.

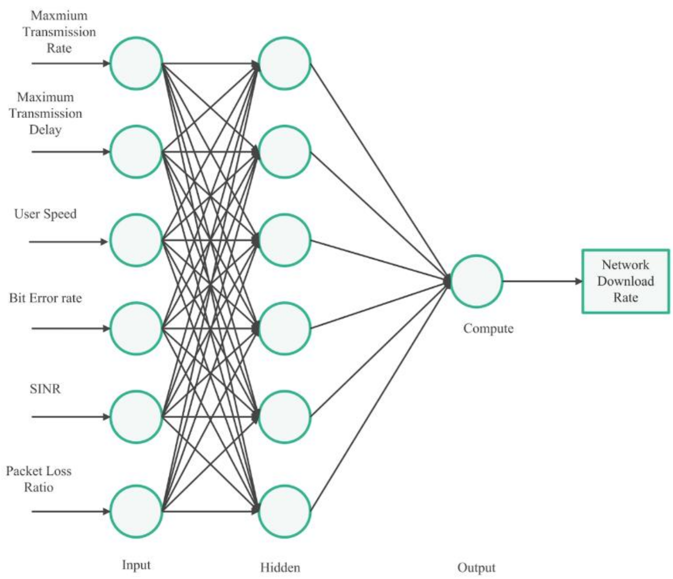

Figure 2: 5G Network Training Model

The construction of the neural network is carried out according to the proposed model is given as follows:

(a) The input layer of the wireless network should be required. In addition, the various factors that can affect the network's performance, such as the packet loss rate, the minimum delay, the SINR, and the user moving speed, are also taken into account to set the BP neural network's input layer neurons. These reference objects will be used to train and learn the learning process of the network. The goal of this algorithm is to ensure that it uses a comprehensive set of network attributes to make effective vertical handover strategies. Additionally, it is designed to assess the surroundings of the five wireless networks based on the user's location. The algorithm will be able to perform the handover process if it chooses the right wireless network. The six neuron nodes are arranged at the input layer of wireless networks' BP models. The six neuron nodes represent various factors that can affect the packet loss and transmission rate of wireless networks..

(b) The goal of this procedure is to design a hidden layer. Eq. 11, which indicates how many hidden layer neurons presented.

$$l = \sqrt{a + n + m} \quad (11)$$

Where a denotes the value from 1 to 10, n denotes the number of input layer nodes, m denotes the number of output layer nodes. l denotes the hidden layer empirical values of the nodes.

The BP model's hidden layer is composed of numerous neuron nodes. The computational power of these nodes is immense. They can perform infinite number of calculations on a given nonlinear function. In order to prevent the computational complexity of the network from increasing, the number of nodes in its hidden layer should not exceed maximum threshold. Overfitting can also occur in complex network computing. If there are only a few hidden layer neurons, the error will most likely increase, which will have a negative impact on the network's performance. The optimal number of hidden nodes can make a difference in reducing the computational complexity. There is a significant correlation between the number of neurons in the hidden layers and their computational complexity. The complexity of the network, as well as the expected errors, are also taken into account when it comes to choosing the optimal number of nodes. After taking into account the various factors that affect the network's performance, a decision is made to set six neurons in the hidden layer. This is accomplished using the formula that considers the network's mean square error function.

(c) The output layer's design is carried out after the six attribute data of the 5G network have been input to the respective models. These data are then trained and predicted using numerical approximation and network training.

After analyzing the various types of wireless networks, the network download rate prediction value is then compared to the selection criteria to choose the most suitable one. For each model, the output layer has one neuron. The proposed network model is then constructed to represent the five networks. The proposed model uses the 6, 6, 1 network model. Through the training of the proposed network model, various factors such as the packet loss rate, minimum delay, user moving speed, and SINR are taken into account to improve the network's performance. The collected sample data was divided into five groups, and a corresponding backpropagation network model reference was created for the different wireless networks used in instructor-led learning. Then, train the models based on the five wireless networks using the standard square error standard. Once they all achieve the specified mean square error level, the data related to various network attributes is examined and fed into the model. The six network attributes are then predicted to the prediction value of the network download rate. After comparing the pre-defined values of the six network attributes and the predicted value of the network download rate, the algorithm will choose the best wireless network for the next switching target.

3.2 Proposed Vertical Handover Mechanism

Algorithm 1 shows the vertical handover mechanism of the proposed method.

Algorithm 1: Vertical Handover

Input: The user terminal can collect network attribute values for a diverse environment that includes five wireless networks..

Process:

(a) The user terminal can subsequently transmit the gathered network attribute values to the input neurons of the BP neural network model.

(b) The BP neural network can perform various computation and approximation procedures based on the expected values and reference values of the input network attribute.

(c) Find out the weights of neural networks are correlated with the wireless networks.

Prediction:

The network model can be used to predict the wireless network download rate based on the collected attribute values, aiding in decision-making.

Comparison:

i. The heterogeneous models network download rate is predicted

ii. Perform numerical comparisons among the predicted network download rates.

Selection:

Select the network with the optimal performance for the vertical handover decision based on the compared numerical results.

Output: Network with the highest predicted performance is chosen for vertical handover decision.

Algorithm 1 outlines the process of making vertical handover decisions wiithin a mixed converged network environment, employing a proposed network model. It involves collecting network attribute parameters, inputting them into the neural network, predicting network performance, comparing predictions, and ultimately choosing the top-performing network for the vertical handover.

4 Experiment Analysis

The evaluation of the algorithm is carried out using the MATLAB R2016b simulation software. Table 1 provides a representation of the network attributes' empirical values. They are then used to set a benchmark for supervised learning.

Table 1: Network Attribute values for Supervised Learning

Network Model	SINR	User Speed	BER	MTR	MTD	Packet loss Rate	Network Download Rate
UMTS	20	3m/s	3×10^{-6}	1024 kbps	20ms	0.006	2mbps
GPRS	18	3m/s	10×10^{-6}	115 kbps	25ms	0.008	300kbps
WLAN	22	3m/s	7×10^{-6}	50mbps	7ms	0.003	100mbps
4G	24	3m/s	15×10^{-6}	20 mbps	18ms	0.001	100mbps
5G	26	3m/s	1×10^{-6}	100 mbps	1ms	0.0001	500mbps

The six network attributes are normalized and given as neural network input. The excitation function is used for the input an hidden layer. The “logsig” function is used for the parameter transfer and “purelin” function is used for the network training. The iteration value is set for 5000 times for the network training, 0.00065 is the expected predicted value which is set as the targeted mean square error. 0.05 is the learning rate. The learning parameters are set as 20 sets. We then input the six environment attributes into the input regions of the network. The handover procedure is performed in the network model's input layer. The resulting simulation results are then analysed by the model's selection of the best network.

Fig. 4 represent the various steps involved in the BP training and validation process. They show the performance of the training process in terms of its cross-validation procedure in iteration and mean square error index. The coloured test line represents the training's final outcome, while the best dotted line shows the algorithm that was utilized for the seventh generation of the neural network. The proposed algorithm was subjected to seven iterations to minimize the mean square error.

Fig. 5 represents the neural network training and test rate of the 5G communication. The training error of the 5G communication is 0.21%. The actual download rate and the predicted rate is almost same. The predicted error rate of the BP model for its various types of networks is not exceeded the upper limit of its training error. This ensures that the prediction pipeline can meet the requirements of its error-tolerant algorithm.

Fig. 6 shows the network selection that was implemented in the proposed method using the vertical handover method on the simulation platform of MATLAB. The algorithm takes into account the download rate of the networks to evaluate their advantages and disadvantages. It also helps the terminal to switch to the network that has the best performance. Based on the simulation's results, the proposed algorithm can predict the download rate of the networks.

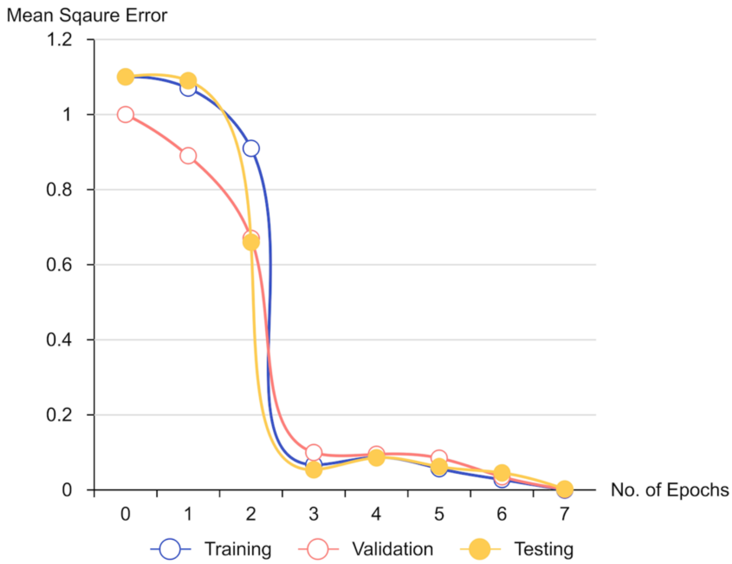

Figure 4: Back Propagation Error Curve

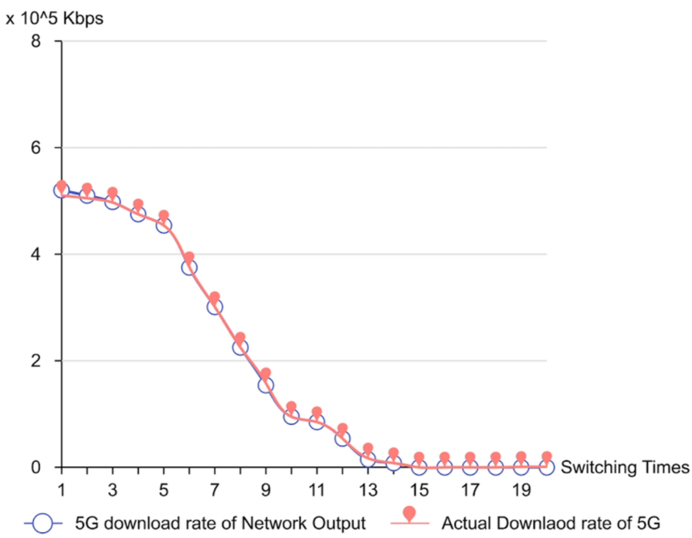

Figure 5: Data Learning and Testing in 5G Communication

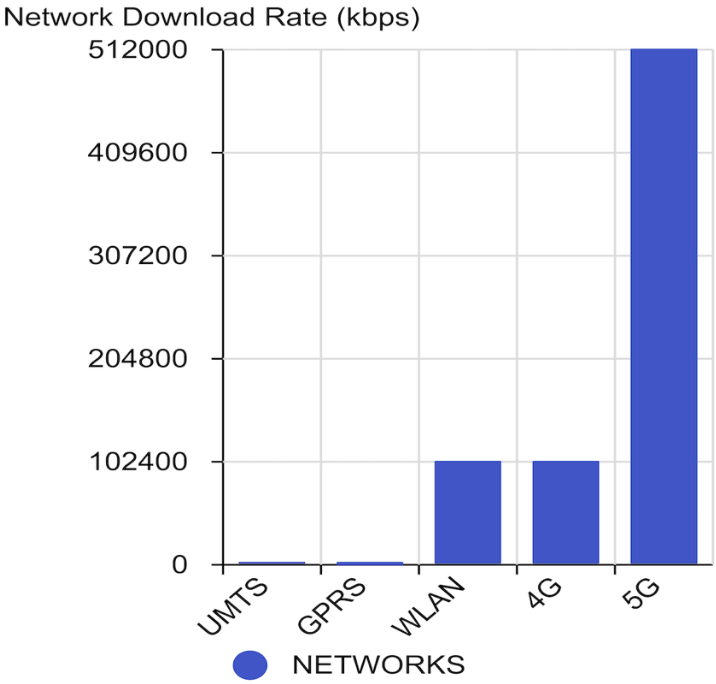

Figure 6: Algorithms Running Result

In Fig. 7, it is observed that the successful handovers of the proposed and existing algorithms. The proposed algorithm is then set up to perform a comprehensive analysis of the network environment, which includes 20 decisions of vertical handover. The 5G network is also set up in the network structure. The major factors that impacts the performance of the network are the downloading rate and the number of connections. In this work, we introduce two types of handover algorithms, namely the vertical and the lateral. The vertical algorithm is designed to perform error-tolerant vertical handover decisions. The vertical handover algorithm has a success rate of 17 out of 20. The success rate of the algorithm is 85%. The complexity of the handover process in heterogeneous wireless networks is often considered when it comes to implementing the vertical handover algorithm. In this work , the performance of the algorithm is compared with the fuzzy logic theory reference set.

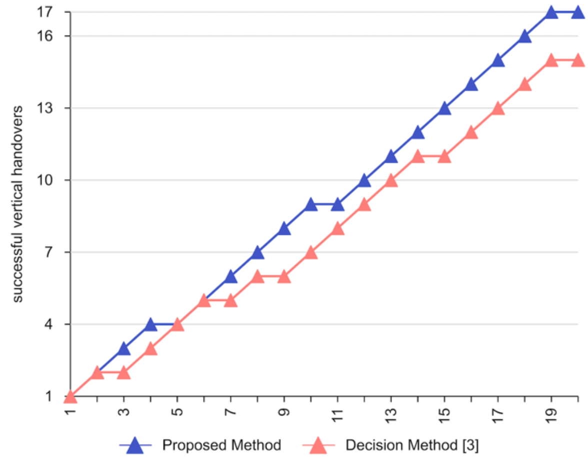

Figure 7: Successful Vertical Handovers of the Proposed and Existing Algorithms

5 Conclusion

This paper proposed an innovative vertical handover algorithm that leverages the capabilities of the BP (Backpropagation) framework, adding a new dimension to its operational process. The algorithm is structured around a three-layer network, designed to adapt to the intricacies of diverse networks. While previous algorithms have explored vertical handover solutions incorporating neural networks, they bear a resemblance to the approach presented in this paper. In terms of performance, the proposed algorithm exhibits a slight advantage over existing methods. However, it's essential to note that the application of this vertical handover algorithm is typically best suited for scenarios involving a limited number of wireless networks with heterogeneous integrated components. In practice, the full realization of this algorithm's potential may be constrained by the availability of comprehensive candidate networks. Nonetheless, this novel approach represents a noteworthy step forward in the realm of vertical handover algorithms, offering improved performance and adaptability within its specified scope.

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