

Interface Selection and Optimization of Weights using Artificial Neural Network in Heterogeneous Wireless Environment

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Abstract

Given the variety of networks, interfaces, mediums, and other resources accessible in a wireless heterogeneous location today, mobile communication is in a healthy competitive environment. When clients or users have access to numerous interfaces at once, a problem occurs. Users therefore require a clever or intelligent system to connect them to the finest services based on their needs and choices. Interface management controls the interfaces that are accessible and links the user to the best. The intelligent usage of various radio accesses/interfaces is made possible in this research by interface management with artificial neural networks (ANNs). Various parameters of different networks are used to make the choice. In this paper, a back propagation neural network (BPNN) method for switching between 3G, WLAN, 4G, and 5G networks is suggested. By allocating appropriate weights, the various network properties are employed as selection parameters. Fuzzy Analytic Hierarchy Process (FAHP) is used to initialize the weights, and the BPNN is used to optimize them. In order to obtain the best value, the goal value and the original value are compared, and the difference between them is used as an adjusting value for the weights. The network is trained using backpropagation techniques. The comparison between the proposed algorithm and the current algorithm demonstrates the new method's flexibility and the network's optimal connectivity with a high rate of successful handovers.

Keywords

Fuzzy Analytic Hierarchy Process (FAHP), interface management, back propagation neural network, wireless networks

1. Introduction

Today's wireless heterogeneous networks come with several interfaces that users can utilize to connect various base stations. A model must interface and synchronize information in this environment of several interfaces to reduce the mistakes associated with ongoing communication, such as delay, inaccurate data, disconnecting, and many others.

To ensure the successful transmission of crucial information, interface management (IM) directly manages these processes. In a multichannel/multi-interface environment, Interface Management (IM) is a set of rules that permits channels for various interfaces. The most important component of wireless heterogeneous networks is interface management as it is essential for efficient communication. As a result, the most current advancements in interface management

systems are examined and potential problems with such systems are looked into. The approaches or procedures utilized in interface management has been changing with technological advancements. Artificial intelligence (AI) and wireless technology complement one another well. While AI algorithms excel at difficult jobs and generative processes, the existing wireless technology allows scalable and interpretable solutions. AI can be used to improve several aspects of wireless technology capabilities. One of them is interface management, where a range of AI approaches can be applied to aggregate features and data from various interfaces. The key to this research is network selection, particularly for assessing the performance of wireless heterogeneous networks with AI solutions. Traditional or classical channel models have hard-coded assumptions and hence the need for onerous field measurements. This study clarifies the pertinent information on interface management, technological advancement, and potential AI strategies to create the finest system. The areas mentioned above are the subjects of numerous research projects, all of which are proving to be difficult.

The design of wireless systems has become increasingly sophisticated as a result of the advancement of mobile wireless technologies from 3G/4G to 5G and 6G. Due to the demands for effective resource sharing among growing user bases, wireless networks have also grown more challenging to operate. Mobile terminals frequently have several network interfaces, which may use various cellular and wireless access protocols. Mobile terminals must choose the appropriate network for different communication at any time, everywhere in heterogeneous wireless networks. This process is known as network selection. This subject has been extensively researched in recent years, utilizing a variety of mathematical ideas. Several mathematical theories based on multiple criteria are discussed in Ref. [1]. A dynamic interface selection with various choices (interfaces) and attributes (interface qualities, user preferences, etc.) may be realized using the algorithmic technique known as MADM. Many traditional techniques such as SAW, WP, and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and three MADM algorithms were compared for performance [2]. The difficulties posed by contemporary systems push engineers to look beyond conventional rule-based methods, and many turn to AI as the go-to remedy. AI has brought in the sophistication required for contemporary wireless applications, from the handling of error-free communication between a number

of mobile subscribers to optimization of resource allocation in mobile conversations. The function of AI will grow as the number of interfaces and channels connected to networks increases in the wireless heterogeneous environment (WHN).

The goal of this effort is to develop a paradigm-shifting AI technology that can change how interface management systems are used, moving away from traditional methods and toward ones that are AI-inspired. The optimal network is chosen in this paper using artificial neural networks (ANNs) and FAHP weight calculation methods, which are explained below.

1.1. Neural Network (NN)

Any wireless device can be activated by an NN, often known as an ANN, which learns and predicts how various environmental characteristics will change over time. A group of connected input/output units with a weight assigned to each connection make up an NN. Using large databases to create prophetic miniatures is a useful approach—a miniature representation of the human nervous system, the mini-brain. It facilitates information-processing skills including direct visual comprehension, mortal literacy (reading and writing), computer address, and others. The NNs are collections of algorithms designed to spot trends and decipher data through labelling or clustering. A method used to carry out the literacy process in NNs is called a training algorithm. A component of AI called an ANN aims to mimic the functioning of a natural brain. The building elements of ANNs are called processing units, and one processing unit is equivalent to one input worker or manual worker. The inputs serve as the basis for the ANN's learning, which creates the veiled affair. A middleware handoff using NN was proposed in Ref. [3] for choosing the best networks. Random weights were taken for input parameters, which affects the performance of the system. NNs are regarded as a significant machine learning style that is used to make a wise and independent choice for the automatic selection of the fashionable available seeker wireless technology.

1.2. Back Propagation Neural Network (BPNN)

An ordinary method of training an ANN is BP. It is made up of a set of learning guidelines intended to decrease training mistakes in an NN using a gradient-based approach. By modifying the

connections between neurons in response to mistakes made in a previous iteration (or epoch), the weights are fine-tuned. A model needs to be correctly calibrated to maximize generalization while minimizing the error rate to be considered dependable. BP is a quick, easy, and programmable method for training NNs. Apart from the quantity of inputs, it has no customizable parameters. Since it does not require prior network information, it is a flexible method. The characteristics of the function do not need to be specifically mentioned or need any specific learning.

A BP network is a multilayer, feedforward, backpropagation network that begins with random weights. Figure 1 depicts the layout of a BP network with five inputs. Input, hidden, and output are the three layers of the network. There could be more than one concealed layer. Only one hidden layer is displayed in this structure to keep things simple. Weights are chosen at random to model the inputs X . From the input layer to the hidden layers and then to the output layer, the output of each neuron is determined. Error BP (actual output–desired output), the difference between the outputs, is determined. The weights in the hidden layers are adjusted to reduce error, and then the procedure continued until the

desired result is obtained. The backpropagation algorithm needs a differentiable activation function, and the most popular ones are tan-sigmoid and log-sigmoid. The weightings are changed as the learning process progresses in order to lower the error E . This is done to improve the correspondence between the system's outputs and its real outputs. When the error rate drops below the permitted level, the network learning process is complete. This ensures that the network appropriately depicts the real world [4].

1.3. Weight Assignment: Fuzzy Analytical Hierarchy Process (FAHP)

Each input's weights convey the significance of that input in predicting the output value. Weights represent the connection between a specific dataset feature and the desired outcome. It can be challenging to choose the best weights for various parameters. Small weight values for input parameters have less relevance than large weight values, which have more significance. Weights have a significant impact on how the line separating two or more classes of data points is oriented and sloped. A system may employ the following general weight initialization methods:

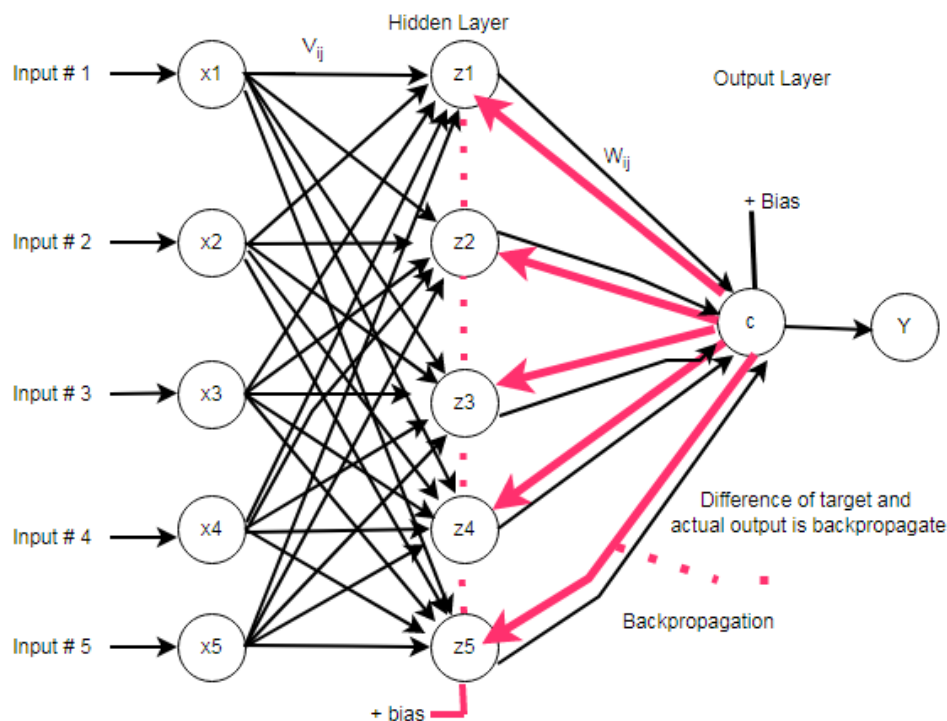


Figure 1: General structure of backpropagation.

strategies for zero and random initialization. Because MADM algorithms are designed to identify the highest-quality network, mobile users can gain from them. Analytical hierarchy processes (AHPs), fuzzy analytic hierarchy processes (FAHPs), analytic networks (ANPs), fuzzy analytic networks (FANPs), and a method for order preference based on resemblance to ideal solution (TOPSIS) are just a few of the methods that are offered in MADM. We weight input parameters in this study using the FAHP approach. The best approach for quality and multicriteria decision-making issues is the fuzzy AHP approach. Compared to other techniques, the FAHP method offers more effective, adaptable, and realistic decisions based on the given criteria and options. The AHP and the fuzzy logic theory are combined to create the fuzzy FAHP. Both use the identical methodology to assess the network's weights, with the exception that the fuzzy AHP technique divides the AHP range into high, medium, and low values.

The introduction of ANNs, backpropagation, and FAHP are covered in Section 1 of this essay. The literature review comes in Section 2. The hierarchy of the task and the system model are presented in Section 3. The interface management with the algorithm is explained in Section 4. The technique's implementation and simulation results are discussed in Section 5. The work's conclusion and the future direction of this investigation are covered Sections 6 and 7.

2. Literature Survey

The literature has thoroughly investigated various network selection algorithms and techniques in the WHN. These strategies, which are discussed in this section, include both traditional methods and AI.

In Ref. [5], a number of MADM methods for selecting an intelligent access network in a multiaccess context were covered. Future heterogeneous 5G networks' biggest issues in service quality and uninterrupted connectivity were also covered. The ideal network choice was demonstrated by comparing load-aware and RSSI-based methods. In Ref. [6], authors suggested initializing weights for the NN randomly but at specific intervals. A resilient backpropagation technique was then used to train the network. As the networks could achieve a minimum of error practically throughout training, the authors demonstrated a higher efficiency of the system than the general random technique. Signal strength, available bit rate, signal-to-noise ratio, feasible throughput, bit error rate, and outage probability metrics were

proposed as criteria for a novel network selection algorithm [7]. For relative dynamic weight optimization, the selection metrics were integrated using particle swarm optimization (PSO). An EDGE (2.5G) and UMTS (3G) heterogeneous environment was used to implement the proposed technique. A utility function was utilized to maintain the appropriate QoS while using the user's switching rate between the available networks as the performance parameter. Based on many factors, including network-related, terminal-related, user-related, application-related, and service-related, an NN was employed [8] to choose the network for handover. The effectiveness of the three networks was assessed using the voice over internet protocol and contrasted with the conventional approach. On the basis of real-network implementations and measurements, a fuzzy logic-based methodology for an automatic network selection was proposed [9]. Fuzzy inference methods that took into account features that influence the selection choice were the foundation of the suggested network selection model. The authors [10] highlighted the most significant new QoS, QoE, and SON aspects connected to the advancement of 5G. Additionally, they examined the drawbacks of older networks and the benefits of 5G for various applications, including M2M, D2D, IOT, and others. A method that enables a complete 802.11 Basic Service Set (BSS) to dynamically hop between the available channels while always selecting the "best" one was proposed, put into practice, and evaluated [11]. In order to maximize resource utilization throughout the system, the selection not only ensures that the hopping BSS performs well, but also reduces interference with other BSSs. In Ref. [12], weights were optimized using the PSO technique. A fuzzy logic system that is fed with comparable measurements as inputs and is aimed at producing the same output makes up the second criterion. These two factors were combined to determine the ultimate network choice. The proposed strategy, which is based on the cost function, PSO, and fuzzy system (C-P-F), performed better in simulations, reducing the number of pointless handoffs (network selection rate), increasing utility, and balancing the load. The network selection rate is dramatically reduced by 50% using the suggested technique (C-P-F). MADM algorithms are used to score the various networks and an FAHP technique [13] to generate the weights. With the aid of the SAW, MEW, and TOPSIS utility function, FAHP, and MADM approach, a network selection algorithm was created. Based on customer preferences and the uniqueness of the service, the system operated. The utility value

of each parameter was calculated using utility functions. With the help of the entropy approach and the fuzzy-analytic hierarchy process (FAHP), the objective and subjective weights were obtained [14]. The networks were ranked using several MADM approaches, and the network with the highest rank was chosen as the best network. Although MADM approaches have been shown to be highly beneficial, they may produce inaccurate answers in some dynamic decision contexts because of the “rank reversals” problem. There is a rank reversal problem with several MADM approaches, including the analytic hierarchical process (AHP) and the TOPSIS [15]. The flow/interface association (FIA) took into consideration energy consumption as a criterion [16]. To choose the best FIA that met all the criteria that were taken into consideration, a novel method known as Smart Tabu Search (STS) was proposed. It took into account network conditions, the financial cost of the network, the QoS requirements of the applications, user preferences, and the energy consumption of the mobile device. The research paper [17] concentrated on the potential use of machine learning—one of the uses for ANNs and a component of them—in wireless communications. The basic architecture, training process, difficulties, and opportunities associated with the various types of NNs, such as feedforward, recurrent, and deep learning NNs, were reviewed. The bandwidth was estimated using an NN approach [18]. A cluster-based cooperative interference control approach for a multi-interface environment was proposed in Ref. [19] to reduce the cross-layer interference of numerous base station cells. In Ref. [20], some requirements for using ML in wireless communication were covered. This document provides information for novices on usage, various ML techniques, benefits, and how it differs from conventional approaches. For the purpose of determining an NN’s weights for linear projections, a novel method was put forth [21]. A five-module approach for user-oriented intelligent access selection in HWNs [22] (input, user preference calculation, candidate network score calculation, output, and learning). The candidate network score calculation module calculates the network score using a fuzzy neural network; the utility function calculates the utility value of the judgment parameter; the user preference calculation module calculates the weight of the judgment parameter using the FAHP approach; and the output module calculates the error between the actual output value and the expected output value. In order to reduce the number of redundant handovers (unnecessary handovers), an NN-based strategy was put

forth [23]. By examining the quality of all the signals between the mobile user and all nearby stations, it improved network efficiency and sped up handover times. It anticipated the subsequent handover target station for a heterogeneous network. Based on input parameters, the authors [24] demonstrated switching between and selection of the optimal networks among many networks, including 3G, 4G, and 5G. The implementation uses the BPNN technique. In this paper, no particular consideration was given to the assignment of weights and applications. It was suggested to use an access selection algorithm [25]. An ideal amount of bandwidth should be distributed among users to increase the wireless network’s transmission rate. To achieve this, we created a link transmission rate model and applied dynamic programming theory to it in order to determine the ideal bandwidth for HWNs. The limitations of prediction-based energy-efficient strategies were covered in Ref. [26]. Additionally, the authors advised conducting context-specific, energy-efficient research in the wireless communication network design. The signal-to-interference-and-noise ratio (SINR) prediction in mobile networks has been proposed [27] using a method known as an ANN. With the use of sounding reference signals (SRSs), radio resource scheduling was often accomplished based on estimated channel conditions, i.e., SINR. The non-linear auto-regressive external/exogenous (NARX)-based ANN strives for greater accuracy while minimizing the rate of delivering SRS. A distributed system for choosing a dynamic network has been suggested [28] taking into account dynamic factors like user mobility and battery life. To optimize cost and energy efficiency, the deep multi-agent reinforcement learning (DMARL) technique was presented. To improve the system’s latency and energy usage, a distributed machine learning solution for a multiuser mobile edge computing (MEC) network was examined [29]. AI methods for enhancing mobile communication [30] were discussed. A quick overview of contemporary AI methods used in wireless communication, as well as various traditional AI techniques. Fuzzy logic, NNs, reinforcement learning, and AI approaches are among the techniques used in mobile communication.

The literature review analyzes the various functional characteristics for various networks, along with their benefits and drawbacks. Therefore, an improved way of network selection is suggested in this research to address the shortcomings of current techniques. The following section highlights the hierarchy or system model of the suggested method.

3. Structure Model

The various networks that are available in the multi-interface environment, together with their settings, are selected based on their outputs. About 90% of mobile phone users access the internet at all times, which effectively necessitates fast speed for data, audio/voice, and video downloads. A fast download speed indicates that the more the options available, the faster is the network. The following steps must be followed before choosing a network based on download speed:

i) Scaling of Input Parameters

Before beginning the training process, data normalization is required in ANN techniques to ensure that the input variable's impact on the model-building process is not influenced by the original values' magnitude or range of variation. The input/output variables are typically linearly transformed to the range (0, 1) as part of the normalization procedure. The two methods for normalizing the values, which are the most used ones, are described here. In the first approach, the inputs are divided into beneficial and nonbeneficial categories, with the former receiving the maximum value and the latter receiving the minimum value (the minimum value should be in the numerator). In alternative techniques, the normalized value X_n is determined using the Eq. (1) formula.

$$X' = (X_{max} - X_{min}) / (X_{max} - X_{min}) \quad (1)$$

In this study, we normalized the input parameters by adhering to a few straightforward methods.

ii) Weight Initialization Method

Inputs are combined with weights to display user preferences and weighting. The higher the value of the weights, and vice versa, the higher the user preference. Weight initialization seeks to stop the forward pass of a deep NN from causing layer activation outputs to explode or vanish. With many MCDM approaches today, such as TOPSIS and AHP, weights can be initialized with predetermined values. As it offers more benefits than other techniques, the FAHP is employed in this work to initialize the weights.

iii) Initialize Network

The parameters and their corresponding weights are used to initialize the network. The neural system maintains a set of weights for each neuron, a bias weight for the activity of the neuron and a weight for each input connection.

iv) Forward Propagate

An input signal is passed through each layer of a network-learning process called "forward propagation" until the final layer produces a projected value. The weighted sum of the inputs is used to compute neuron activity as the first step. Then, the real output is checked using various activation functions.

v) Back Propagate Error

The difference between the outputs from the target outputs is the backpropagated error. Using a backward pass, the network's total error, which later spread from the hidden layer to the output layer, is used to update the weights.

vi) Train, Network, and Predict

Iteratively exposing a training dataset to the network, forward propagating the inputs, backpropagating the error, and modifying the network weights are required for building an NN. Update weights and train network are the two parts of this operation. It may be more beneficial to utilize the function that returns the class prediction as opposed to just printing an integer result. By choosing the class value with the higher probability value, we may convert these values into a clear prediction. This is referred to as `argmax()` after the Python function.

The primary components of the WHN are 3G, 4G, WLAN, and currently 5G networks (since 2G, UMTS, and GSM networks are no longer in use). These networks each have a network model that accepts inputs from functional parameters. These values are scaled from 0 to 1 values due to the various functional parameter ranges. These input values are given various weights based on the user's preferences using the FAHP approach. The output of the feed-forward model is calculated by adding the sum of the inputs and weights. At the output layer and hidden layer, activation functions are carried out. Next, an NN

model is trained for the goal values and to produce the least amount of error. For each network, weights are optimized to produce the most output with the least amount of inaccuracy.

4. Selecting Interfaces with Proposed Algorithm

The suggested system is designed for the many networks that are now available and their characteristics, such as download speed, latency, bandwidth, packet loss rate, and jitter. While other factors undoubtedly play a big part as well, these are the key factors that determine how effective a network is. The hierarchy of the proposed system shown in figure 2 is used for network selection for different application: video, audio, web browsing, and data transfer. For various networks, these parameters range in value from minimum to maximum. Table 1 displays the parameter range for the various wireless networks.

To evaluate the effectiveness of the networks, various input parameter values were used in this article. The network design with five inputs and one output outperformed the other setups that were examined in terms of download rate. Varied users have varied preferences; some may want high-quality audio while others may prefer high-quality video. For web browsing, searchers need a fast connection and some need continuous, quick data transfer. Therefore, we individually calculate the weights for each application in this study, which are displayed in Table 2. A fully connected NN receives the various inputs along with the weights appropriate for various purposes. The system is taught to get the smallest value of error by adjusting the parameters of the backpropagation network, which calculates the difference (target value–actual output).

The values of the weights determined by FAHP and related to inputs are displayed in Figures 3–6.

The NN algorithm computes the difference (target value–actual output), and by adjusting the weights appropriately, the system is trained to obtain the smallest value of error.

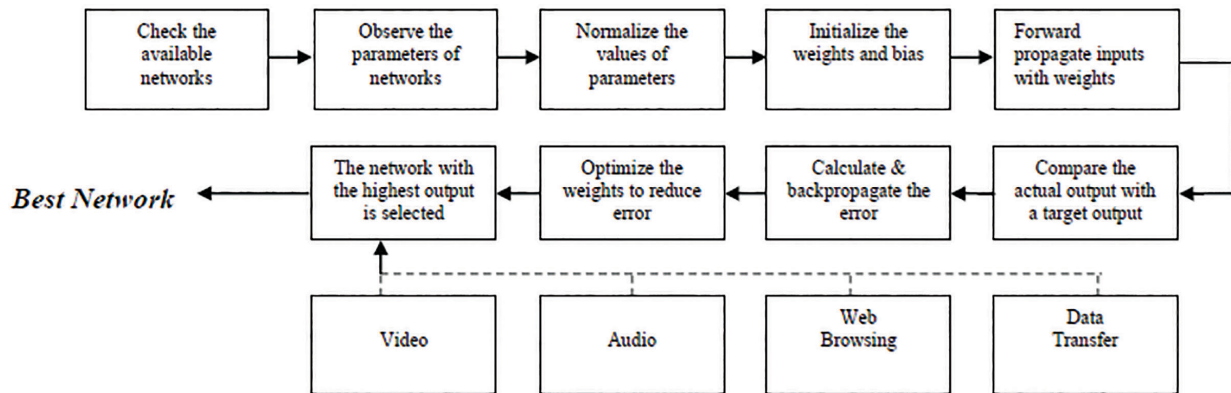


Figure 2: Hierarchy of the system.

Table 1. Parameters of different networks [24, 25]

Networks	Network download speed (Mbps)	Latency (ms)	Bandwidth	PLR (%)	Jitter (ms)	Target output (maximum download speed) Mbps
3G	144 kbps–2 Mbps	30–200	0.1 Mbps–3 Mbps	2–10	10–30	3–7.2
WLAN	1 Mbps–8 Mbps	80–300	2 Mbps–10 Mbps	4–15	30–80	450–600
4G	15 Mbps–90 Mbps	20–150	200 Mbps–1 Gbps	4–20	15–40	20–200
5G	150 Mbps–10 Gbps	1–10	1 Gbps–10 Gbps	0–10	10–20	1000–10,000

Table 2. Normalized weights for different applications

Application	DS	L	BW	PLR	Jitter	Total
Video	0.3101	0.1661	0.2912	0.0519	0.1808	1
Audio	0.4427	0.2843	0.1127	0.0639	0.0964	1
Data transfer	0.5232	0.1924	0.1331	0.1152	0.0361	1
Web browsing	0.3686	0.3743	0.1242	0.0868	0.0461	1

DS, Download Speed, L, latency, BW, Bandwidth, PLR, Packet Loss Rate.

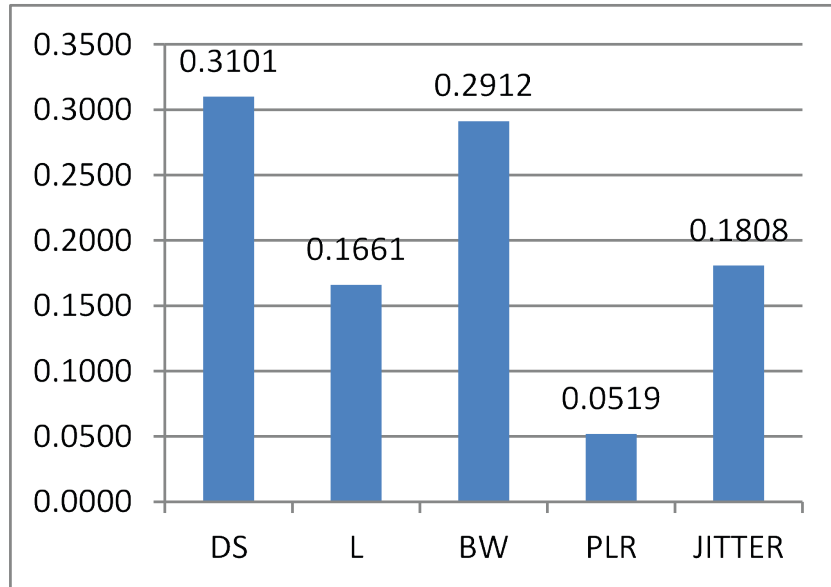


Figure 3: Weights for video application.

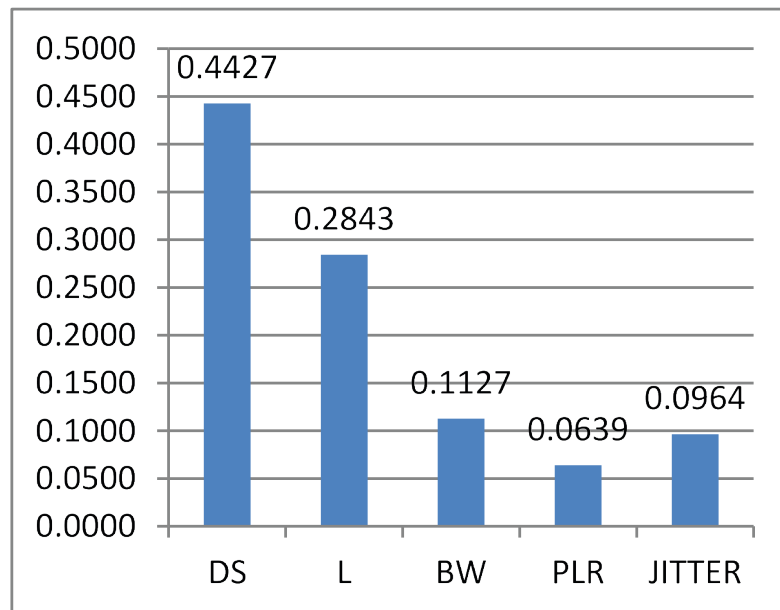


Figure 4: Weights for audio application.

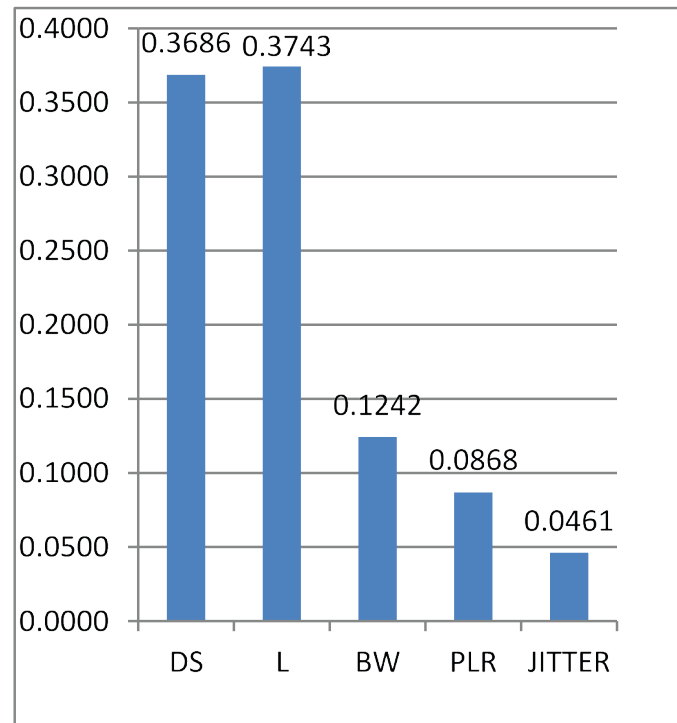


Figure 5: Weights for web browsing application.

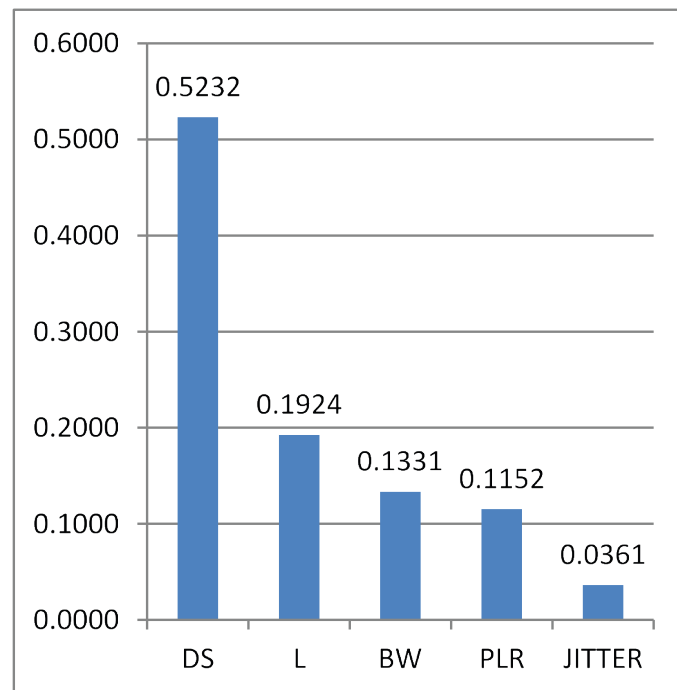


Figure 6: Weights for data transfer application.

```

//Pseudocode to optimize weights for network
selection using BPNN//
//Acquire dynamic values of input parameters.
//Compute normalize values of inputs.
//calculate weights using FAHP.
//Initialize the bias value (-0.5-0.5)
//Fix learning rate (0-1)
//Fix momentum factor
//SET target value T (dynamically)
Calculate  $Z_{in} = X_n * W_{ij}$ 
Activate function on hidden layer
Calculate Error =  $T - Y$ 
//Check with following conditions//
IF error == 0 THEN
END
Plot output(Y)
ELSE
Re-iterate the process
//Compare the output of all networks
MAX (OUT1, OUT2..... OUTn)
Select the network with highest output.

```

5. Implementation and Results

The proposed prediction systems are simulated and their efficacy evaluated using MATLAB. Results are obtained using various networks and apps. Here, we have four different networks (3G, WLAN, 4G, and 5G), five different parameters, and four different apps (web browsing, video, and audio streaming). Depending on the application, different targets are defined. We evaluate the algorithms' performance using the maximum download rate, which is one indicator of a network's strength.

For instance, weights 0.3101, 0.1661, 0.2912, 0.0519, and 0.1808 are obtained to download speed, latency, bandwidth, packet loss rate, and jitter, respectively, with FAHP when it comes to video applications. Similar to other apps, weights are computed using the FAHP approach for audio, web surfing, and data transmission. The fundamental BPNN method generates results with a low amount of inaccuracy.

Figure 7. reflects the outcome of video applications, where network 3G was selected twice, 4G three times, 5G four times, and WLAN just once. Results for audio applications are given in Figure 8, where 3G was picked twice, five times for 4G, twice for 5G, and once for WLAN.

In Figure 9, the output of programs used for web browsing, when 3G was twice selected, was displayed. Five times, 4G was chosen. WLAN was chosen just once, but 5G was chosen twice. The FAHP method was used to calculate the weights: The outcome of data applications is displayed in Figure 10. Given that it was chosen four times, the 4G network is the best network for this application. 3G was chosen twice, 5G was chosen three times, and WLAN was chosen once. The switching of networks is dependent on these outputs for various purposes, such as video, music, web surfing, and data transmission; the higher the output, the more appropriate network is chosen. All networks' inputs were chosen at random, and the target was set as a variable. The appropriate network with the highest value at that specific instant was chosen when the output changed. In a HWN setting, choosing a network access method needs careful evaluation of a number of judgment criteria,

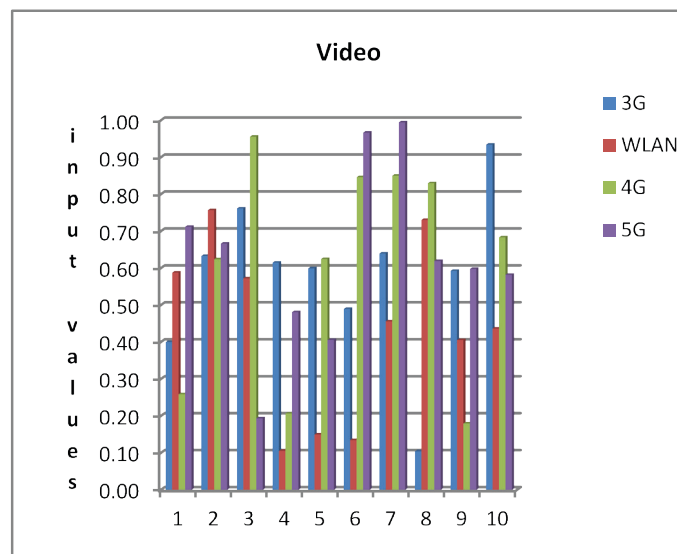


Figure 7: Network outputs for video application.

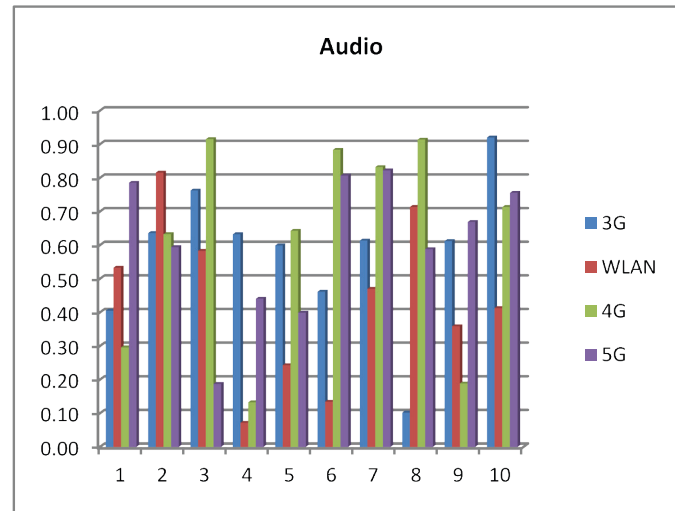


Figure 8: Network outputs for audio application.

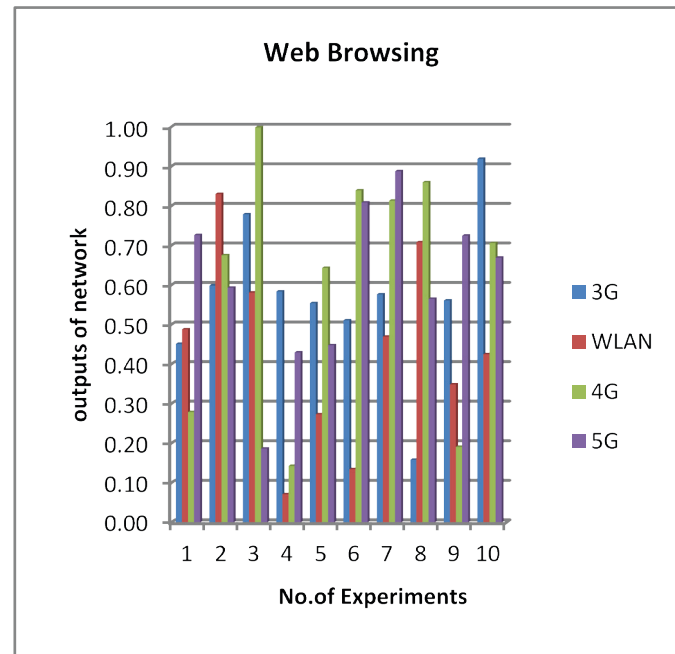


Figure 9: Network outputs for web browsing application.

including RSS, bandwidth, network load, delay, jitter, packet loss rate, movement speed, service cost, and energy consumption. Quantitative analysis is the term used for this. Graphs and numbers are used to represent quantitative research. Users can access the best network by using quantitative analysis because user service kinds and network transmission performance vary. It is employed to evaluate networks and discover data that can be applied generally. The evaluation should also take into account qualitative factors like

the network's correctness, stability, resilience, and security. It helps people comprehend ideas or past events. A few common qualitative techniques are stability, signal-to-noise ratio, and accuracy. We can check the mean square error value (MSE) to see how accurate MATLAB's interface management is. The average squared difference between outputs and targets is known as the mean squared error (MSE). Lower numbers are preferable, and the network will benefit from fewer errors. In an ideal scenario, zero

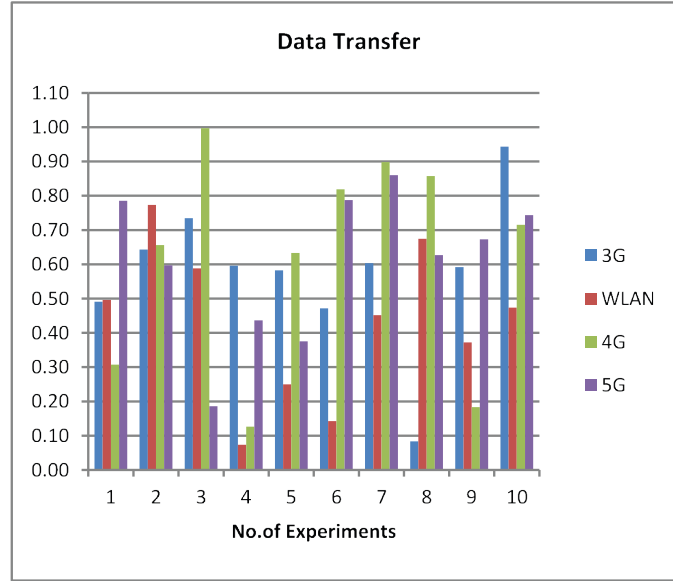


Figure 10: Network outputs for data application.

Table 3. Mean square error of available networks

Network	Mean Square Error
3G	0.005272
WLAN	0.00499
4G	0.004527
5G	0.008507

equals no error. The following formula provides the Mean Square Error:

$$\text{Mean Square Error} = (1/n) \sum [t(i) - a(i)]^2 \quad (2)$$

where $t(i)$ is the desired target and an (i) is the actual target.

In Table 3, 3G network's mean square is calculated to be 0.005272, a 4G network's is 0.004527, a WLAN network's is 0.004527, and a 5G network's is 0.008507, which is a very low value. It implies that the suggested algorithm is accurate across all networks.

The criterion that determines how much data may go through a network is called throughput. The throughput and intended output should ideally match. However, in reality, it is not true. It is determined by:

$$\% \text{Throughput} = \frac{\text{Obtained output (Mbps)}}{\text{delivered output (Mbps)}} * 100 \quad (3)$$

The throughput of the proposed algorithm for each network is calculated in Table 4, and shown in Figure 11.

The ANNs have received a lot of attention from researchers as a potential solution to challenging issues in wireless diverse environments. They promoted machine learning as a standout solution for challenging issues in a variety of fields, including image, research, and industry, among others. For wireless networks, the various ANN approaches, including deep neural, recurrent, and spiking, were studied. We have looked into the effectiveness of BPNN with NNs using the fuzzy logic system [21] and random weight selection [20] techniques. The originality of this switching algorithm covers multimedia applications in the switching range of heterogeneous integrated networks, in contrast to the majority of the existing vertical handover methods.

A quick and well-communicated transfer is what is meant by a high-quality handover. There is not a single, ideal handover procedure. A handover outgoing success rate of >95% is ideal. The following equation can be used to determine the handover success rate.

$$\text{Handover success rate} = \frac{\text{successful handovers}}{\text{attempted handovers}} * 100 \quad (4)$$

Figure 12 illustrates the amount of handovers with three techniques and demonstrates that the proposed algorithm speeds up network switching compared to

Table 4. Throughput of networks

Network	Obtained output (normalized values)/s	Delivered output (normalized values)/s	% Throughput
3G	0.8817	0.9524	92.58
WLAN	0.896	0.966	92.75
4G	0.9243	0.955	96.79
5G	0.9182	0.988	92.94

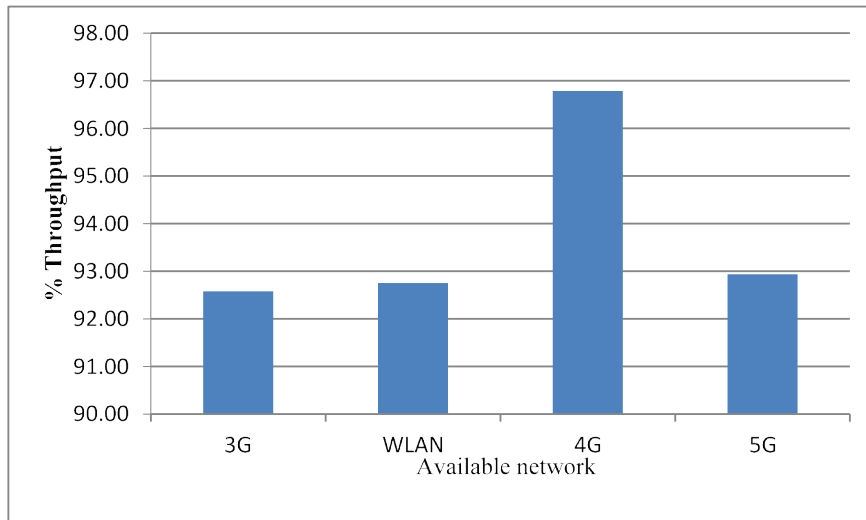


Figure 11: % Throughput for all networks.

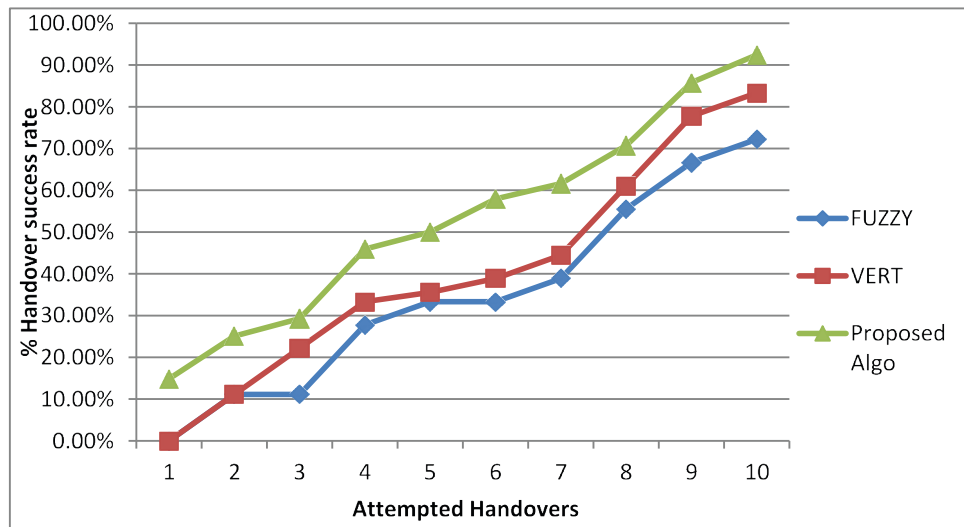


Figure 12: Comparison with existing algorithm.

existing strategies. Even then, it is <95% still, or close to optimal values. As a result, it has been determined from the findings that the BPNN's performance enhances the system in terms of a number of wireless parameters.

6. Summary

Wireless heterogeneous networks, computer science systems, IoT devices, and defensive systems all heavily rely on the interface management system. Due to recent technological improvements, interest in a variety of multimedia applications such as audio, video on demand, data transfer, and web browsing has increased dramatically. The utilization of internet services must be maximized for these applications. Multiple networks and interfaces are integrated in a WHN. There are several service or functional parameters for each of these. Interface management ensures that the best interface for that specific application is available. The optimal network is chosen by taking into account the various properties of the available networks using an intelligent BPNN, which is a well-known AI technique. With BPNN, inputs are propagated from the top layer to the bottom layer (often hidden layers), until they reach the output layer. FAHP weight initialization gives the implementation more realistic weights. The networks' service type and functional weights are determined using FAHP. The network attributes are normalized to verify the bias between each network parameter. The simulations are performed using MATLAB. Error is calculated as the difference between targets and real, and weights are modified to obtain the least error as the algorithm runs and simulations are completed. Both the output layer and the hidden layer employ the activation function. The function might take numerous forms. The suggested algorithm's performance is measured in terms of MSE. Figure 12 compares the effectiveness of several approaches. According to the findings, the proposed technology switches networks 93% more effectively than the 72% and 85% methods already in use for multimedia applications.

7. Future Scope

Future work may include deeper exploration of interface management tactics. In the future, new networks like 6G and so on and more input parameters may be used to produce outcomes that are more accurate and efficient. Security issues with the handover authentication standards can also be taken into consideration as future challenges. The present

authentication schemes are unreliable for detecting and preventing attacks. The other open challenges are energy efficiency, long latencies, need a lot of communication, and large computing overheads. In order to provide reliable networks and service types for massive mobile devices and data, the solutions to these problems will be needed to be created.

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