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An Energy Efficient Vertical Handover Protocol In Heterogeneous Wireless Mobile Networks Using Reinforcement Learning

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ABSTRACT
Today's mobile networks are dominated by multimedia applications that occupy high bandwidth as well as consume high level of energy. It is also a well-known fact that there are plethora of wireless mobile technology from which a mobile terminal can select channels from for data transmission. These various mobile network applications have different capabilities which make them suitable for different types of data transmission. It is therefore imperative that a protocol be designed to manage how mobile terminals utilize the different mobile technologies for the transmission of mobile applications. Handover is the process by which a mobile terminal switches from one channel to an alternative channel in order to have seamless transmission when moving from one cell site to another, Handover can either be horizontal when the transition is within the same mobile technology, or vertical when it involves heterogeneous mobile networks. A very important criteria for measuring the effectiveness of mobile data transmission includes energy efficiency, QoS (Quality of service) and QoE (Quality of Experience) parameters., This paper proposes a protocol which provides an intelligent decision-making support system based on Q-learning for saving the energy of mobile devices involved in vertical handover, within an integrated LTE, WiMAX and Wi-Fi network. Experiments conducted in a simulation environment show an improvement of 15% of the technique employed in this paper over current protocols employed in literature.

Keywords: QoE, Vertical handover, QoS, PNSR, SSIM, VQM

I. INTRODUCTION

There is a demand for increased new services on the internet to cater for the yearnings of consumers. This demand has led to a change on how users connect to the internet. In this post COVID-19 era there is a leap in the volume of transactions done on the internet. The increasing demand for new services, technologies, and content must invariably change the technique through which communication is done so as to provide optimum delivery for all users on the internet. According to Cisco, by 2022, 74% of the mobile devices will generate 98% of the traffic data, and 78% of this will originate from video traffic [1]. The increase in the use of multimedia applications, coupled with the increase in the number of mobile users, necessitates the deployment of an architecture with high transmission rate and improved quality.

The current and the future of the wireless network environment will be geared towards the use of a combination of different wireless technology which enables effective transmission of data packets from various application. This is necessary because the different mobile technologies such as Bluetooth, Wi-Fi, WiMAX, and LTE are effective over different categories of mobile applications, hence the need for a protocol that enables optimum use of these technologies for the vertical handover between various applications. It is therefore imperative that mobile terminals be configured to be compatible with these different mobile technologies. This implies that the mobile terminals will be equipped with devices supporting multiple network interfaces so as to have access to multimedia services through different access networks by means of its radio transceiver. By implication, the heterogeneity of a wireless environment provides the opportunity to assess and select the best network from a range of others, on the basis of the required conditions of a multimedia service.

The essence of handover in wireless mobile networks is to enable the seamless and continuous connection of a mobile device in the event of either transiting from one cell site to another or transiting from one mobile application to another. The bottom line is the design of a protocol that enables mobile terminals to be always connected (ABC, Always Best Connected [2]) to a network, so that their application will not be disrupted while transiting from one location (cell site) to another.

Different mobile terminal users require an optimum multimedia experience. The delivery of video of a high quality is a more challenging task in wireless networks due to the varying QoE requirements of different users and the different requirements from the heterogeneous wireless networks itself. The challenge lies in developing a protocol for handover in mobile networks that meets the requirements of low energy consumption, low latency, and optimum data delivery under different network scenario. A protocol for an energy efficient handover in mobile network must satisfy various performance metrics for effective data transmission, this includes: QoS (Quality of Service), RSS (Received Signal Strength), bandwidth utilization, the battery consumption rate, and optimum data delivery involving user mobility.

The concept of Quality of Experience (QoE) can be defined as the overarching experience a user has due to his continuous use of a particular artifact (software), and it is becoming an important performance metrics in the measurement of the degree of quality of a multimedia service through the perception of the user. In essence the satisfaction of the user can be measured through required conditions based on social psychology, cognitive science, and engineering science [3]. The satisfaction (QoE metrics) for different services and application vary among different users. This is because different user expects different requirements from a network. This may be minimizing data access cost, high video quality or high download rate. This necessitates that a mobile terminal be configured with a decision making protocol that will be adaptive to these various requirements The traditional concept of QoS (Quality of service) excludes the fact that the satisfactions of the user should be included among the performance metrics for data transmission. QoS is only concerned with optimizing the network properties through metrics designed for the delivery of content [4–5]. This means that QoE should be an important attribute to take into account in the handover decision-making process.

Another performance metric to take into consideration in mobile network handover is the power consumption of the mobile terminal in the use of a particular mobile network technology and by extension the remaining battery energy of the mobile terminal prior to handover. This is because video applications consume a large amount of energy, hence energy saving is of paramount importance in the design of any protocol for handover in mobile network so as to extend the lifetime of the mobile terminal particularly in heterogeneous wireless networks as envisaged in this paper. However, designing a protocol to select an ideal network that takes account of the users' preferences while, at the same time being energy efficient is a big challenge.

It is noteworthy to know that the different types of technology occupy different bandwidth of the communication spectrum, and also require different power consumption for data transmission. Therefore, there should be a balance between bandwidth and energy consumption, because of the varying QoE needs of the users, i.e. there will be times when the user decides for a network with more bandwidth, which results in reducing the battery life, as there will be times when the user will opt to migrate to a network with less bandwidth but with a longer battery life [6], [7]. For this reason, the Q-learning algorithm will have as one of its inputs the battery consumption.

This paper designs a protocol for vertical handover decision-making based on Q-learning and it takes account of the following when selecting the best network: QoE and QoS criteria, energy consumption and the mobility of the user.

The paper is structured in the following way: The Section 2 provides a brief overview of studies related to vertical handover; The Section 3 describes the Q-learning algorithm for heterogeneous wireless networks; The Section 4 provides the results and analysis of the experiments, while Section 5 provides the summary the conclusion of the study and makes suggestions for further research in the field.

II. RELATED WORKS

This section gives an overview of different related works on heterogeneous architectures for vertical handover in wireless mobile networks There exists numerous researches in the literature, an instance is in [8] where the researcher proposed a handover mechanism based on the coordination between MIH (Media-Independent Handover) and PMIPv6 (Proxy Mobile IPV6) to support user mobility. The researcher focused on the reduction of failed handovers, packet loss, and QoS requirements. However, the researcher did not consider support for energy saving and QoE. In the work of the researchers in [9] they proposed an algorithm which optimizes the parameters of Time-to-Trigger (TTT) and Hysteresis Margin in their design. Their design provided improvements in energy efficiency and Ping Pong Handover Ratio, however, the design did not take into consideration the quality of user experience in its algorithm.

In the work of the researchers in [10], they employed decision mechanisms strategies based on Multiple Attributes Decision-Making (MADM). The proposal [11] designed a handover decision algorithm with focus on energy efficiency support based on the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), here the different mobile networks technology was assigned an integer value (rank) which is a function of the order of their relevance for the mobile application in context. The higher the integer value, the more appropriate is the mobile network for the mobile application in question. The parameters used in the algorithm are power consumption, traffic class, and percentage of remaining energy of the battery on each network interface of the mobile device. The researchers in [12] presented a comparison of different MADM methods, considering the battery level standard. The techniques used in their research were AHP (The Analytic Hierarchy Process), ANP (Analytical Network Process), Fuzzy AHP, and Fuzzy ANP, the methods were combined in 120 combinations for evaluation, and the results from their experiments concluded that the best methods of combinations were Euclidian-normalization-TOPSIS-FANP and Sum normalization-GRA-FANP. Even though the proposals in [9] – [12] gave analysis on the energy consumption, it fails to include QoE in its analysis,

In the work of the researchers in [13] the handover design made use of the fuzzy system for the decision making. The model employed a combination of QoS parameters and QoE (Mean Opinion Score) indicators. The work of the researchers in [14] uses the QoE to select the best connection; the QoE was evaluated using Mean Opinion Score (MOS) in real time, through the PSQA (Pseudo Subjective Quality Assessment) technique based on statistical learning through RNN (Random Neural Network). In [15] the handover used a fuzzy decision strategy which was based on a Software-Defined Networking (SDN) architecture using QoS and QoE requirements; the fuzzy system is able to monitor a set of APs (Access Points) for the selection of the best AP to the user. In [16], the design employed a multi-criteria algorithm which combined fuzzy system and utility function as a decision strategy. The fuzzy system was used to model the imprecise input information, while the utility function was employed to reduce the number of handovers. Though the papers [13] – [15], proposed improvements to QoE, they do not provide support for energy consumption. In the same vein the proposal in [16] considers multiple criteria such as delay, available bandwidth, and received signal strength, however it did not consider the QoE and power consumption.

The researchers in [16] proposed the vertical handover decision algorithm, based on Artificial Neural Networks (ANN), which uses a learning method based on neural network. The algorithm used the parameters of QoE and QoS in its decision mechanism, however the algorithm was complex and the energy efficient criteria was not tested in its analysis. In the proposal in [17] and [18] the researchers used a QoE evaluation mechanism based on RNNand fuzzy logic respectively in order to search the mapping relationship between QoS values and MOS (Mean Opinion Score) values. In addition, a vertical handover algorithm which employs a QoE-Q was proposed, using Q-learning theory, to maximize user experience quality. Simulation results point to an increase in QoE performance as well as improvements in mobile device energy consumption. However, the proposal has, as main focus, a vertical handover mechanism based on the correlation between QoE and QoS in heterogeneous networks.

From the afore-mentioned, none of these algorithms provide a joint approach that involves a solution for both energy-saving and vertical handover with QoE support. The protocol in this article is to propose a handover decision mechanism which is (i) energy-efficient (ii) provide optimum data delivery for vertical handover (without the ambiguity sometimes inherent in the fuzzy logic system design) (iii) satisfies QoE requirements and (iv) support user mobility. Table 1 compares the related works in relation to the current proposal.

Table 1 Comparison of the various vertical handover algorithms

Proposal	**QoE**	**Energy Efficiency**	**Decision Strategy**	**Proposal Focus**
[8]	No	No	Coordination between MIH and PMIPv6	Reduce number of Ping Pong events and

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				handover failures
[9]	No	Yes	Time-to-Trigger (TTT) and Hysteresis Margin	Improve energy efficiency and Reduce Ping Pong Handover Ratio
[10]	No	Yes	MADM - TOPSIS	Reduce power consumption
[11]	No	Yes	MADM - Euclidian-normalization-TOPSIS-FANP and Sum normalization-GRA-FANP	Support for reducing energy consumption
[12]	Yes	No	Fuzzy Logic System	Selection of the best network using QoE
[13]	Yes	No	RNN (Random Neural Network)	Selection of the best network using QoE
[14]	Yes	No	SDN and Fuzzy Logic System	QoS and QoE support
[15]	No	No	Fuzzy Logic System and Utility Function	Reduction in the number of handoffs
[16]	Yes	No	Artificial Neural Networks (ANN)	Reduction in the number of handoffs and delay
[17]	Yes	Yes	RNN (Random Neural Network)	Correlation between QoE and QoS in heterogeneous networks
[18]	Yes	Yes	Fuzzy Logic System	Selecting the best network considering trade-off between QoE and energy efficiency
Current	Yes	Yes	Q-learning	Optimizing for QoE QoS, energy efficiency User mobility

III. A Q-LEARNING SYSTEM FOR A HETEROGENEOUS WIRELESS NETWORK ARCHITECTURE WITH AN ENERGY-EFFICIENCY SUPPORT SYSTEM

This section presents a design using Q-learning for seamless handover and energy-efficient support for mobile multimedia communication while at the same time minimizing latency to the barest minimum.. The objective of the proposed algorithm is to save battery and latency in handover decision in heterogeneous environment networks with multiple devices while at the same time taking cognizance of the QoE requirements as expected for Future Internet environments.

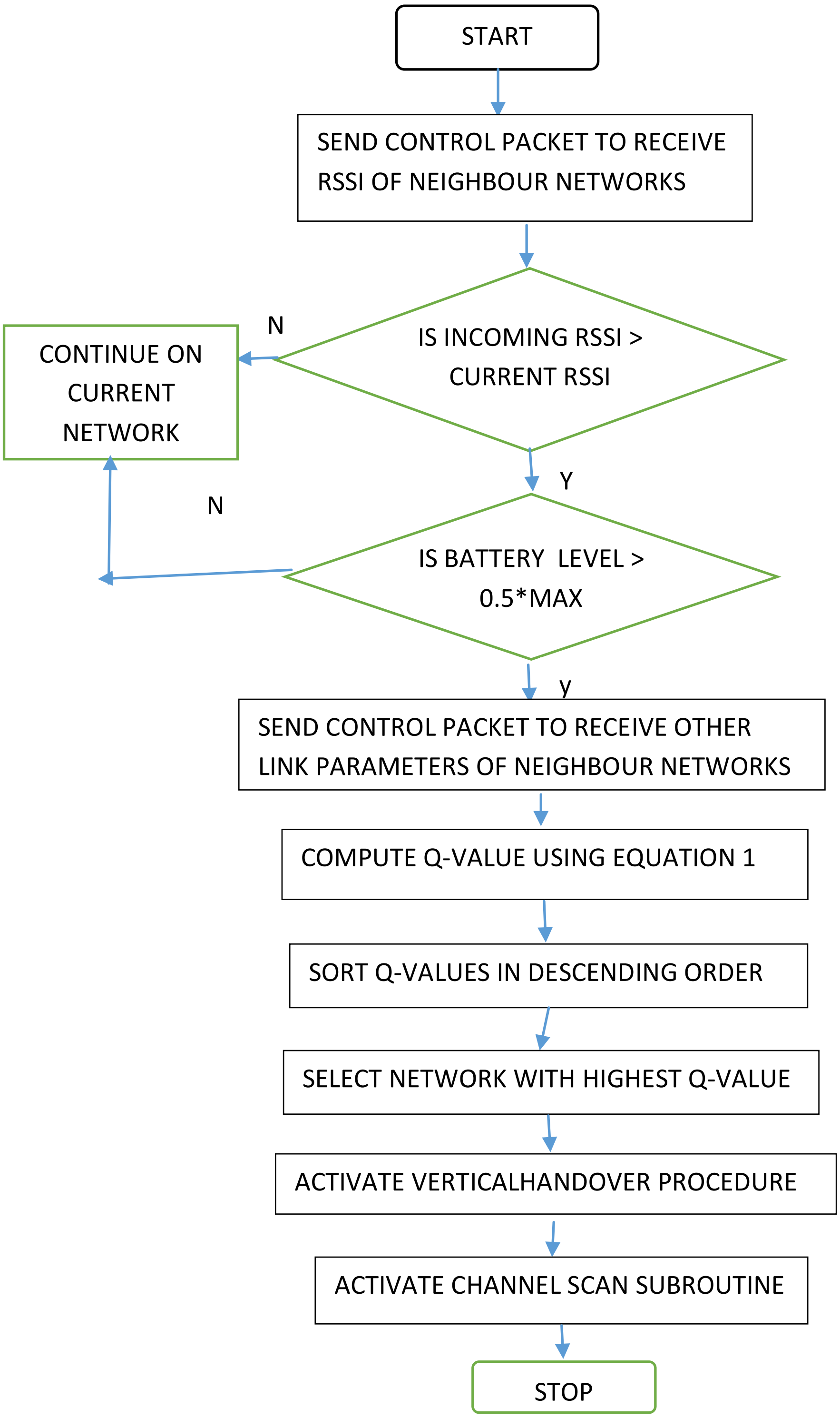

Figure 1 FLOWCHART FOR VERTICAL HANDOVER

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3.1. Problem Statement and Major Contributions

The energy efficient vertical handover in heterogeneous wireless mobile network is modelled using Q-learning and Partially Observable Markov Decision Process. These two paradigms can be useful in modelling sequential decision making in a partially observable environment. The protocol for the handover procedure is divided into two steps. (i) the selection of the most suitable mobile network technology among the three used in this paper, i.e. Wifi, WiMAX and LTE (ii) The selection of a channel from the chosen mobile network.

The Q-learning model used for the first instance stated above comprises of the following:

- **Agent States:** The states comprises of the three mobile network technologies stated above. It is represented by the symbol (N, path) where N is the target mobile network and path is the handover path from the current to the target network.
- **Actions:** The actions are the handover decision from the current to the target network. The action may be either to stay in the current network or to handover to a target network. This is denoted by $E(t) = p \{(T_{t+1})|S_tA_{\{} \}$ where E(t) is the expectation of handover, where $p \{(T_{t+1})| A_t \}$ is a conditional probability of performing handover to a target mobile network T at time t+1 giving that handover request was made in mobile network A at time t.
- **Q-Values:** This represents the goodness of an action, and the goal of an agent is to learn whether to stay on the current channel for data transmission or to handover to a neighbouring mobile network based on the Q-values of the various combinations of the mobile networks and RSSI measurements of the competing channels used in the model. Here Q-values will be bound to represent the real cost of either moving to a target mobile network or remaining on the current network. The cost is a weighted function of the following parameters: (i) RSSI (ii) percentage remaining battery energy of the mobile terminal, (iii) time lag that the target channel performed successful handover, (iv)velocity of the mobile terminal and (v) QoE parameters. More detailed explanation on how these parameters are computed are given in the next section. The vertical handover protocol is shown in figure 1.
- **Q-value update:** In order to learn the real value of the actions, the agent must receive the reward values from the environment. Here each free channel to which the handover request is made stores its Q-value based on the Q-value returned from the computation using equation

The value of the updated Q value is as shown in equation 1

$$Q_{new}\ (a_i) = Q_{old}\ (a_i) + (R(a_i) - Q_{old}\ (a_i)) \quad (1)$$

where $R(a_i)$ is the immediate reward value and R is the learning rate of the algorithm. R = 0.85 is used here because the initial value of the Q-value was 0 and to make the protocol converge in record time. A new update replaces the old one only when the weighted value of the updated reward is higher than the previous one, else the previous value is kept.

It should be noted here that a sensor is equipped in the mobile terminal to sense for free channels on the neighbour mobile network. Selection of this channel is based on a Q-learning model. Q-value is assigned to each channel based on the time such a channel was involved in successful data transmission. The channel selection routine follows the following process:

(i) Scan the available free channels

At the beginning of scanning, a Q-value of zero is assigned to all channels signifying that the agent knows nothing yet about the mobile network environment.

(ii) Allocation of time stamp

A time stamp is allotted to know the last time the target channel was involved in data transmission. The shorter the time stamp the higher the Q-value. The range of time lag is between 30ms – 3s. This Q-value is based on an exponential function $2^{0.03-T}$, where T is a range between 0.03 and 3. This time lag is chosen because a channel with time lag less than or equal to 30ms is discarded from being saved because it is assumed to be involved in ping-pong handover, while any channel whose time lag is greater than 3s is assumed to be down and hence a channel reactivation subroutine will be activated to restore such channel. This procedure is used in order to reduce the number of channels to the scanned so that the computation of the Q-value converge in reasonable time, the channels whose time stamp is less than 30ms or higher than 3seconds are excluded from the scanning. These are channels which are thought to cause ping-pong effects or defective.

(iii) Selection of channels

The protocol agent stores the channels with the highest two Q-values. The channel with the highest Q-value is the preferred channel on the target mobile network while the other is the back-up channel. Here in case the first channel was busy during the handover request, the back-up channel will be used.

The selection of a channel among the free channels in the target network is modelled as a POMDP and Q-learning. Here at any point in time the busy channels are tracked by appropriate label on the data control packet sent to the mobile

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network. Among the free channels, an algorithm is designed to select the channel with the highest Q-value. The procedure of the algorithm is described in figure 3. The following paragraphs describe the Q-learning algorithm in detail.

The first parameter used in determining the Q-value is RSS (Received signal strength). When the signal strength of the current network is below a threshold value, an alternate network is scanned and the network with the highest RSS value is selected.

The second parameter used to determine the Q-value is the percentage of remaining battery energy of the mobile terminal. The percentage remaining battery energy of battery in the mobile terminal is modelled as an exponential function $\beta = 5^{x/100}$ where β is the rank value and x is the percentage of remaining battery energy of the mobile terminal. This means that the highest Q-value attributed to the battery is 5, i.e. when the percentage of remaining energy in the battery is 100%, while the lowest value is 1, i.e. 5^0.

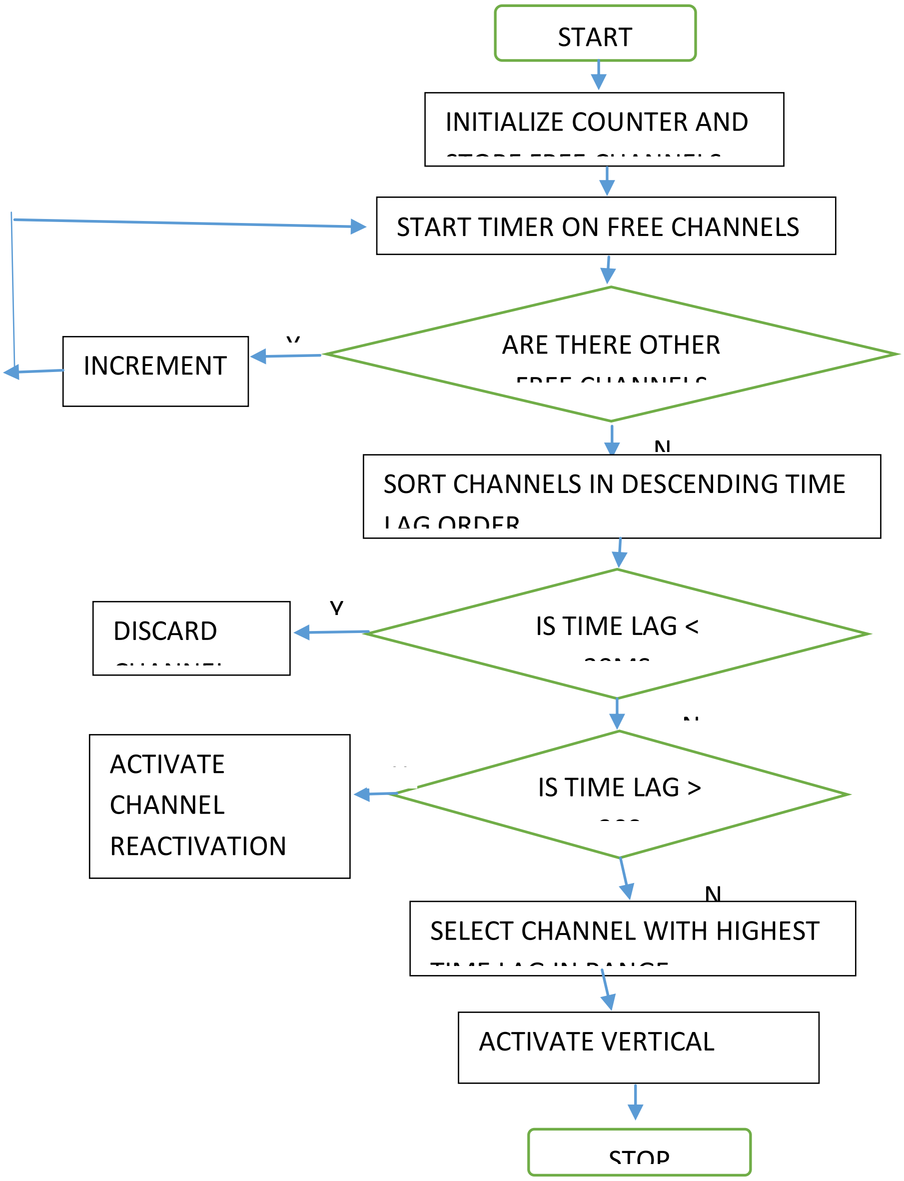

Figure 2 FLOWCHART FOR CHANNEL SELECTION

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(iv) Q-value update

This scan continues until the last free channels are scanned. However at each step a channel is scanned, if the next scanned channel has a higher rank than the current rank the new channel is stored in the Q-learning table, otherwise the current channel is retained. This operation is continued until the last channel is scanned. This procedure enables the channel with the highest probability of success to be selected.

3.2 COST METRICS FOR THE PROTOCOL

This represents the cost function used to calculate the initial value for the VHO (Vertical Handover). It is a combination of the five parameters stated in the previous section. Each parameter is assigned a weighted value to show their relevance to the QoE requirements. The value for the weighted value Y is computed using equation 2.

The initial Q-value is 0 which means that the agent has not learnt about the environment (network). The operation is as follows when a mobile terminal (MT) is in a mobile network field of multiple mobile network namely, Wifi, WimAX and LTE, it computes the Q-value using the formula

Y = μ(RSS) + β(% rem. battery energy of MT) + E(t) + π(velocity of MTl),+ Ω(QoE). ----- (2)

where RSS (received signal strength) is inversely proportional to distance.

$P_r(d) \alpha 1/ \mu$, where $\mu = 1/d^4$, --- (3)

Where $P_i(d)$ is the signal power at distance d and d is the distance between the mobile terminal and the mobile network base station. $\beta = 5^{x/100}$ whereβ is the weighted value for the second parameter, while x is the percentage of remaining battery energy of the mobile terminal. E is the expectation that the channels are free in the neighbour mobile network based on the time lag explained earlier in section 3.1. With this, the requirement that a sensor be equipped in the mobile terminal to sense the status of the channels in each of the mobile network will not be required. The operation of the protocol for selecting the most appropriate mobile network and the corresponding channel is as follows:

(1) When the MT detects a targeted neighbour network, it sends a Link Detected message to the target network, and this message allows the targeted network to recognize the mobile terminal.

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(2) The targeted network replies with a Link Parameters Report message, which contains networkinformation, such as RSSI and the level of Quality of Experience being offered by the new network as shown in equation 3.

(3) The MT passes a control packet consisting of the remaining energy of the mobile terminal and, the QoE and mobility information to the Q-learning model.

(4) Based on this parameters the Q-values for the neighbouring mobile network is computed using equation 3 and the handover routine is activated based on the mobile terminal with the highest Q-value.

(5) After this the MT sends a Handover Initiate message to the mobile network with the highest Q-value in order to trigger the vertical handover.

(6)The MT sends a Link Down control message about the need to change to a new network.

IV. EVALUATION OF THE ARCHITECTURE

This section evaluates the architecture designed to provide both QoE and minimized handover delay with maximized battery power. The performance assessment was carried out through MATLAB and Evalvid Tool (to transmit the video in the simulation) [19]. The aim here is to demonstrate improvements offered by the proposed protocol in relation to the compared architecture researched in the literature. The protocol was compared with those in papers [15–17]. The mobility model used was Random Way Point, so the movements and speed of the mobile users were random in the simulation.

The video used in this simulation was “Sintel”, and it is made up of 1253 frames with the YUV format, sampling 4:2:0 and dimensions of 1080x720, which was compressed through a MPEG-4 CODEC and sent at a 30 frame/s rate [20].The video was chosen because the “Sintel” video is high definition.

The simulated parameters that were configured for all the experiments, are shown in Table 2 which represents the normal values for Wi-Fi, WIMAX and LTE networks. The simulation parameters for the evaluation of energy consumption are described in Table 3. The initial battery voltage was 1000 joules and different power transmission and reception charges were adopted for each technological system. In

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Table 2 Simulation Parameters

	Wifi/Wimax	LTE
Rate transmission	108 Mbps	150 Mbps
Coverage area	100 m	1000 m
Videos	Resolution: 176 x 144 CIF Resolution: 352 x 288 CIF Resolution: 1080 x 720 CIF Frames rate: 30 frames/s Colour Mode: Y, U, V	
Queue	Drop Tail (40 ms delay)	
Packet size	1052 bytes	
Maximum Fragmentation packet	1024 bytes	
Number of simulations	50	
Confidence interval	95 %	
Number of videos	3	

Table 3 Energy Simulated Parameters

	Transmission (W)	Reception (W)
Wifi	1.3	0.9
Wimax	1.9	1.6
LTE	2.4	1.8

The QoE is determined using three parameters (i) Peak Signal to Noise ratio (PSNR) This is a weighted value between 0 and 1 , (ii) Structural similarity Metric (SSIM) (iii) Video Quality metric (VQM). The data are collected using the MSU Video Quality Measurement Tool (VQMT). The PSNR is an estimate of the correlation of the original digital image from the source to the digital image received at the target mobile network. It is expected that the bits representing the source image should most likely match that at the receiver. It is a decimal value between 0 and 1, where 0 means there is a zero correlation with the original image i.e. complete noisy image, and 1 means exactly the same image i.e. with no noise. The SSIM index is a decimal value between 0 and 1, It is used to measure the pixel quality of the source and target image, where 0 means there is a zero correlation with the original image, and 1 means exactly the same image. The VQM determines the level of multimedia quality based on human eye perception and subjective factors, including blurring, global noise, block distortion and colour distortion. The results of the VQM estimates range from values of 0 to 5, where 5 is the best possible score. This is in accordance with the network parameters Ω in equation 2.

In modelling the battery consumption, a different battery model is designed for each of the three mobile network technology considered in this paper, i.e. Wi-Fi LTE and WiMAX, as shown in table 3. Each of this mobile network technologies also have different battery levels for each device status. In each of the considered mobile network. The battery discharge rate is different for idle , send and receive status of the mobile terminal. The network parameters for the three mobile networks is shown in table 2. The battery model used in the simulation was Rakhmatov–Vrudhula,

The algorithm for implementing the Quality of Experience was included in the base stations and access points. The mobile device normally send control packet information to the base station and access point to which it is connected, The base station/access points responds with a measurement of the number of video packets received which is computed against the bench for the video type. This number allows the level of QoE being offered, to be classified.

4.1. The Rakhmatov–Vrudhula Model

The mathematical model used for the energy simulation (equation 4) the Rakhmatov–Vrudhula battery model [21] it takes account of the transmission states, and for each state there is a different type of electric discharge. This model includes different battery capacity and rates of recovery (in idle mode it is possible to increase the lifetime of the battery) for different types of batteries (alkaline, lithium ions).

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$$\alpha = \sum_{k=1}^{n} 2I_{k-1} A\left(L, t_k, t_{k-1}, \beta\right)$$

where, I_{k-1} is the current discharge during the period $k-1$,A represents the discharge rate of the non-linear battery model, L = battery lifetime, t_k is duration time of k period, and t_{k-1} is duration time of k – 1 period and β is the exponential distribution of the remaining energy of the battery of the mobile terminal.

4.2. The Power Consumption Results

This analysis was used to use to compare the battery life when the mobile user is connected in the four architectures used in this paper. From the analysis it was observed that the mobile user in the architecture without Fuzzy System (Original Architecture) was connecte 4 roximately 47 minutes, the connected time in paper [16] was 48,5 minutes, in paper [17] was 51,2 minutes, in the protocol using fuzzy logic, the connected time was 52 minutes and while the mobile user with an energy-saving policy was connected for 58 minutes (Figure 3). There is a gain in energy because with the Q-learning System the handover in the network takes place when the battery level of the device is low. Secondly the increase in connection time is also due to the fact that the decision is discrete, and does not involve an overlap as in the fuzzy logic protocol. In this case, there will be a loss in quality for the user but an increase in the lifetime of the battery.

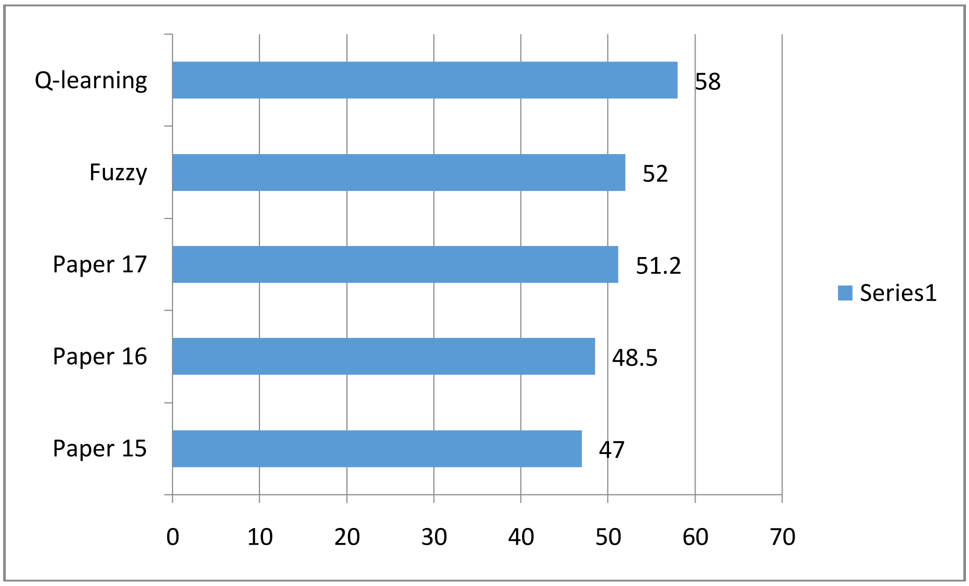

Figure 3 Connection time

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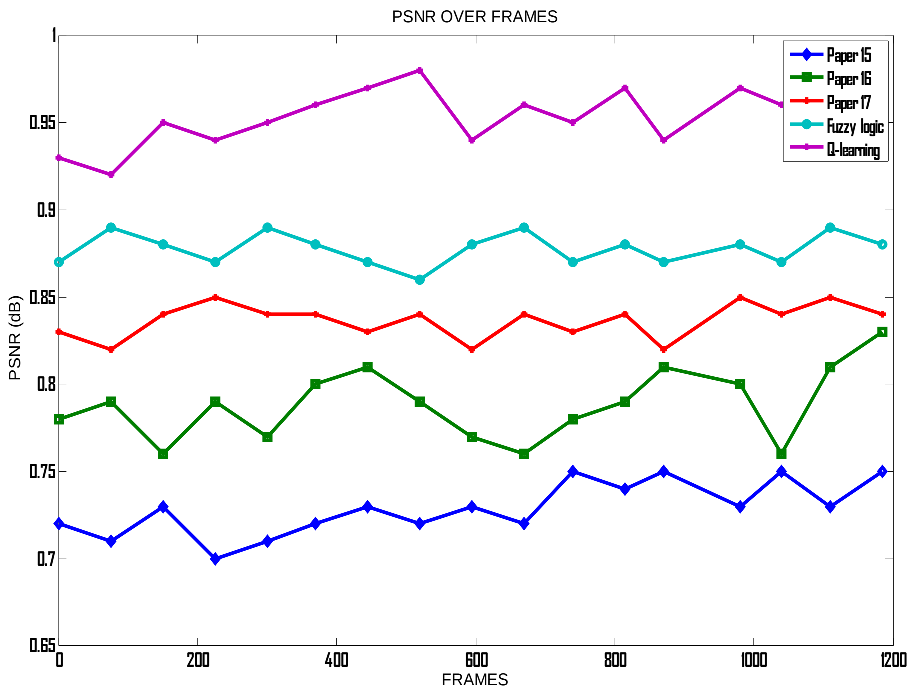

Figure 4

Energy-Saving over time.

The result shown in Graph (Figure 4), shows the enegy savng ability of the Q-learning protocol From the results, the algorithm without fuzzy logic had an average signal to noise ratio of put of 0.95 dB, , the algorithm in paper 16 had an average SNR of 0.83 dB the algorithm n paper 17 had an average SNR of 0.77dB, the fuzzy logic system had an average SNR of 0.9dB while that of the Q-learning algorithm had an average SNR of 0.95dB. This represents an improvement of 6% over the closest algorithm. It can be noted that there is a loss of flow in the high-mobility mobile devices which carried out the ping-pong handover

4.3. QoE Results

This section analyses the simulations with a video application. The video results are evaluated by means of the following objective QoE metrics: (i) Peak Signal to Noise Radio (PSNR), (ii) Structural Similarity Metric (SSIM) and (iii) Video Quality Metric (VQM). The data are collected by using the MSU Video Quality Measurement Tool (VQMT). As explained earlier, the PSNR is a traditional objective method used to estimate the standards of multimedia services based on the opinions of the user. The SSIM index is a decimal value between 0 and 1, where 0 means there is a zero correlation with the original image,and 1 means exactly the same image. The VQM determines the level of multimedia quality based on human eye perception and subjective factors, including blurring, global noise, block distortion and colour distortion. The results of the VQM estimates range from values of 0 to 5, where 5 is the best possible score. In accordance with the network parameters, the Fuzzy system will keep the user longer in the network that offers the best quality.

4.4 Throughput over Time.

In this section, simulation analysis, was done to model mobile devices with high mobility within the coverage area of the networks. From the analysis, it can be deduced that the algorithm without the fuzzy logic i.e. papers [15–17] had no mobile support for the selection of a network, the high-mobility devices carried out the ping-pong handover. In other words, they were connected to a new network, (which was offering less bandwidth) and were later connected again to their previous network. This unnecessary exchange of network impaired the customer flow rate and for this reason the networks provided poor throughput. However in the fuzzy logic system, the high-mobility mobile devices failed to carry out the ping-pong handover thereby maintaining its quality of service. There was further improvement in the system using the Q-learning approach because in certain scenarios where the signal parameters were close the fuzzy system chose one of the network at random, while the Q-learning system was able to select the best

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because of its ability to learn the long term conditions of the network, using its update criteria. The result is shown in Graph (Figure 6), From the results, the algorithm without fuzzy logic had an average throughput of 0.85 Mbps, , the algorithm in paper 16 had an average throughput of 1.2Mbps the algorithm n paper 17 had an average throughput of 1.3 Mbps, the fuzzy logic system had an average throughput of 1.71 Mbps while that of the Q-learning algorithm had an average throughput of 1.96 Mbps. This represents an improvement of 15% over the closest algorithm. It can be noted that there is a loss of flow in the high-mobility mobile devices which carried out the ping-pong handover.

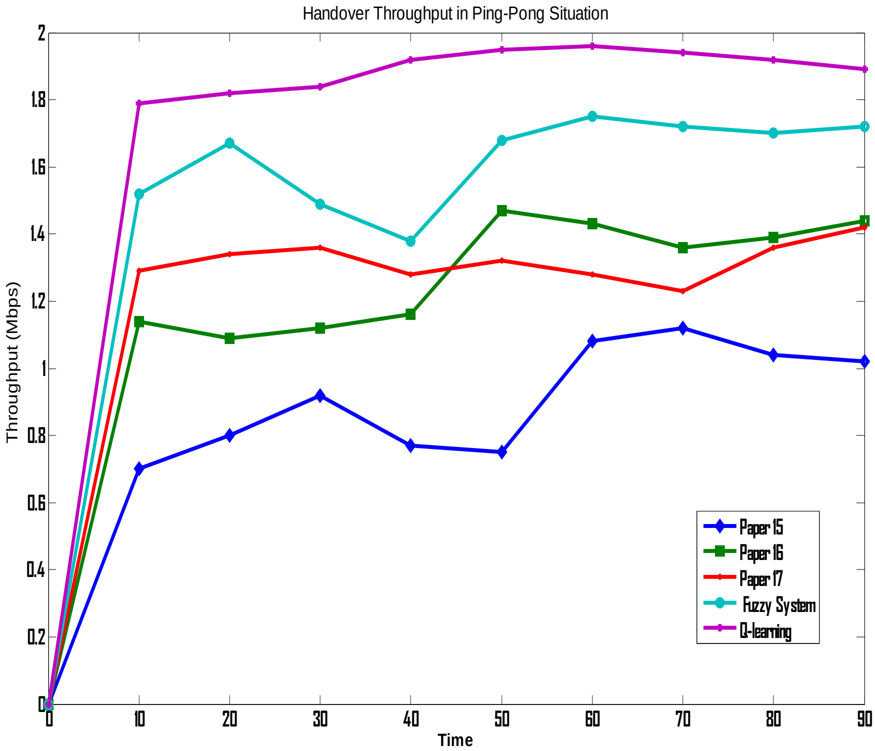

Figure 5 Throughput on ping-pong handover situation.

The videos transmitted with the Q-learning System were superior to the other compared protocols. From the analysis, it can be deduced that the normalized PSNR value for a video without the Fuzzy System was 0.71dB which can be rated as a fair video, the normalized PSNR value for video in paper [16] was 0.78dB and rated as fair video, the normalized PSNR value for video in paper [17] was 0.83dB which can be rated as a fair video, the normalized PSNR value for video in paper using the fuzzy logic was 0.88dB and rated as good video, the normalized PSNR value for video using the Q-learning system was 0.97dB which can be rated as an excellent video. The video transmitted with the Q-learning system had a better performance during the transmission and kept a balance between energy and QoE (see Figure 6).

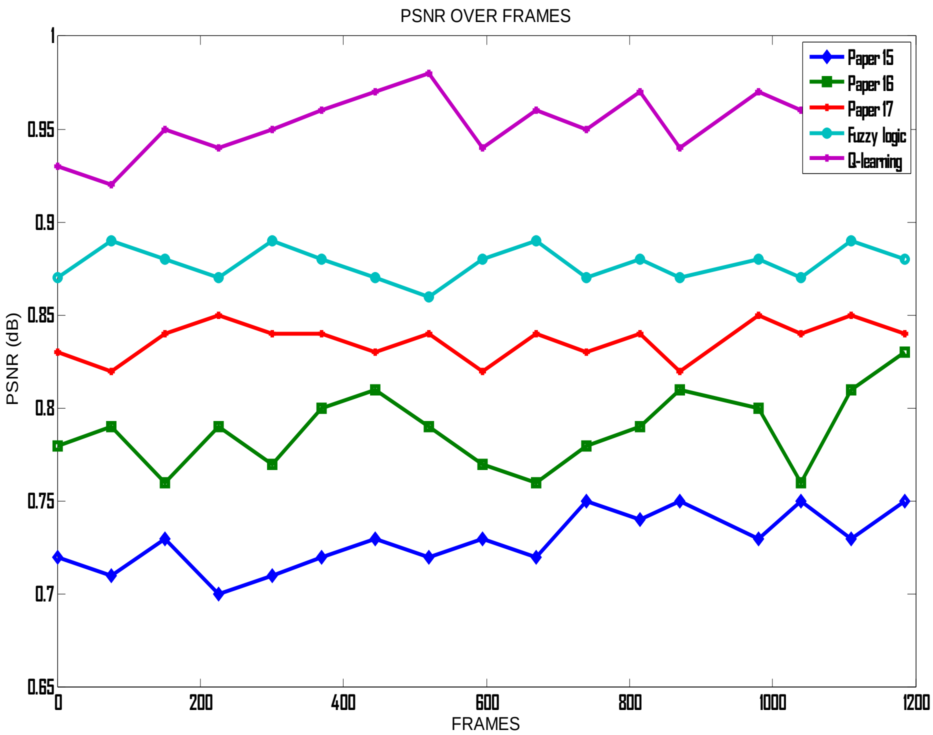

Figure 6 PSNR over frames

The reason for this improved performance is attributed to the fact that that the Q-learning system includes in its algorithm a feature that enables a user to select the type of video he/she prefers before the computation of the Q-values were effected. This is unlike in the case of the fuzzy logic and the other compared protocols where a generalized scenario of user experience paradigm is used. The use of an explicit user experience parameters as in the case of Q-learning brings about better user satisfaction. From the analysis, it can be seen that the Q-learning algorithm has an improvement of 10% over the closest algorithm.

The second parameter used for the QoE was the SSIM value. From the analysis,it can be deduced that for a video without the Fuzzy System [15], the SSIM value was 0. 71, the SSIM value for video in paper [16] was 0,78, the SSIM value for video in paper [17] was 0,83, the SSIM value for video using the fuzzy logic was 0,87, while the SSIM value for video using the Q-learning was 0,95 (see Figure 7. This represents an improvement of 8% over the algorithm which employed the fuzzy system. This improvement can be attributed to the up to date information received from the mobile networks by the Q-learning agent. Secondly the Q-learning agent is also able to take definite action on the mobile network for handover quicker than the fuzzy system

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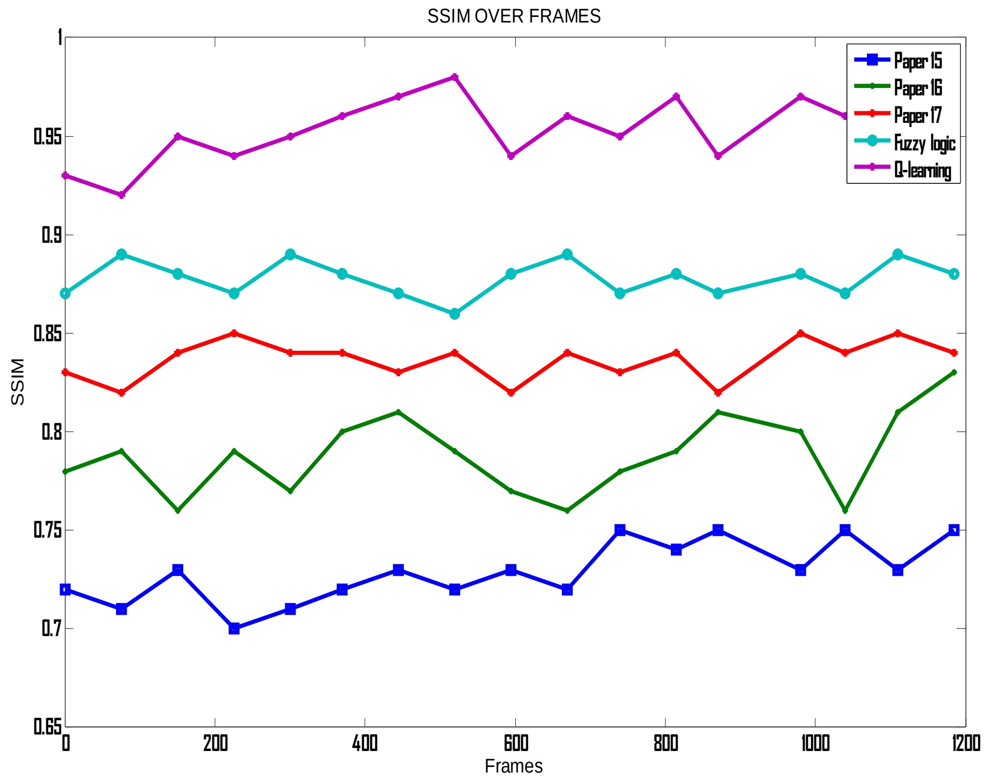

Figure 7 SSIM over Frames

The third parameter used for QoE was the VQM value. It can be deduced from the simulation as shown in figure 8 that, for a video without the Fuzzy System [15], the average value for the VQM was 2.08, the average value for the VQM for video in paper [16] was 2.57, the average value for the VQM for video in paper [17] was 3.03, the average value for the VQM for video using fuzzy logic system [18] was 3.39, while the average value for the VQM for video using the Q- learning algorithm was 3.78. This represents an improvement of 12% over the fuzzy system which is the best among the other compared protocols.. he reason for this is as explained for the other video parameters i.e. SSIM and PSNR.

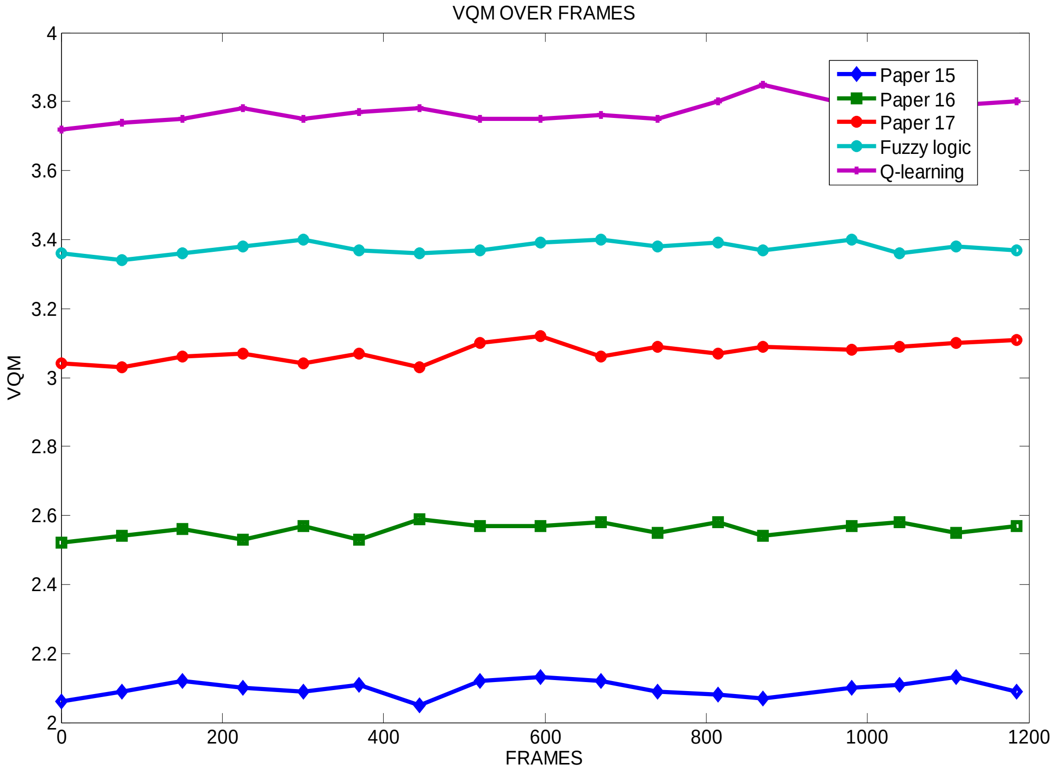

Figure 8 VQM over frames

Finally figure 9 shows the simulation analysis for the delay in handover from one mobile network to another. From the figure it can be deduced that the video transmitted with the Q-learning system had a better performance, since the delay was less than the video transmitted with the other compared protocols. For the video without the Fuzzy System [15], the average delay was 0.33 ms,, the average delay for the protocol employed in paper [16], the average delay was 0.21 ms, the average delay for the protocol employed in paper [17] was 0.13 ms, the average delay for the paper that used the fuzzy logic system was 0.09 ms while the average delay for the Q-learning protocol was 0.06 ms. A lower delay signifies ,a faster and more efficient delivery of the frames (packets). The results from this analysis confirms the superiority of the video transmitted with the Q-learning system. It also shows an improvement of 30% over the protocol that employed the fuzzy logic system. which is the best among the other compared protocols. This improvement can be attributed to the quicker decision made by the Q-learning agents especially after the Q-values in the protocol have converged. The update received by the agent from the various mobile network enables it to make a fast and informed decision over the best network and channel for handover.

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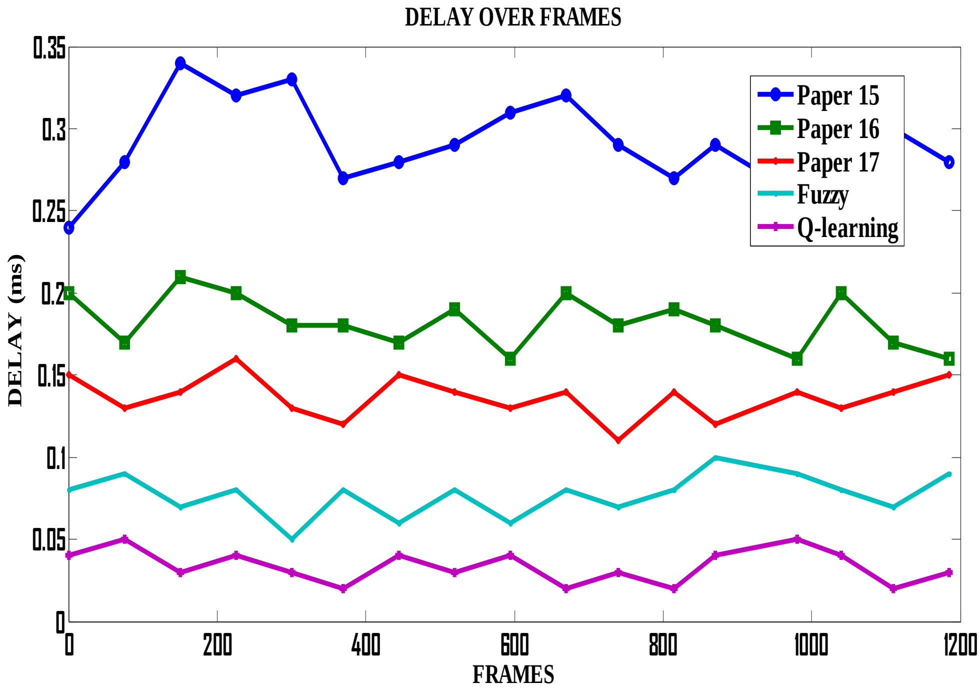

Figure 9 Delay over Frames

V. CONCLUSION AND SUGGESTIONS FOR FUTURE WORK

Due to the different multimedia experience required by users over the internet, mobile devices must be compatible to different mobile networks. This is because different multimedia applications perform best under different mobile networks. Also the requirements of users vary, hence it is necessary that they should have the freedom of selecting the type video quality they need, and this will translate to a protocol being able to select a network that will meet the user's expectation. These myriad of requirements needs a protocol that does not involve an explicit model of the environment, due to the energy constraint of the mobile terminals

This paper proposes a Heterogeneous Wireless System formed of LTE, Wifi and Wimax networks that makes use of Q-learning algorithm to support an energy-efficient approach for saving battery power, while also satisfying the QoE requirements of the users. The simulation analysis performed in this paper has justified this assertion.

In future studies, the architecture will include new technologies, inputs for the Q-learning Systems, and battery models, as well as dynamic scenarios with mobile users competing in more mobile networks.

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