A Hybrid Intelligent Model for Network Selection in the Industrial Internet of Things

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ABSTRACT

Industrial Internet of Things (IIoT) plays an important role in increasing productivity and efficiency in heterogeneous wireless networks. However, different domains such as industrial wireless scenarios, small cell domains and vehicular ad hoc networks (VANET) require an efficient machine learning/intelligent algorithm to process the vertical handover decision that can maintain mobile terminals (MTs) in the preferable networks for a sufficient duration of time. The preferred quality of service parameters can be differentiated from all the other MTs. Hence, in this paper, the problem with the vertical handoff (VHO) decision is articulated as the process of the Markov decision aimed to maximize the anticipated total rewards as well as to minimize the handoffs' average count. A rewards function is designed to evaluate the QoS at the point of when the connections take place, as that is where the policy decision for a stationary deterministic handoff can be established. The proposed hybrid model merges the biogeography-based optimization (BBO) with the Markov decision process (MDP). The MDP is utilized to establish the radio access technology (RAT) selection's probability that behaves as an input to the BBO process. Therefore, the BBO determines the best RAT using the described multi-point algorithm in the heterogeneous network. The numerical findings display the superiority of this paper's proposed schemes in comparison with other available algorithms.

1. Introduction

Heterogeneous wireless networks that are used for seamless mobility often face prominent problems in the industrial internet of things (IIoT), a system in which different networks and technologies are working together. This is because there are different factors that would significantly affect the various technologies used for accessing the network, such as the optimized handovers or vertical handovers. Some of these factors are congestion, load, strength of the signals, bandwidth, connection stability, battery life as well as other factors that are temporal and spatial. A mobile user in a heterogeneous wireless network might have to carry out the handovers over various network domains to sustain the connection of data and QoS. The VHO process can be categorized into 3 stages consisting of the information gathering handover, decision-making of the handoff, and the execution of the handoff. The information that is acquired is utilized to identify the present and most suitable networks for specific applications in the following stage which is known as the stage of handover decision-making.

The industrial IoT is an emerging application of IoT technologies in several situations such as automation, intelligence controls, smart buildings, intelligent transportations, and smart grids [1, 2]. Without the creation of an infrastructural network, the adoption of industrial IoT solutions will be impossible. It is important to consider specific IoT characteristics while adapting these techniques for wireless IoT networks. One of the important features of IoT networks is the collaboration among heterogeneous IoT devices. With rapid improvement in digital electronics and wireless communications, the application areas of the Internet of Things (IoT) have increased significantly. It now supports a wide

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range of applications including industrial automation, intelligent transportations, medical and eHealth care services [3]. Low-weight efficient communication between sensing devices and interoperability between different communications mechanisms are the critical problems faced by the IoT.

Several challenges are present in the wireless multi-hop networks [4– 7] as well as in the decision stage of the vertical handover while the handover procedure is going on. At certain times, the terminal is rapidly moving in its path. Thus in this type of robust scenarios, the algorithm that supports the VHO decision stage must also be quick and offer solutions as close to real-time as possible. In fact, in the future, mobility and ubiquitous network access are the main drivers for the Internet. However, the existing algorithms for decision making use many parameters for the loading-point mathematical measurements, and several parameters for the QoS or the discovered networks which are available during terminal movement. The high computations are in contrary to the low response time, especially in low performance processors that are found within most mobile devices. Thus, there is a need to design an efficient algorithm capable of performing intelligent decision-making and dynamic adaptation to different situations in a proper time frame due to rapid changes in the wireless environment.

Existing algorithms for the vertical handover decision such as those that include computational intelligence methods were proposed in recent studies [8–13]. Wilson et al. [14] reported that certain algorithms are based on multiple criteria [15, 16] which need assistance from artificial intelligence mechanisms including fuzzy logic [17], neural networks, as well as algorithms that genetically suffered from problems of modularity and scalability. These were not able to easily manage the increasing number of RATs as well as the criteria for heterogeneous wireless networks. This type of algorithms engage the entire input of the various RATs simultaneously to a single fuzzy logic block, which resulted in problems of modularity and scalability when RATs or functions of membership were increased given the tremendous rise of the amount of inference rules [14].

In addition, [18] suggested a mobile node (MN) prediction scheme that was mobile. In particular, they first utilized the probability as well as the process of the Dempster–Shafer to predict the tendency of the following destination for mobile network users that are arbitrary according to the habits of the users, such as locations that were often visited. Next, at every junction of the road, the chain process of the second-order Markov was applied to predict the tendency of the following road transition segment, based on the route of the original trip to that particular junction of the road as well as the destination direction. The proposed scheme was assessed based on actual mobility traces and the simulation's findings showed that this proposed method outperformed other conventional methods.

In this research, the Markov models are used to analyze the systems according to the real life system of actual behavior, which results in trustworthiness as well as cost-effective estimation for the prediction of performance and mobile system optimization. In this work, we proposed an algorithm for decision making on vertical handoff for networks that are wireless and heterogeneous, and used MDP as a strong technique for making decisions in developing an adaptable algorithm. This issue is articulated as a process of the Markov decision that is integrated with the BBO. A link reward function is proposed to model the properties of the QoS. In addition, a cost function for the signaling overhead as well as the processing load during the occurrence of the vertical handoff is proposed. Moreover, the mobile QoS relates to the packet loss, delay in the VHO and the cost of signaling. The total cost for signaling is highly dependent on the information as well as the information gathering method. Hence, an analytical model which involves the metrics that describes the handoff as well as the cost of signaling, packet loss, and the VHO delay is presented to assess performance.

The proposed technique for the dynamic handoff is based on the Markov decision process and is used to improve the network's performance as inspired by [19]. It assists in finding the overall cost function. Furthermore, Markov models are analytical methodologies for the analysis of such systems based on actual real life system behaviors, leading to both credible and cost-effective approximations for performance prediction and optimization of mobile systems. Hence, the Markov process is utilized in the performance modeling of wireless and mobile communication systems.

This study presents a vertical handover decision algorithm based on two main schemes, namely the BBO [20-22] as well as the MDP [23]. The process of the Markov decision formulates the problem. The Markov chain method is preferable when developing the cost model. The QoS optimal values can also be established in the wireless networks by utilizing the Markov process to minimize the cost function. Thus, this study's objective is to propose a new optimized algorithm with the benefit of two current approaches that address the requirements stated above.

There are recent relevant cases that can be adopted by our proposed hybrid model. The cases with utility potential can be categorized into four main classes namely industrial wireless scenarios, vehicular ad hoc network (VANET), wireless backhaul for small cell domains and unmanned aerial vehicles (UAV) deployment scenarios for disaster management. In industrial scenarios, the manufacturing cells and factories with multiple access points are serving multiple mobile robots. In these cases, mobile communications need to conduct vertical handovers to use robust links with low latency and higher mobility among multiple access points. Also, vehicular networks require seamless mobility designs because coverage is often incomplete with very short communication which needs high-speed transmission over heterogeneous networks that have different access technologies. Even though the backhaul is point-to-point, it requires a vertical handover to use the parallel radio links with low latency for 5G and the Internet-of-things (IoT). The usage of UAVs in disaster management has some networking-related research challenges such as handover among the UAVs. A handover consists of replicating the exact operational state in each UAV such as forwarding tables, packets in the buffer, and data fusion rules which increases messaging between the UAVs. Motivated by these observations, we have proposed an efficient algorithm to perform intelligent decision-making during the vertical handover process.

The rest of the paper is organized as follows. The related work is carried out in Section 2. Section 3 describes the network model and Section 4 formulates the problem of the VHO as the Markov decision process. Section 5 describes the process of biogeography based on optimization and presents the designed solution. Section 6 discusses the proposed scheme and the results obtained are expounded in this section. Finally, Section 7 will present the conclusion.

2. Related work

In most of the existing studies, a wireless environment is limited to a notebook or a mobile phone used over a pedestrian mobility scenario or a model with low mobility levels. In addition, many of these studies assess the VHO by just utilizing two technologies namely the WiFi and the UMTS, and only a few studies have even taken into consideration more than three technologies [24]. In the past decade, vehicular communication has been enhanced to include communication devices of short and long distances, the GPS, as well as vehicle sensing systems. The capabilities of communication utilize an extremely robust vehicular environment [25]. Using GPS information to enhance the process of handover and the selection of network within the parameter of a single wireless network has also been widely studied [26–28].

Existing algorithms in [29] take into account the service charges, information on received signal strength indicator (RSSI) and user preferences. As opposed to the conventional RSSI based algorithm, the algorithm that is proposed significantly improves the outcomes for users and the network due to the proposed fuzzy-based handover techniques. Furthermore, a fuzzy-based algorithm greatly lowers the number of handovers in comparison to a SAW-based algorithm. This algorithm is able to switch between GSM, WiFi, UMTS, and WiMAX. Nevertheless, this algorithm has several disadvantages cased by its high execution duration that could cause high handover latency. In addition, interface engine inputs could be become more accurate by utilizing artificial intelligence approaches, such as the neural network. The research excluded the effects of other environmentally linked determinants and findings in order to examine the mobile parameters of the QoS including the delays in handover as well as packet loss.

Given the emergence of new wireless technologies over the last decade, certain researches [30-33] have attempted to address the issue of VHO over various types of wireless technologies including WiFi, UMTS, LTE, ZigBee, wireless broadband, RFID, multimedia broadcast/multicast service, digital video broadcasting and low Earth orbit (LEO) satellite [34].

Wang et al. [35] proposed a VHO approach, which utilizes certain factors including the data rate, RSS, the trend of movement, and the bit error rate (BER) that enables the selection of the best-suited network along with the parameter of the prioritized decisions. The decision tree is utilized in this approach according to the selected parameter at each node of the decision-making process, where it could stop or continue at that point accordingly. Moreover, this approach takes into consideration the underlying connecting technology including IEEE 802.11p, 3G, or WiMAX.

Cross layer handover strategies can be projected to offer services that are seamless for mobile terminals within the heterogeneous networks that are wireless [36-38]. By intending to lower the delay period during handovers, the link layer ought to activate the handover protocols of the 3 layers in a timely manner. This would enable them to complete the handover processes before the present wireless link terminates. Due to the restricted power of computing within the mobile terminal as well as a bigger rate of packet loss in the vertical handover [39], a novel mechanism for triggering based on gray predictions was proposed. First, the duration needed to perform the handover was projected. Second, the time to trigger a Link_Going_Down was identified based on the convex optimization theory, where both the signal strength received from the presently linked network as well as the targeted access network was taken into account. Simulation findings proved that the mechanism could achieve more accurate predictions using the similar prediction method [40]. Besides that, the rate of packet loss could be controlled to 5% where the moving speed of the terminal was 5m/s or less.

In [41], Nadembega et al. proposed a novel dynamic access network selection algorithm which was capable of adapting to prevailing network conditions. Their algorithm was a dual stage estimation process where network selection was performed using the sequential Bayesian estimation which relied on the dynamic QoS parameters that were estimated through bootstrap approximation. Simulations demonstrated the effectiveness of the proposed algorithm which outperformed static optimization approaches in a highly efficient manner. However, this algorithm suffers from high computation times. Moreover, according to Ong et al. [42] the network selection problem in heterogeneous wireless networks with incomplete information was formulated as a Bayesian game. Every user has to decide on an optimal network selection based on only partial information about the preferences of other users. The dynamics of network selection were applied using the Bayesian best response dynamics and aggregated best response dynamics. The Bayesian Nash equilibrium was considered to be the solution of this game, and there was a one-to-one mapping between the Bayesian Nash equilibrium and the equilibrium distribution of the aggregate dynamics. The other dynamics of the network selection were applied using the maximization scoring function [43], designing an algorithm and protocol that takes into account the QoS parameters when the end user is receiving IPTV [44] and scheming depending on the requirements of the IPTV client [45]. Also, other proven algorithm types for the decision phase included multiple criteria decision-making (MCDM) algorithms, such as simple additive weighting (SAW) and technique for order preference by similarity to ideal solution (TOPSIS) [46]. There have been evaluations on the workings of the proposed scheme against the TOPSIS [47] and grey relational analysis (GRA) [48] decision-making models.

Researchers in [49] developed an algorithm which could reduce computing time by preventing large and slow computing due to direct search techniques. The selection of an optimal wireless network to set the link required a metric, one that could relay the quality level of the network that was available within a fixed duration. The network quality was measured using certain weights allocated to the quality of service parameter based on user preferences. The function of fitness (F) was responsible for providing this measure as inputted in the phase for VHO decision making. Some of the algorithms in this research included the SA that was based on an adaptive method and GA which was based on an evolutionary method. The SEFISA is a heuristic proposition derived from the SEFI based on the Simulated Annealing (SA) algorithm. The algorithm for SA was instigated from the process of cooling metal, which includes searching for a final minimum energy structure. After going through several stages, the final structure which has a more cooled structure is achieved. Researchers in [49] introduced an algorithm using the Genetic Algorithms (GAs) to get a higher level of performance compared to the SEFISA. They managed to work through certain limitations including the generation of numbers, the emergence of the stop factor, overflow of limits for search space, stagnation in the optimized solution, etc. In the end, the Genetic Algorithms had the best performance in terms of computing time and precision even when compared against the better performing algorithms.

In conclusion, based on the literature review, the hybrid VHD algorithm utilizes certain forms of intelligence for decision-making and it is able to robustly adapt to situations regularly due to the necessary dynamic changes in the wireless environment. In the next section, we mainly describe the network models involved in network selection during the vertical handover process in heterogeneous wireless networks.

3. Network model

Wireless heterogamous networks consist of different types of networks such as wireless personal area (WPAN) networks, wireless wide area (WWAN) networks, as well as Wireless Local Area (WLAN) networks. The various networks in this situation that are using both 3GPP (HSPA, EDGE, LTE, UMTS) as well as non-3GPP (WiFi, WiMax) standards must be inter-linked optimally in order to ensure the Quality of Service provided to the users. This research offers three settings that define handover signaling to achieve integrated WiMAX, WiFi, as well as UMTS networks. The first setting demonstrates the signaling in which the MT is found in the overlapping area and is able to select a connectivity that is better, hence utilizing the ABC concept. Fig. 1. reveals the MT in the overlapping area between WiFi and WiMAX. The next setting denotes the signaling for a user who is obliged to implement the handover since the present connectivity will be lost as it is moving into a tunnel or a subway, as shown in Fig. 1. through the WiMAX movement to the UMTS. The third setting demonstrates the signaling whereby the MT is found in the overlapping area and is able to select a connectivity that is better, utilizing the concept of ABC. Fig. 1. reveals the MT in the overlapping area between UMTS and WiFi.

There are two factors tha should be taken into consideration when making a decision on the handoff. Firstly, the MT should aim to maximize using a high bandwidth with a low network access cost while reducing the amount of handovers that are not needed. This would prevent the degradation of the QoS of the present communication as well as prevent overloading the network with signaling traffic.

All mobile connectivity would undergo a certain amount of vertical handoffs within its lifetime connectivity. It is assumed that the mobile terminal receives information from the networks that are located within regular receiving ranges. The information that is advertised from the networks could engage with usable bandwidth with a delay time that is acceptable, which the IETF IP performance metrics process is able to estimate. At each point in time, the terminal for the mobile establishes whether the connectivity should utilize the network that has been presently chosen or if it should route to some other network with a higher level of performance with reduced cost and a guarantee of a higher QoS. The connectivity re-routing involves a complicated and challenging process, which would in turn cause the signaling load as well as the processing to go up. Therefore, a tradeoff occurs between the connection’s QoS and the signaling load as well as the processing [50].

4. A Markov decision process used for the VHO decision problem

The subsequent sections will describe the methods used to design the decision problem of the vertical handoff as the process of a Markov decision [51]. A decision model using the Markov process has certain main elements. These include the decision epoch, state, action, transition probabilities, and the rewards. The MT establishes the course of action when it has passed the particular time duration. As the MT velocity has physical property constraints and its future speed is not influenced by past speeds, this study has adopted the Gauss-markov model suggested by [52] to define the mobility model. Shadow fading as well as the mobility of the MT might result in signal attenuation in a wireless environment. The RSS is described in dBm in discrete time [53]:

$$RSS[t] = P_T - L - 10n\log(d) + N[t] \tag{1}$$

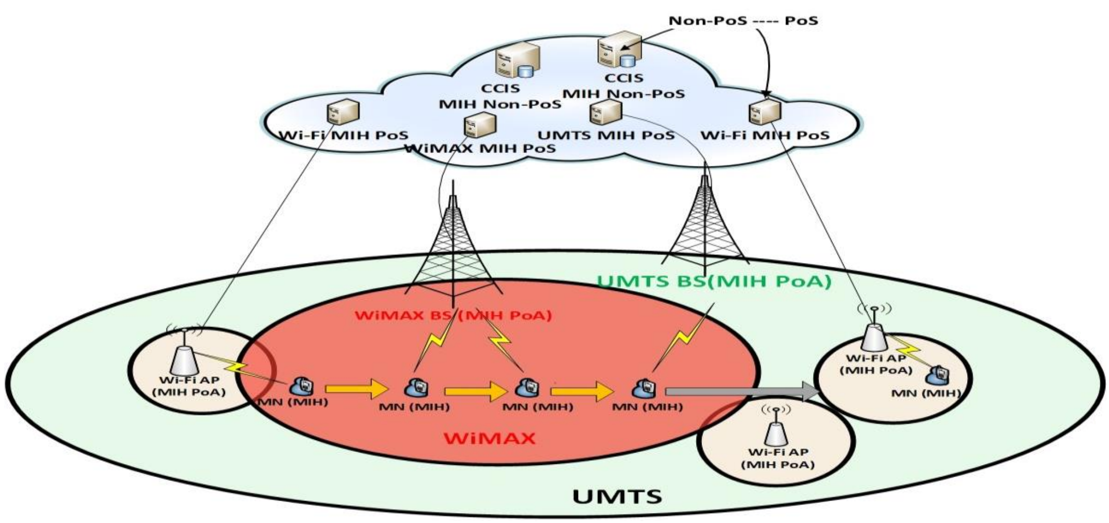

Fig. 1. Heterogeneous wireless networks.

Where t represents the discrete time index, P_T represents the power transmission of AP, L represents the pass loss that is fixed, n represents the pass loss factor, d represents the distance in the WLAN's MT as well as the AP, and $N[t]$ represents the fading of the shadow. The MT is able to interact with the present network when the value of the RSS is above the threshold. The average RSS is defined as shown in the following:

$$\overline{RSS} = \frac{\sum_{i=0}^{S_{av}-1} RSS\,[t-i]}{S_{av}} \tag{2}$$

Where S_{av} represents the average size of the window in the slope estimation and $R\,[t]$ represents the changing rate of the RSS. The threshold for handoff is a significant parameter that directly affects the performance of the network. As the threshold value of the handoff is fixed and not able to adapt to the network conditions that vary according to time, we have designed the relationship between the velocity of the MT and the threshold value of the handoff as:

$$TH\,[t+1] = TH + \omega \times \frac{V_t}{V} \tag{3}$$

Where TH represents the basic threshold for the handoff, ω represents the adjusting weight that is linked to the present state of the network, V_t represents the present MT velocity while V represents the original velocity. The sampling size of the window is considered when calculating the RSS average value and changes based on the mobility of the MT by using the equation S_{av} and S_j as $S_{av} = \left\lfloor \frac{D_{av}}{VT_j} \right\rfloor$ and $S_j = 2\left\lfloor \frac{D_S}{VT_j} \right\rfloor$ in [6]. D_{av} and D_S represents the window's average and the window's slope distance, respectively. The probabilities of the transition are described in Table 1.

The conditional probabilities of $P_{\text{Mobile input/output}}$ [t + 1] depend on the decision approach. In line with [54], these probabilities are also defined as:

$$P_{\text{Mobile input/output}}\ [t+1] = P_{(SN\ |PN)}[t+1]P_{CN}[t] \tag{4}$$

Where $P_{SN}|P_{PN}$[t] represents MT's probability of linking to the chosen network at the t instant as it is related to the past network at the t-1 time instant. The amount of handoffs, represented by N_{HO}, has an effect on the flow of the signaling, and it is the sum total of the Mobile's input as well as output. Thus, N_{HO} is represented by the instant probability of Mobile input and output as per Equation (4). The equation for N_{HO} is:

$$E\{N_{HO}\} = E\left\{\sum N_{\text{Mobile input/output}}\right\} = \sum_{t=1}^{t_{max}} (P_{\text{Mobile input/output}}[\text{t}]) \tag{5}$$

Where t_{max} represents the time instant as the MT reaches the edge, and it is represented by the velocity of the MT and the present network's coverage. $N_{\text{Mobile input/output}}$ represents the expected numbers of $N_{\text{Mobile input/output}}$.

Table 1 Transition probabilities.

Parameter	Description
$P_{WiFi}[t]$	MT's probability of connecting with the Wi-Fi at the t time instant.
$P_{WiMAX}[t]$	MT's probability of connecting with the WiMax at the t time instant.
$P_{WiMAX}\|P_{WiFi}[t]$	MT's probability of connecting with the WiMax at the t time instant given that it is associated with the Wi-Fi at $t-1$ time instant.
$P_{WiFi}[t+1]$	$P_{WiFi}\|P_{WiMAX}[t+1]P[t] + (1 - P_{WiMAX}\|P_{WiFi}[t+1])P_{WiFi}[t]$
$P_{WiMAX}[t+1]$	$P_{WiMAX}\|P_{WiFi}[t+1]P[t] + (1 - P_{WiFi}\|P_{WiMAX}[t+1])P_{WiMAX}[t]$
$P_{WiMAX}[t]$	MT's probability of connecting with the WiMax at the t time instant.
$P_{LTE}[t]$	MT's probability of connecting with the LTE at the t time instant.
$P_{LTE}\|P_{WiMAX}[t]$	MT's probability of connecting with the LTE at the t time instant given that it is associated with the WiMAX at $t-1$ time instant.
$P_{WiMAX}[t+1]$	$P_{WiMAX}\|P_{LTE}[t+1]P[t] + (1 - P_{LTE}\|P_{WiMAX}[t+1])P_{WiMAX}[t]$
$P_{LTE}[t+1]$	$P_{LTE}\|P_{WiMAX}[t+1]P[t] + (1 - P_{WiMAX}\|P_{LTE}[t+1])P_{LTE}[t]$
$P_{LTE}[t]$	MT's probability of connecting with the LTE at the t time instant.
$P_{WiFi}[t]$	MT's probability of connecting with the Wi-Fi at the t time instant.
$P_{WiFi}\|P_{LTE}[t]$	MT's probability of connecting with the Wi-Fi at the t time instant given that it is associated with the LTE at $t-1$ time instant.
$P_{LTE}[t+1]$	$P_{LTE}\|P_{WiFi}[t+1]P[t] + (1 - P_{WiFi}\|P_{LTE}[t+1])P_{LTE}[t]$
$P_{WiFi}[t+1]$	$P_{WiFi}\|P_{LTE}[t+1]P[t] + (1 - P_{LTE}\|P_{WiFi}[t+1])P_{WiFi}[t]$

$T = \{1, 2, \ldots, N\}$ sequence demonstrates the moments of successful decision making time. N, which is the random variable, represents the duration taken for the connection to terminate. The terminal that is mobile has to establish decisions at each point of time for the connection to utilize the network that is presently selected or it would face re-routing to other networks.

M represents the sum of networks that are collocated. The A action $set = \{1, 2, \cdots, M\}$ as well as the Y_t random variable represents the action selected during the decision epoch t. The terminal that is mobile selects an action according to the present state of information as represented by S. In every $s \in S$ state, the state information involves the network's number of identification or the address to which the terminal that is mobile is presently linked to the bandwidth that is available, the average delay and the probabilities of packet loss offered by all the available networks collocated in the area.

The random X_t variable represents the state at which the t decision epoch is made. The present state is represented with an s while the action that is selected is represented by a. Thus, the probability of the transition function for state at the next s'state is represented with a $P\ [s' |\ s, a]$. This can be identified as a Markovian function as it relies solely on the present state as well as action.

The function for the rate of transition at $f\ (X_t, Y_t)$ represents the QoS that is offered by the network that is selected to connect at intervals of $(t, t+1)$. Function of cost, which is $c\ (X_t, Y_t)$ represents load for signaling as well as the processing that occurs during the time when the connectivity moves from one network to the other. If the connection maintains the utilization of a similar network over the duration of the intervals, $(t, t+1)$, thus c (X_t, Y_t) would be equivalent to zero. It is defined as follows for easy interpretation: r (X_t, Y_t) = f (X_t, Y_t) - c (X_t, Y_t).

The decision rules offer the process of choosing the actions at every state of particular decision epochs. Decision rules that are Markovian in nature are functions of δ_t: S → A, as it identifies the action choice while the system possesses the s state at the decision epoch of t. The policy of π = $(\delta_1, \delta_2, \ldots, \delta_N)$ represents the sequence for the decision rule that is utilized at all the decision epochs.

If v^{π}(s) denotes the total reward that is expected of the first decision epoch up until the conclusion of this connectivity while the π policy is utilized with the initial s state, the following is expected:

$$v^{\pi}\ (s) = E_s^{\pi}\left[E_N\left\{\sum_{t=1}^{N} r(X_t, Y_t)\right\}\right] \tag{6}$$

Where E_s^{π} represents the expectation in terms of policy π and the initial s state and E_N represents the expectation in terms of random N variable. It should be noted that a different policy π and the initial s state would change the selected a action. It could also lead to different probability functions for state transitions at $P\ [S'|s, a]$for utilization in the anticipated E_s^{π}. The N random variable representing the termination point of the connectivity is presumed to have a geometric distribution with a mean of 1/ (1-λ). It can be written as follows based on [55]:

$$v^{\pi}\ (s) = E_s^{\pi}[\{E_s^{\pi}\left[\left\{\sum_{t=1}^{\infty} \lambda^{t-1}\, r(X_t, Y_t)\}\right\}\right] \tag{7}$$

Where λ is inferred as the model's discount factor at $0 \leq \lambda < 1$.

The state space of S is described as follows in the proposed decision algorithm for vertical handoff:

$$\begin{aligned} S = \{1,2, \ldots, M\} \times B^1 \times D^1 \times P^1 \times TH^1 \times BER^1 \times C^1 \times Sec^1 \times J^1 \times B^2 \times D^2 \times P^2 \times TH^2 \times BER^2 \times C^2 \times S^2 \\ \times J^2 \times \ldots \times B^M \times D^M \times P^M \times BER^M \times C^M \times S^M \times J^M \end{aligned} \tag{8}$$

Where M is the quantity of available networks that are collocated and B^m , D^m, P^m , TH^m, BER^m , C^m , S^m and J^m are the set of bandwidths, packet loss, delay, throughput, cost of bit error rate, security, and jitter that are available from the m network ($m = 1, 2, \ldots, M$), accordingly. Given the present s state as well as the selected a action, the function of the link reward$f\ (s, a)$ is described as follows:

$$f(s, a) = \omega f_b(s, a) + \omega f_d(s, a) + \omega f_p\ (s, a) + \omega f_{th}(s, a) + \omega f_{be}(s, a) + \omega f_c(s, a) + \omega f_s(s, a) + \omega f_j(s, a) \tag{9}$$

Where ω represents the factor of weight and $0 \leq \omega \leq 1$, a suitable weight factor represents every parameter in the significance of the vertical handoff decision. Based on Equation [9], $\mathrm{f_b}(s, a)$ represents the function for bandwidth whereas $\mathrm{f_d}(s, a)$represents the function of delay, $f_p(s, a)$ represents the function of packet loss, $f_{th}(s, a)$ represents the function of throughput, $f_c(s, a)$ represents the function of monetary cost, $f_s(s, a)$ represents the function of security, $f_j(s, a)$ represents the function of jitter, and $f_{be}\ (s, a)$ represents the function of bit error rate. The following is utilized for every QoS parameter:

$$f_{QoS}(s, a) = \begin{cases} 1, & 0 < QoS_a \leq L_{QoS} \\ (U_{QoS} - QoS_a)/(U_{QoS} - L_{QoS}), & L_{QoS} < QoS_a < U_{QoS} \\ 0, & QoS_a \geq U_{QoS} \end{cases} \tag{10}$$

Where the constants L_{QoS} and U_{QoS} represent the minimum as well as the maximum e QoS rate needed by the connectivity. The reward function r (s, a) of the two continuous handoff decision epochs that are vertical can be described as follows:

$$r(s, a) = f(s, a) - c(s, a) \tag{11}$$

The total cost function is given by,

$$c(s,a) = w_g\ g(s,a) +\ w_v V(s,a) \tag{12}$$

and the factors of weighting fulfill w_g+ w_v =1. The $g(s,a)$ function for signaling cost is represented in the following:

$$g(s,a) = \begin{cases} SC_{i,a,} & i \neq a \\ 0, & i = a \end{cases} \tag{13}$$

Where $SC_{i,a}$ represents the switching cost (involving the signaling load as well as the re-routing operations) from the present i network to the new a network. Furthermore,

$$v(s,a) = \begin{cases} v - v_{min}/v_{max} - v_{min,} & if\ i \neq a, \quad v_{min} < v < v_{max} \\ 1, & if\ i \neq a, v \geq v_{max} \\ 0, & Others \end{cases} \tag{14}$$

Where $v_{min}$and v_{max} are the minimum and maximum velocity threshold, accordingly. A bigger velocity will lead to more call droppings while the process of vertical handoff is going on. Lastly, due to the present state, $S =$ [i, b_1 , d_1,p_1, th_1, be_1, c_1, sec_1, $j_{1,}$…,b_M, ,d_M, p_M, th_M, be_M, c_M, sec_M, j_M] as well as the chosen action a, the probability function of the following state would be:

$$S' =\ [j, b'_1, d'_1, p'_1, th'_1, be'_1, c'_1, sec'_1, j'_1, \dots, b'_M, d'_M, p'_M, th'_M, be'_M, c'_M, sec'_M, j'_M] \tag{15}$$

is given by

$$P[S'|s,a] = \begin{cases} \prod_{m=1}^{M} P[b'_m, d'_m, p'_m, th'_m, be'_m, c'_m, s'_m, j'_m | b_m, d_m, p_m, th_m, be'_m, c'_m, s'_m, j'_m] & j = a \\ 0, & j \neq a \end{cases} \tag{16}$$

The issue of the decision with the VHO is defined as a Markov decision. Rewards that are appropriate as well as flexible with the functions of cost are determined to embody the trade-off among the resources of the network utilized by the connectivity (the QoS-based bandwidth that is available, packet loss, delay, bit error rate, as well as throughput) besides the processing load that takes place and the network signaling when executing the VHO. The goal of the formulation of the Markov decision is in maximizing every connection's anticipated total reward. This kind of problem with the optimization is defined as:

$$v(s) = \max_{a \in A} \left\{ \mathrm{r(s,a)} + \sum_{\acute{s} \in S} \lambda\, \mathrm{P\ [s'|\ s,a]}\ v(s') \right\} \tag{17}$$

Where $v(s)$ stands for the anticipated reward, a stands for the set with the potential action (such as the network to utilize), r(s,a) stands for the function of reward, and P [s'| s, a] stands for the state transition probability in various access technologies. Moreover, $v^{T+1}(s)$ [17] stands for the anticipated reward at $(T+1)$:

$$v^{T+1}(s) = \max_{a \in A} \left\{ \mathrm{r(s,a)} + \sum_{\acute{s} \in S} \lambda\, \mathrm{P\ [s'|\ s,a]}\ v(\mathrm{s'}) \right\} \tag{18}$$

The norm function contains several definitions. The norm function in this study can be described with $v\ =\ max\ |v(s)|$ for $s \in\ S$. According to the IEEE 802.21 standard [13], a terminal that is mobile and establishes this proposed decision algorithm for vertical handoff can regularly gain information about the networks that are collocated in its receiving path by utilizing the present network interface. The provided information by the MIIS from the MIHF is utilized to project the parameters of the linked reward functions as seen in Equation (11) as well as the cost function as in Equation (12). The information regarding the bandwidth available and the average network delay is calculated through standardized processes for performance metrics of the Internet service as described by the Internet Engineering Task Force IP Performance Metrics Working Group [56]. The processes are developed so that they could be introduced by the network operators to offer precise as well as non-biased quantitative measurements with this type of metrics. The standardized metrics' examples include connectivity, packet loss and delay, variation of packet delay, as well as linked capacity of bandwidth.

Thus, a framework is proposed here to integrate the vertical handoffs with the preferences of the user. Firstly, we categorize B^{m} ,and D^{m}, P^{m}, and TH^{m}, and BER^{m} from the network m as QoS parameters that are network-based as well as parameters that are user-based, such as the cost of access and security. A screening phase is invoked if the mobile terminal discovers itself in the vicinity of the collocated coverage area due to information gathered from the IEEE 802.21 MIIS. This phase is able to filter networks that are not appropriate for carrying out vertical handoff according to the user-based QoS parameters. Only the appropriate candidate networks would be taken into consideration for the vertical handoff decision.

A list of current and future available point of attachments (PoAs) was retrieved and locally stored to be used by the decision-making branch. This database contains information about the present neighborhoods in the units on board. The MIIS PoA information database offers information including the ID of the network, the ID of the PoA, location, coverage, monetary cost per MB, the offered nominal rate of data, achieved rate of data by the most current users and bandwidth offered.

Every input in the neighborhood's database keeps the properties for every PoA in the neighborhood and the PoA's beneficial time of coverage. The beneficial time of coverage is the time spent by the mobile in the area of cell coverage with the ability to gain the peak rate of data from that particular cell. This time could differ based on certain factors including whether the itinerary crosses the area of coverage in a tangent or if there is an overlap in the area of coverage on the itinerary route. In addition, the beneficial time for coverage could also differ because of the fluctuations in the QoS at the cells edge that is linked to faulty wireless signals including fading and path loss. The cost function module will be utilized to measure the border cell of the QoS, which assures that the QoS is up to a certain distance along the route.

When approaching the end, the vertical handoff decision is based on the MDP optimal policy VT+1 (s) which takes into consideration the QoS parameters that are network-based such as $B^{m}$and , D^{m}, P^{m}, TH^{m} and BER^{m}. Fig. 2. shows the integrated process of BBO with MDP to determine the best RAT using the described multi-point algorithm in the heterogeneous networks.

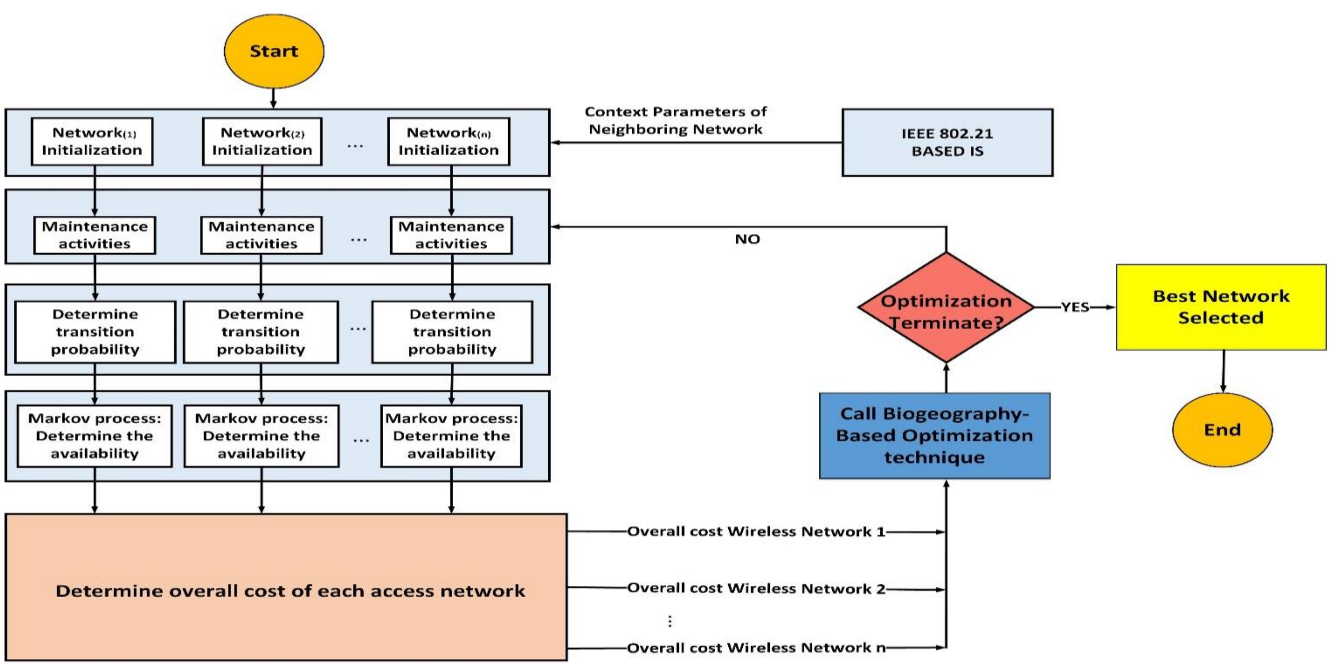

Fig. 2. Hybrid model of BBO with MDP to select the best network

The MDP-BBO algorithm utilizes real-time dynamic information because information changes rapidly and is updated constantly. This real-time dynamic information is retrieved from network and mobile sides. For real-time applications, the integrity of information is more important. By extensions in MIH, the MDP-BBO algorithm accesses critical real-time parameters used when selecting the target network to hand off the MN. This research proposes an evolution of the MIH with the capability to store, process and manage real-time dynamic information obtained from both the network and the terminal side entities.

As the MDP-BBO algorithm is established in the serving point of service (PoS), it is easier to use in real applications. The PoS decides the target of the handover based on the available resource status at candidate networks. The network, according to this study, initiates the process of handover by signaling to the MN when a handover is deemed necessary. In this case, the policy function of the network selection remains in the network. The network utilizes the MIH_Net_HO_*** set along with the commands from the MIH_N2N_HO_*** to initiate the handover. The network can utilize these commands for querying the currently used resources list from the MN; the service network is able to reserve the necessary resources at the candidates target network while the network is able to command the mobile node to perform the handover to a particular network.

5. Proposed Biogeography-based Optimization

This section discusses the details of the MDP-BBO algorithm. Biogeography refers to the study of geographical distribution of species over geological time frames. There is extensive literature on biological subjects. In 2008, Simon [20] first utilized the biogeography analogy to the concept of engineering optimization and introduced the BBO approach. This is a method based on a population that works with a set of candidate solutions across generations. It examines the combined big solution spaces using a stochastic method as used by most other evolutionary algorithms [57-59].

It copies the species' geographic distribution to present the problem and the solution to candidates in the search location by utilizing the species mutation and migration process to re-distribute the solution instances over the search location in search of the solutions that are almost globally optimal. BBO as it is or in differing form has been examined in different combinations and constrained/unconstrained optimization challenges [60] involving such as the Traveling Salesman Problem [61-62], classification of satellite images [63], as well as sensor selection [20] among others. Nevertheless, since 2012, research using BBO as a technique for choosing genes for data analysis of micro-array gene expression has not been reported. This study attempts to examine the BBO for selection and categorization of genes. There is an ecosystem or population in the BBO that possesses certain island habitats. Every habitat contains the index of habitat suitability that is the same as the fitness function and relies on most of the island's traits or attributes. When a value is given to every trait, habitat H's HSI is this value's function. These variables that collectively characterize the suitability of the habitat formulate the 'suitability index variables' (SIVs).

Therefore, in terms of the issues related to the gene selection, a habitat's SIVs (solution candidate) are the chosen subset of the genes derived from the grouping of the entire genes. Therefore, the ecosystem is a randomized group of gene candidate subsets. A proper solution is analogous to a proper HSI and vice versa. Proper solutions of HSI are likely to share the SIVs with weak solutions of HSI. This type of sharing, which is known as migration, is governed by the habitats' rates of immigration and emigration. This model has been purposefully maintained to be uncomplicated as it follows the original simple linear migration model.

The BBO algorithm [20, 64] contains two main stages, namely migration as well as mutation. A mechanism for mutation in the proposed MDP-BBO is engaged to improve the capability of investigating in the search location. A detailed algorithm for the BBO can be retrieved from [20]. The subsequent sub-sections report the proposed algorithm of the MDP-BBO for optimization of the weight coefficients when choosing the best RAT in heterogeneous networks.

In general, studies normally apply different ideas to generate a feasible solution by managing the quantity of diversity. The process of mutation in the BBO improves the population diversity. It should be realized that the rate of the mutation changes the SIV of the habitat in a randomized approach according to the rate of mutation. In addition, the rate of mutation is inversely in proportion to the species count probability. Therefore, in a fundamental BBO, if a solution is chosen for mutation, it will be replaced using a random method to develop a new set of solution. Thus, this randomized mutation has an effect on the investigation of the basic BBO capability. The process of mutation is modified to enhance the investigating ability of the BBO as detailed in Section 3 in order to refine the habitat and to reach an optimal solution using a better method. For the BBO algorithm, a short introduction is provided; then, the operation is explained with a pseudo code.

The species selection (Ps) probability changes from one specific time to another as shown in Equation (16) in this paper. Changes are not performed in the migration potion of the proposed MDP-BBO algorithm to sustain the ability to exploit. The modification performed in the mutation section with the MDP improved the capability for investigation. Therefore, the proposed MDP-BBO leads to a balanced investigation and the ability to exploit the algorithm. The proposed MDP-BBO algorithm's pseudo code is presented in Table 2. The proposed MDP-BBO algorithm is used in this study to perform the optimization of weight in an algorithm with multi-point decision making and to choose the best RAT for the considered networks that are heterogeneous, where E and I represent the maximum rates of emigration as well as immigration, which are normally fixed at 1. Individual rates of immigration as well as emigration (λ and μ, accordingly) are measured using a similar formula as the simple linear model suggested by [20].

6. Results and discussion

We utilized MATLAB and OMNET++ to evaluate network performance. OMNET++ is a well-designed, component-based, modular and open-architecture simulation environment with strong GUI support and an embeddable simulation kernel.

Table 2. Pseudo code for the proposed MDP-BBO algorithm

```
Function MDP − BBO ( )
Initialize_randomly(population)

Calculate_fitness()// ……………………………………………………………………………by Eq. (12)
Sort_asc_best_to_worst(population)
Count_Probability(for all Habitat)
If  termination criteria is not achieved   then
        arrElistim[ ] ← Save the best H's
        Map suitability of H index(HSI)for al Habi
        Perform Migration
        Perform Mutation // ……………………………………………………………………by Eq. (16)
        Calculate_fitness()
        Sort_asc_best_to_worst(population)
        Update best solution ever found
Endif
BestCost = Choose(Best Costs)
End
```

Standard Pseudo Code for Migration

```
For   i = 1   to   NP   do
        Select  Hi  with probability based on  λi
        If  Hi is selected  Then
            For   j = 1   to   NP   do
                Select  Hj  with probability based on  μj
                If  Hj is selected  Then
                    Randomly select a  SIV(s)  from  Hj
                    Copy them  SIV(s)  in  Hj
                End if
            End for
        End if
End for
```

Standard Pseudo Code for Mutation

```
For   i = 1   to   NP   do
    Use λi and μi to compute the probability Pi
    Select  SIV Hi(j) with probabi;lity ∝ Pi
    If    Hi(j)  is selected   Then
        Replace Hi(j)  with a randomly generated SIV
    End if
End for
```

OMNET++ is a general-purpose simulator capable of simulating any system composed of devices interacting with each other. Although the original implementation did not offer a great variety of protocols, it did provide a hierarchical nested architecture which enabled developers to model and modify all layers of the protocol stack accurately. The simulations were made in the OMNET++ simulator using the network address translation (NAT) add-on. Notice that the OMNET++/INET module, by default, does not provide make-before-break handover mechanisms but rather break-before-make. Therefore, modifications were made to the NAT module, such as support for network-side 802.21 entities and control of the link layer access technologies to obtain seamless handovers. A cross-layer module was implemented in OMNeT++ with NAT functionality to provide a seamless handover. It contributed to the INET framework of OMNeT++ by implementing the NAT operation in network layers with an update mechanism achieved through a cross layer module.

Tables 3 and 4 show the parameters of the Markov-VHO. The average time for decision epochs that are continuous is set at 15 s. The unit for bandwidth is 16 kb/s, the unit for jitter is 2.5 ms, and the unit for traffic is 0.5 erl.

The highest as well as the lowest velocities are 5 units and 1 unit respectively as suggested by [65-67]. The cellular area is 3 times bigger than the WLAN while the MTs' special density in the cellular network is 8 times bigger than the WLAN. Rates of peak data in the Wimax are DL: 75 Mbps UL: 25 Mbps and in the LTE DL: 100 to 324.6 Mbps UL: 50 to 86.4 Mbps. The algorithm for the Markov-VHO that is proposed in this study is evaluated with other schemes in terms of average number of handoffs, available bandwidth, etc. Figures 4 to 10 show the performance of the network during the handoffs.

The average time of the continuous decision epoch is 15 s. The unit of bandwidth is 16 kb/s, the unit of jitter is 2.5 ms and the unit of traffic is 0.5 erl. The highest as well as the lowest velocities are 5 units and 1 unit as suggested by [23]. The cellular area is 3 times bigger than the WLAN and the MTs' special density in the cellular network is 8 times bigger than the WLAN.

The released signals propagate on the module hierarchy up to the root (network module). As a result of this, a radio listener registered at a compound module can receive signals from all modules in its sub-module tree. To record simulation results based on the signals mechanism in OMNET++, we have added one or more @statistic properties in a module's NED definition. In terms of RSSI, we have considered the following declaration of a statistic by recording the average RSSI value measured by nodes in a wireless network: @statistic[statRSSI](source="rssiSignal";record=mean). However, placing the statement on network level would result in a single RSSI value averaged over all RSSI measurements made by the nodes in the network.

MiXiM, a simulation framework for OMNeT++ is able to simulate wireless networks, mobile networks and energy consumption. MiXiM can maintenance wireless and mobile simulations. It can provide several ready-to-use modules such as Log Normal Shadowing, Simple Path loss and Rayleigh-Fading using the Jakes-model. This model is applied by a maximum Doppler shift based on the carrier frequency $f_c$and velocity v of the object with the highest level of velocity which can be applied in the propagation environment, e.g. a moving user. This model of fading is established by utilizing Rayleigh distributed signal domains that lead to rapidly expanding the distributed SNR $\gamma_{i,j}$ for the channel from mobile terminal i to mobile terminal j rapidly. We have investigated the path loss, the log-normal shadowing with standard deviation of 8 dB and Rayleigh fading. The path loss models between the base station and mobile station as well as between relay station and mobile station links, 31 + 40 log 10 d(dB), are acquired from the models in [68] which have the carrier frequency of 2.5 GHz, where d (meters) is the distance from the transmitter to the receiver. For shadowing, the correlation model in [69] is used with the decorrelation length of 50 m and the Rayleigh fading is applied using a Jakes spectrum model.

Table 3. Parameters of Simulation for Markov-VHO

Notations	Definitions of Parameter	Values in network 1	Values in network 2	Notations	Definitions of Parameter	Values in network 1	Values in network 2
d^i_{max}	Delay maximum in network i	8 units	8 units	D_{av}	Average window	0.5 m	
j^i_{max}	Jitter maximum in network i	4 units	2 units	D_s	Slope distance window	5m	8m
p^i_{max}	Packet loss maximum in network i	6 units	4 units	$T_{\text{mobile Input}}$	Predefined threshold mobile input	-85dbm	-
th^i_{max}	Throughput maximum in network i	8 units	8units	$T_{\text{mobile output}}$	Predefined threshold mobile output	-	-80dbm
be^i_{max}	Bit error rate maximum in network i	4 units	2 units	**NRANs**	Number of RANs	5	
c^i_{max}	Cost maximum in network i	2 units	4 units	**NMN**	Number of MNs (per SN)	10	100
s^i_{max}	Security maximum in network i	4 units	4 units	λ	Rate of VHO triggers per mobile node	In range [0.01, 0.1]	
n_1	Cost of switching from network 1 to network 2	0.3	-	BW_L	Wired Link Bandwidth (Mbps)	1000	
n_2	Cost of switching from network 2 to network 1	-	0.3	BW_{WL}	Wireless Link Bandwidth (Mbps)	10	
c_1	Cost of access to network 1	1	-	**P**	Packet Length: (bits)	12000 (1500 × 8)	
c_2	Cost of access to network 2	-	1	**DIS**	Mean IS Delay: (sec)	0.01	
P_T	Transmission power network	100 mW	120 mW	**DCN**	Mean Process Delay (CN): (sec)	0.030	0.300
n	Pass loss factor	3.3	3.3	u_{wired}	Cost of unit packet transmission for the wired links	0.1	
D_{av}	Average window	0.5 m		$u_{wireless}$	Cost of unit packet transmission for the wireless links	3.84 x 106	

Table 4. Reward function Parameters

Notations	Definition of Parameter	CBR	FTP
L_B	Accessible minimum bandwidth required	2 units	2 units
U_B	Accessible maximum bandwidth required	4 units	16 units
L_D	Required Minimum delay	2 units	8 units
U_D	Required Maximum delay	4 units	16 units
L_P	Required Minimum packet loss	2 units	4 units
U_P	Maximum packet loss required	4 units	16 units
L_{TH}	Minimum throughput required	2 units	4 units
U_{TH}	Maximum throughput required	4 units	16 units
L_{BER}	Required Minimum bit error rate	2 units	8 units
U_{BER}	Required Maximum bit error rate	4 units	16 units
L_C	Minimum cost required	2 units	4 units
U_C	Maximum cost required	4 units	6 units
L_S	Minimum security required	2 units	4 units
U_S	Maximum security required	4 units	8 units
L_J	Minimum jitter required	2 units	8 units
U_J	Maximum jitter required	4 units	16 units

The basic concept of the TOPSIS method is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The positive ideal solution is a solution that maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria [70].

Several assessments exist based on the workings of the proposed scheme versus the TOPSIS [44, 45] decision-making models. The proposed scheme performance is examined in different mobility settings based on TOPSIS and GRA. Both these techniques offer rankings to the networks that are available according to multiple parameters, such as the network traffic load, mobile speed and type of service. Based on these parameters, the highest-ranked network is chosen. In terms of mobile communications, these techniques could be utilized to consolidate the information received during the network discovery stage to rank all the available candidate networks wisely according to the present requirements of the application [71].

Fig. 3. demonstrates the simulated results of the total reward using various handoff signaling loads. The total reward reduces as the handoff signaling load rises, as the signaling load increases each time the connection causes a drop in the actual reward. This proposed algorithm reduces the call dropping probability as well as the signaling and processing cost by considering the velocity of the MT. Thus, the decrease in the total reward is less compared to the other algorithms.

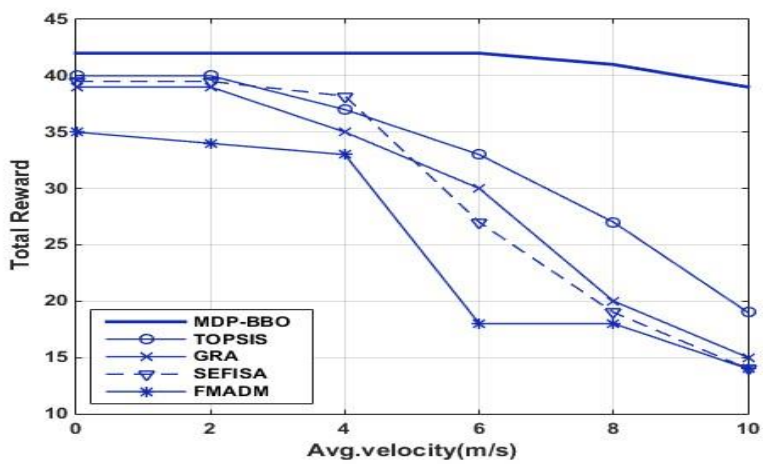

Fig. 3. Comparisons of total reward under various velocity of the MT

Fig. 4. shows the average number of HOs using various signaling loads. It is observed that when the signaling load for the handoff goes up, the number of average handoffs goes down. The signaling load for the handoff that keeps rising leads to the candidate network's real total reward. This is significantly reduced compared to the present one in which the MT stays. Thus, the algorithm that is proposed is able to prevent many unnecessary handoffs.

In addition, several tests were performed at various MN speeds. In the initial simulation, the amount of the MNs was not much however at the time of simulation, the researchers tried to increase the MNs slowly to examine the functioning of the model that is proposed in a high traffic environment. The number of handovers are recorded with the proposed scheme, GRA, as well as TOPSIS. The handoff rates using GRA and TOPSIS increased as more MNs joined the network.

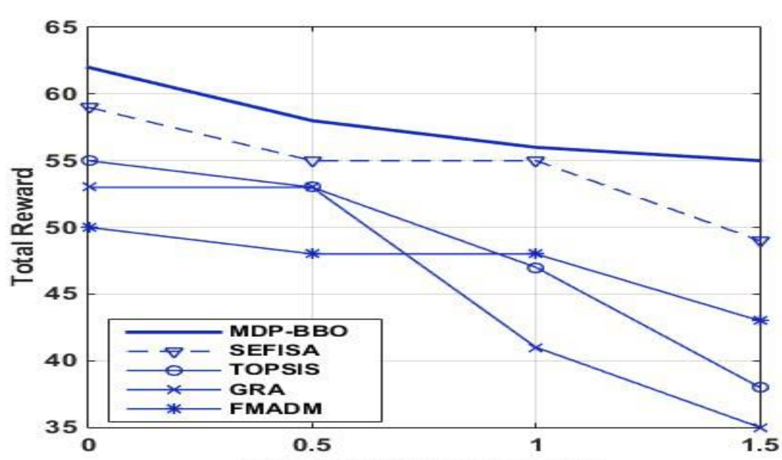

Fig. 4. Comparisons of average numbers of HOs under various signaling loads

The handoff rates in the proposed scheme in comparison with GRA and TOPSIS are demonstrated in Fig. 5.

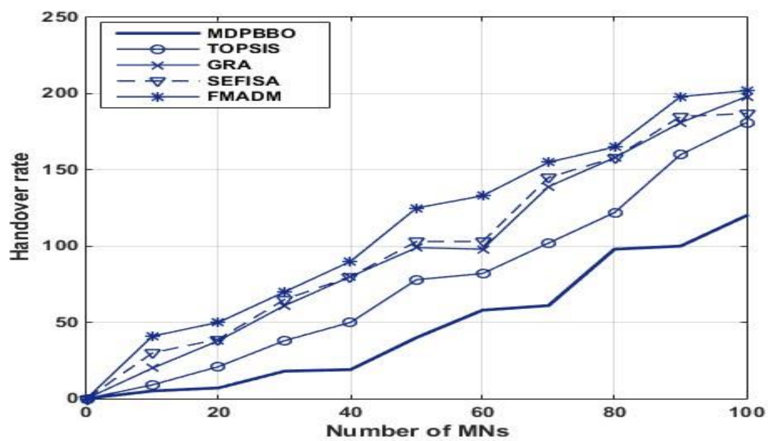

Fig. 5. Analysis of handoff rates

Among the reasons seen during the simulation is the unsuitable handover that is triggered because of the RSS in relation to GRA and TOPSIS. The technique for the proposed handover triggering lowers the rate of handoff significantly. We have conducted performance comparisons between our algorithm MDP-BBO and other algorithms structured in the literature, namely SEFISA [49] and FMADM [72]. In a study by Jaraiz-Simon et al. [49], the proposed algorithm was designed to decide on the best network to establish connection in a vertical handover process as the SEFISA is based on the simulated annealing (SA) algorithm. In addition, the FMADM is a fuzzy multiple attribute decision making algorithm that selects a suitable wireless access network during the vertical handover process.

Likewise, the packet loss is minimized significantly in the proposed scheme. GRA and TOPSIS have high packet losses in comparison to the proposed scheme due to the regular switching of various networks. In general, a scheme with a multi-criteria decision needs a high amount of handover time in comparison to a model with a single criteria decision. However, because of the proposed MDP-BBO method, the MN has additional time to scan as well as choose an optimized network in a heterogeneous network setting. Fig. 6. demonstrates the packet loss ratio comparison.

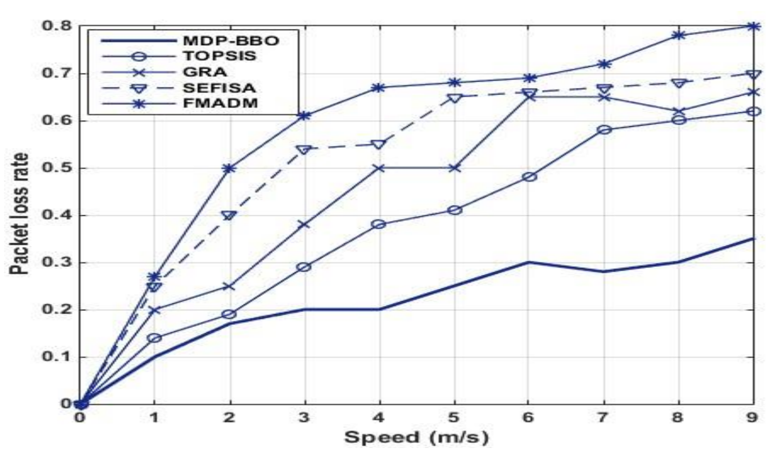

Fig. 6. Packet losses during handovers

The scheme that is proposed has also enabled the computation of the throughput gain. The throughput relies on the indirect loss of the packets. The GRA and TOPSIS possess high loss of packets and as such, they offer a low throughput gain due to unsuitability in the selection of the handover network. However, the proposed scheme also faces a lower packet loss due to the optimal network selection and the proposed handover triggering method. The throughput relies on the delay of the handover and the needed time to redirect the data via a new network. The handover that is proposed offers the MN sufficient time while the handover occurs. Thus, the data is redirected via a network that is new and as such, the MN goes through a high level of throughput. Fig. 7. shows the throughput gain comparison in the proposed scheme, GRA, and TOPSIS decision models. At first, the MN has a low level of throughput, however after a certain duration, the throughput increases. Two reasons for this increase include i) the previous throughput (bytes) arriving through the present AP/BS is added to the new bytes arriving from the new AP/BS; ii) the suggested triggering as well as selection of network offers the MN with a suitable AP/BS that increases the throughput.

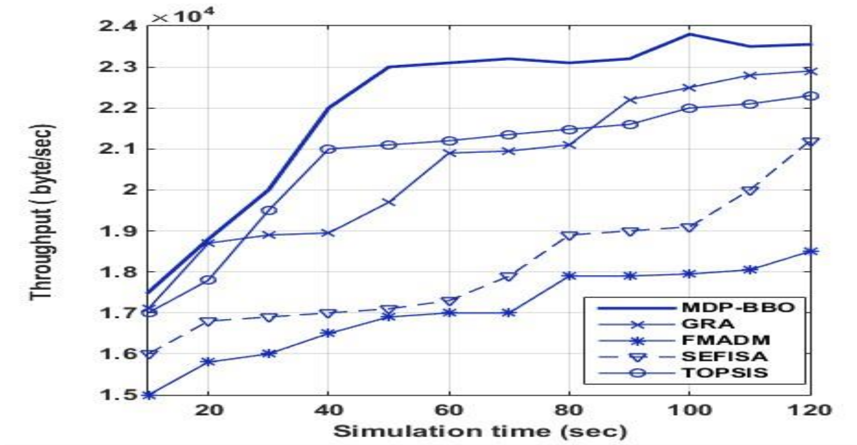

Fig. 7. Throughput gains

The proposed scheme outperforms in the area of minimizing the rate of handoff and in maximizing the throughput with the decision models of GRA and TOPSIS. Simulation results in Fig. 8. corresponds to the best costs for TOPSIS, GRA, SEFISA, FMADM and MDP-BBO for number of networks = 4 and number of QoS = 15. The datasets consist of several networks characterized by the following QoS parameters: B = bandwidth (kbps), E = BER (dB), D = delay (ms), S = (dB), C = cost (eur/MB) , L = network latency (ms), J = jitter (ms), R = burst error, A = average retransmissions/packet, P = packet loss (%), G = received signal strength indication RSSI (dBm), N = network coverage area (km), T = reliability, W = battery power requirement (W), and V = mobile terminal velocity (m/s).

Fig. 9. shows the impact of mobile speed on handover latency. In this simulation, the total number of mobiles is fixed at 50 nodes. Whenever the mobile node speed rises, the handover latency also rises. The MDP-BBO and SEFISA models have better performance than the TOPSIS, GRA and FMADM models because they have high levels of handover time and thus, increase the handover latency.

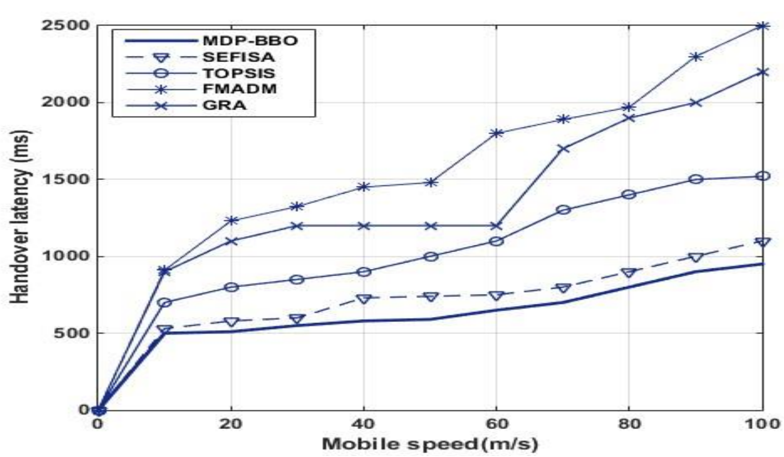

Fig. 8. Best costs

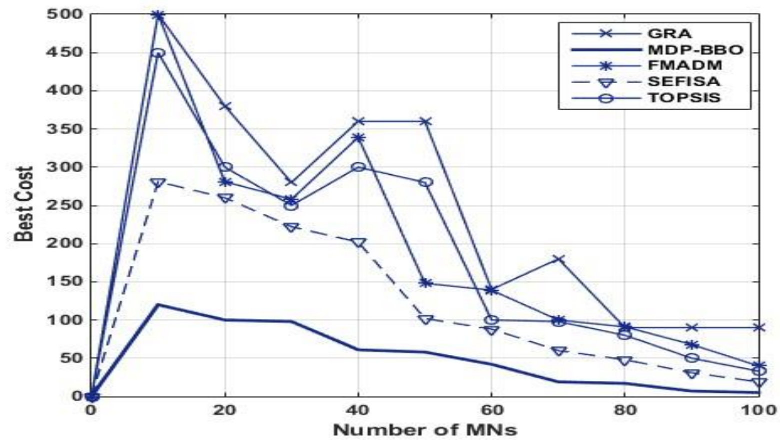

Fig. 9. Handover latency vs Mobile speed

Fig. 10. shows the impact of various mobile nodes densities on handover latency. The number of mobile nodes are adjusted between (10 -100) per mobile node when moving at a fixed speed (50 m/s). In place of the mobile node density rise, the handover latency also rises as density causes more congestion. Thus, the handover latency will be increased. The MDP-BBO and SEFISA models show the best performance followed by the TOPSIS, GRA and FMAMD models.

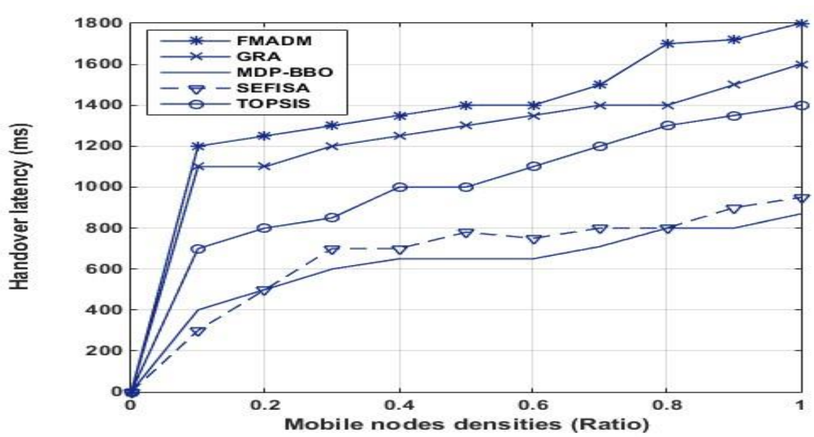

Fig. 10. Handover latency vs. Mobile nodes densities

The scheme utilized when selecting a network is based on different parameters namely jitter, delay, BER, loss of packets, cost of communication, time to respond, and network loading. A comparison is made in the proposed scheme as well as the TOPSIS and GRA decision models in the context of failed attempts at handovers, handovers that are frequent, ratio of packet loss, as well as the throughput. The proposed scheme outperforms in the area of minimizing the rate of handoff and in maximizing the throughput with the decision models of GRA and TOPSIS. Among these algorithms, the one based on the hybridization of MDP and BBO demonstrated the best performance, in terms of precision and cost function.

Fig. 11. shows the signalling overhead versus average session arrival rate. Based on the handover procedure for each option, the signalling overhead was evaluated. From the figure, as the average session arrival rate increases, the signalling overhead for all the possible options increase. This is because more handovers occur with the increase of the session arrivals. The figure also shows that MDP-BBO and SEFISA scenario have lower signalling overhead than TOPSIS, GRA and FMADM. This is because the handovers in MDP-BBO and SEFISA do not involve routing delays and the IEEE 802.21 interface introduced between nodes also shortens the delay required to send a signalling message.

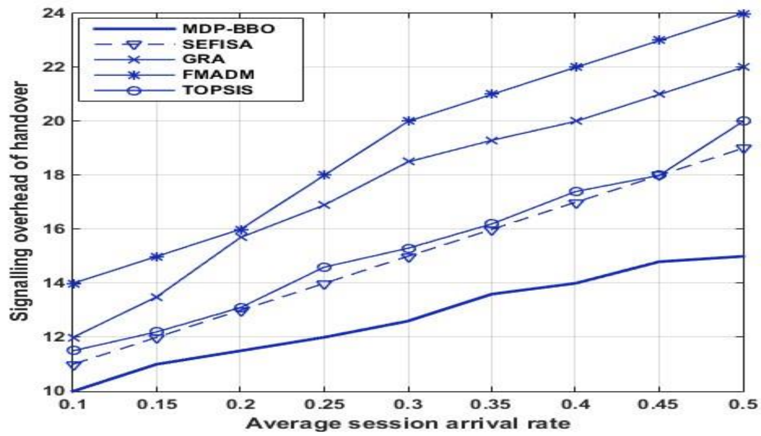

Fig. 11. Signalling overhead versus average session arrival rate

The QoS requirements of real-time audio and video streaming traffic are the factors considered when determining the QoS of the available networks to provide uninterrupted services to mobile users. Real-time applications such as voice over IP (VOIP) and video conference (VC) are used in the scenario. The holding time of the real-time service is set as 10 min. For each setting, the simulation is conducted 100 times and the average is obtained. The proposed model can be used for real-time simulations up to a data rate of 16 kbps. It can simulate up to 100 nodes without losing its real-time capabilities. For simplicity, voice and streaming data traffic are simulated, all bandwidth is assumed to be completely shared by all traffic flows, and real-time traffic has priority over the data. Simulations show that voice and streaming traffic have similar performance results. Since the voice traffic requires low bandwidths, it has higher trunking efficiencies and speed degradation abilities compared to the audio/video streaming traffic at the same traffic load. The results indicate that speed increases the delay as QoS of the real-time traffic. Speed degradations are effective in increasing real-time traffic delays, and high speed levels are involved in delayed degradations.

Fig. 12. and Fig. 13. represent the handover delays for audio and video services respectively. From the simulation results, it is not surprising that the handover delay increases in the MDP-BBO, SEFISA, TOPSIS, GRA and FMADM as the moving speed of the MN increases. The original MIH scheme is coupled with an MDP-BBO mechanism that updates the audio/video encoding parameters in real-time, allowing audio/video QoS adaptation. The simulation results indicate that the proposed enhanced MIH framework achieves a lower delay for audio and video applications of 30% and 47%, respectively, compared to other scenarios. In this experiment, simulation results show that this research can improve the QoS of real-time applications by integrating the MDP-BBO algorithm with the MIH to make accurate decisions.

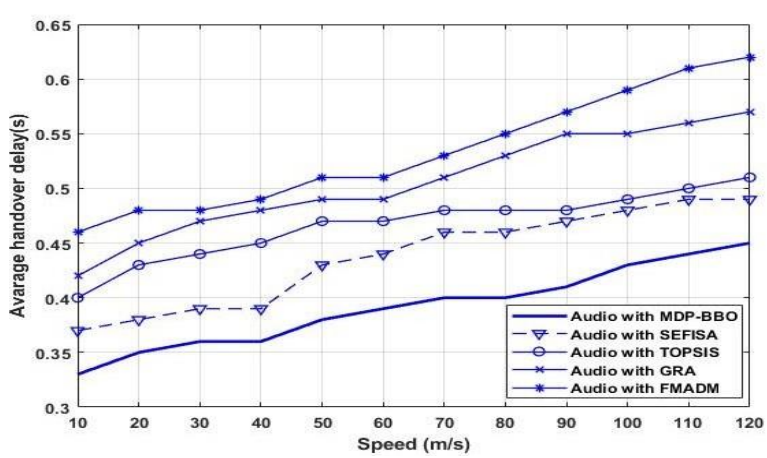

Fig. 12. Handover delays for audio versus moving speed of MNs

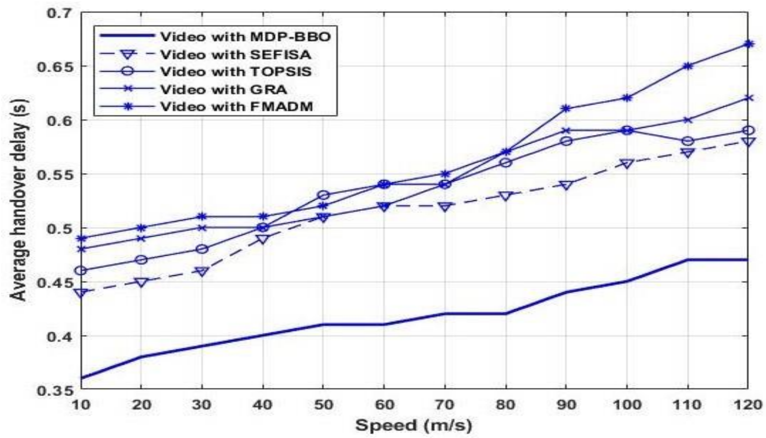

Fig. 13. Handover delays for video versus moving speed of MNs

7. Conclusion

Wireless communication systems in the future will encompass different forms of networks with wireless access. Accordingly, seamless vertical handoffs from various networks are a challenging issue for IIOT. Although several algorithms for vertical handoff decisions based on machine learning are being suggested, many of these do not take into account the effect of call drops that occur while the vertical handoff decision is taking place. Furthermore, many of the present multi-attributed vertical handoff algorithms are not able to dynamically project the circumstances of the MTs. To ensure the QoS of various MTs, this study has proposed a MDP-based algorithm for vertical handoff decisions in single and multi-attributed conditions, in order to maximize the anticipated total rewards and reduce the average amount of handoffs. Our work took into consideration the velocity of the MT, the cost of the network access, the cost of switching in the vertical handoff decision and developed a reward function that modeled the properties of the QoS. We applied the MDP to measure the weight of every QoS determinant in the reward function, and an iterative algorithm was adopted using the Markov decision procedure to gain the maximum value for total reward and the related optimal policy. Moreover, by considering the velocity of the MT, unnecessary handoffs were prevented. We also compared our algorithm with other recent related algorithms to evaluate the performance of the network. The findings revealed that the MDP-BBO algorithm is able to outperform other algorithms in terms of number of handoffs, bandwidth availability, and decision delays. The proposed algorithm displayed better expected total rewards as well as a reduced average account of handoffs compared to current approaches.

With regards to future work, we are planning to conduct studies about the usability of the proposed work for vehicular ad hoc networks (VANET). First, we plan to improve the MDP-BBO optimized code for infrastructure-based VNs rather than VANET-based solutions. Then, we want to use car-to-car communications protocols such as DSRC and IEEE 802.11pto deliver information to the MIIS databases. Furthermore, different types of available wireless access networks with their corresponding QoS values for mobile terminals will be identified and MDP-BBO will be used to evaluate performance, behaviors and other possibilities. As part of future work, we will further explore sophisticated methods of network selection based on fog computing. We will extend our mobility management framework to support more complicated use cases along with diverse devices in order to measure the effectiveness of our approach with more realistic test-beds in fog computing environments.

As another consideration for the future, we aim to propose a hybrid model for handover management between the UAVs. Due to its good maneuverability, low cost and versatile preparation, remote-controlled UAVs have recently attracted significant interest in the field of wireless communication.

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References

[1] Da Xu, Li, Wu He, and Shancang Li. Internet of things in industries: A survey. IEEE Transactions on industrial informatics 10, no. 4 (2014): 2233-2243.

[2] Cui, Laizhong, Shu Yang, Fei Chen, Zhong Ming, Nan Lu, and Jing Qin. A survey on application of machine learning for Internet of Things. International Journal of Machine Learning and Cybernetics (2018): 1-19.

[3] Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., & Ayyash, M. (2015). Internet of things: A survey on enabling technologies, protocols, and applications. IEEE Communications Surveys & Tutorials, 17(4), 2347-2376.

[4] Al-Fuqaha, Ala, Mohsen Guizani, Mehdi Mohammadi, Mohammed Aledhari, and Moussa Ayyash. Internet of things: A survey on enabling technologies, protocols, and applications. IEEE Communications Surveys & Tutorials 17, no. 4 (2015): 2347-2376.

[5] Jiang, Dingde, Zhengzheng Xu, Wenqin Wang, Yuanting Wang, and Yang Han. A collaborative multi-hop routing algorithm for maximum achievable rate. Journal of Network and Computer Applications 57 (2015): 182-191.

[6] Jiang, Dingde, Yuanting Wang, Chunping Yao, and Yang Han. An effective dynamic spectrum access algorithm for multi-hop cognitive wireless networks. Computer Networks 84 (2015): 1-16.

[7] Jiang, Dingde, Zhengzheng Xu, Wenpan Li, and Zhenhua Chen. Network coding-based energy-efficient multicast routing algorithm for multi-hop wireless networks. Journal of Systems and Software 104 (2015): 152-165.

[8] Ahmed, Atiq, Leila Merghem Boulahia, and Dominique Gaiti. Enabling vertical handover decisions in heterogeneous wireless networks: A state-of-the-art and a classification. IEEE Communications Surveys & Tutorials 16, no. 2 (2014): 776-811.

[9] Paul, Subharthi, Jianli Pan, and Raj Jain. Architectures for the future networks and the next generation Internet: A survey. Computer Communications 34, no. 1 (2011): 2-42.

[10] TalebiFard, Peyman, Terrence Wong, and Victor CM Leung. Access and service convergence over the mobile internet–a survey. Computer Networks 54, no. 4 (2010): 545-557.

[11] Movahedi, Zeinab, Mouna Ayari, Rami Langar, and Guy Pujolle. A survey of autonomic network architectures and evaluation criteria. IEEE Communications Surveys & Tutorials 14, no. 2 (2012): 464-490.

[12] Jiang, Dingde, Xu Ying, Yang Han, and Zhihan Lv. Collaborative multi-hop routing in cognitive wireless networks. Wireless personal communications 86, no. 2 (2016): 901-923.

[13] Goudarzi, Shidrokh, Wan Haslina Hassan, Mohammad Hossein Anisi, and Ahmad Soleymani. A comparative review of vertical handover decision-making mechanisms in heterogeneous wireless networks. Indian Journal of Science and Technology 8, no. 23 (2015).

[14] Wilson, A., Andrew Lenaghan, and Ron Malyan. Optimising wireless access network selection to maintain qos in heterogeneous wireless environments. In wireless personal multimedia communications, pp. 18-22. 2005.

[15] Wang, Gai-Ge, Xingjuan Cai, Zhihua Cui, Geyong Min, and Jinjun Chen. High performance computing for cyber physical social systems by using evolutionary multi-objective optimization algorithm. IEEE Transactions on Emerging Topics in Computing (2017).

[16] Wang, Gai-Ge, and Ying Tan. Improving metaheuristic algorithms with information feedback models. IEEE Transactions on Cybernetics (2017).

[17] Soleymani, Seyed Ahmad, Abdul Hanan Abdullah, Mohammad Hossein Anisi, Ayman Altameem, Wan Haslina Hasan, Shidrokh Goudarzi, Satria Mandala, Zaidi Bin Razak, and Noorzaily Mohamed Noor. BRAIN-F: Beacon rate adaption based on fuzzy logic in vehicular ad hoc network. International Journal of Fuzzy Systems 19, no. 2 (2017): 301-315.

[18] Pedrasa, Jhoanna Rhodette, and Aruna Prasad Seneviratne. Determining network availability on the move. In Communications (APCC), 2011 17th Asia-Pacific Conference on, pp. 301-306. IEEE, 2011.

[19] Goudarzi, Shidrokh, Wan Haslina Hassan, Mohammad Hossein Anisi, Seyed Ahmad Soleymani, and Parvaneh Shabanzadeh. "A novel model on curve fitting and particle swarm optimization for vertical handover in heterogeneous wireless networks. Mathematical Problems in Engineering 2015 (2015).

[20] Simon, Dan. Biogeography-based optimization. IEEE transactions on evolutionary computation 12, no. 6 (2008): 702-713.

[21] Wang, Chen, Yi Wang, Kesheng Wang, Yang Yang, and Yingzhong Tian. An improved biogeography/complex algorithm based on decomposition for many-objective optimization. International Journal of Machine Learning and Cybernetics (2017): 1-17.

[22] Wang, Gai-Ge, Amir H. Gandomi, Amir H. Alavi, and Dunwei Gong. A comprehensive review of krill herd algorithm: variants, hybrids and applications. Artificial Intelligence Review (2017): 1-30.

[23] Stevens-Navarro, Enrique, Yuxia Lin, and Vincent WS Wong. An MDP-based vertical handoff decision algorithm for heterogeneous wireless networks. IEEE Transactions on Vehicular Technology 57, no. 2 (2008): 1243-1254.

[24] Márquez-Barja, Johann, Carlos T. Calafate, Juan-Carlos Cano, and Pietro Manzoni. An overview of vertical handover techniques: Algorithms, protocols and tools. Computer communications 34, no. 8 (2011): 985-997.

[25] Soleymani, Seyed Ahmad, Abdul Hanan Abdullah, Wan Haslina Hassan, Mohammad Hossein Anisi, Shidrokh Goudarzi, Mir Ali Rezazadeh Baee, and Satria Mandala. Trust management in vehicular ad hoc network: a systematic review. EURASIP Journal on Wireless Communications and Networking 2015, no. 1 (2015): 146.

[26] Dutta, Ashutosh, Sunil Madhani, Wai Chen, Onur Altintas, and Shengwei Cai. GPS-IP based fast-handoff for Mobiles. In 3rd New York Metro Area Networking Workshop, vol. 9. 2003.

[27] Montavont, Julien, and Thomas Noel. IEEE 802.11 handovers assisted by GPS information. In Wireless and Mobile Computing, Networking and Communications, 2006.(WiMob'2006). IEEE International Conference on, pp. 166-172. IEEE, 2006.

[28] Hsiao, Wei-Der, You-Xing Liu, and Han-Chieh Chao. An intelligent WiMAX mobile network handoff mechanism with GPS consideration. In Proceedings of the International Conference on Mobile Technology, Applications, and Systems, p. 110. ACM, 2008.

[29] ÇAlhan, Ali, and Celal ÇEken. Case study on handoff strategies for wireless overlay networks. Computer Standards & Interfaces 35, no. 1 (2013): 170-178.

[30] Safa Sadiq, Ali, Norsheila Binti Fisal, Kayhan Zrar Ghafoor, and Jaime Lloret. Advanced mobility handover for mobile ipv6 based wireless networks. The Scientific World Journal 2014 (2014).

[31] Sadiq, Ali Safa, Kamalrulnizam Abu Bakar, Kayhan Zrar Ghafoor, Jaime Lloret, and SeyedAli Mirjalili. A smart handover prediction system based on curve fitting model for Fast Mobile IPv6 in wireless networks. International Journal of Communication Systems 27, no. 7 (2014): 969-990.

[32] Sadiq, Ali Safa, K. Abu Bakar, Kayhan Zrar Ghafoor, and Jaime Lloret. Intelligent vertical handover for heterogeneous wireless network. In Proceedings of the World Congress on Engineering and Computer Science, vol. 2, pp. 774-779. 2013.

[33] Lloret, Jaime, Alejandro Canovas, Joel JPC Rodrigues, and Kai Lin. A network algorithm for 3D/2D IPTV distribution using WiMAX and WLAN technologies. Multimedia tools and applications 67, no. 1 (2013): 7-30.

[34] Wang, Li-Chun, Anderson Chen, and Hung-Hsi Chen. Network selection with joint vertical and horizontal handoff in heterogeneous WLAN and mobile WiMax systems. In 2007 IEEE 65TH VEHICULAR TECHNOLOGY CONFERENCE, VOLS 1-6, pp. 794-798. 2007.

[35] Wang, Shangguang, Cunqun Fan, Ching-Hsien Hsu, Qibo Sun, and Fangchun Yang. A vertical handoff method via self-selection decision tree for internet of vehicles. IEEE Systems Journal 10, no. 3 (2016): 1183-1192.

[36] Yang, Jianbo, and Xinsheng Ji. A VERTICAL HANDOVER TRIGGER MECHANISM BASED ON GRAY PREDICTION. Journal of Theoretical & Applied Information Technology 48, no. 2 (2013).

[37] Goudarzi, Shidrokh, Wan Haslina Hassan, Aisha-Hassan Abdalla Hashim, Seyed Ahmad Soleymani, Mohammad Hossein Anisi, and Omar M. Zakaria. A novel RSSI prediction using imperialist competition algorithm (ICA), radial basis function (RBF) and firefly algorithm (FFA) in wireless networks. PloS one 11, no. 7 (2016): e0151355.

[38] Nadembega, Apollinaire, Abdelhakim Hafid, and Tarik Taleb. A destination and mobility path prediction scheme for mobile networks. IEEE transactions on vehicular technology 64, no. 6 (2015): 2577-2590.

[39] Ong, Eng Hwee, and Jamil Y. Khan. Dynamic access network selection with QoS parameters estimation: A step closer to ABC. In Vehicular Technology Conference, 2008. VTC Spring 2008. IEEE, pp. 2671-2676. IEEE, 2008.

[40] JAKIMOSKI, KIRH, and Toni Janevski. Radio Access Technology Selection and Vertical Handover Decision Algorithms for Heterogeneous Mobile and Wireless Networks. Adhoc & Sensor Wireless Networks 27 (2015).

[41] Al-Hashimi, Haider Noori, and Waleed Noori Hussein. PMIPv6 Assistive Cross-Layer Design to reduce handover latency in VANET Mobility for Next Generation Wireless Networks. Network Protocols and Algorithms 7, no. 3 (2015): 1-17.

[42] Carmona-Murillo, Javier, David Cortés-Polo, Jesús Calle-Cancho, José-Luis González-Sánchez, and Francisco-Javier Rodríguez-Pérez. Analytical and experimental evaluation of handovers in IPv6 mobility management protocols. Network Protocols and Algorithms 8, no. 1 (2016): 104-125.

[43] Opricovic, Serafim, and Gwo-Hshiung Tzeng. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European journal of operational research 156, no. 2 (2004): 445-455.

[44] Kantubukta, Vasu, Sumit Maheshwari, Sudipta Mahapatra, and Cheruvu Siva Kumar. Energy and quality of service aware FUZZY-technique for order preference by similarity to ideal solution based vertical handover decision algorithm for heterogeneous wireless networks. IET networks 2, no. 3 (2013): 103-114.

[45] Kuo, Yiyo, Taho Yang, and Guan-Wei Huang. The use of grey relational analysis in solving multiple attribute decision-making problems. Computers & industrial engineering 55, no. 1 (2008): 80-93.

[46] Marquez-Barja, Johann M., Hamed Ahmadi, Sergio M. Tornell, Carlos T. Calafate, Juan-Carlos Cano, Pietro Manzoni, and Luiz A. DaSilva. Breaking the vehicular wireless communications barriers: Vertical handover techniques for heterogeneous networks. IEEE Transactions on Vehicular Technology 64, no. 12 (2015): 5878-5890.

[47] Sadiq, Ali Safa, Kamalrulnizam Abu Bakar, Kayhan Zrar Ghafoor, Jaime Lloret, and Rashid Khokhar. An intelligent vertical handover scheme for audio and video streaming in heterogeneous vehicular networks. Mobile Networks and Applications 18, no. 6 (2013): 879-895.

[48] Canovas, Alejandro, Diana Bri, Sandra Sendra, and Jaime Lloret. Vertical WLAN handover algorithm and protocol to improve the IPTV QoS of the end user. In Communications (ICC), 2012 IEEE International Conference on, pp. 1901-1905. IEEE, 2012.

[49] Jaraiz-Simon, Maria D., Juan A. Gomez-Pulido, and Miguel A. Vega-Rodriguez. Embedded intelligence for fast QoS-based vertical handoff in heterogeneous wireless access networks. Pervasive and Mobile Computing 19 (2015): 141-155.

[50] Garcia, Miguel, Jaime Lloret, Miguel Edo, and Raquel Lacuesta. IPTV distribution network access system using WiMAX and WLAN technologies. In Proceedings of the 4th edition of the UPGRADE-CN workshop on Use of P2P, GRID and agents for the development of content networks, pp. 35-44. ACM, 2009.

[51] Andrews, Jeffrey G., Sarabjot Singh, Qiaoyang Ye, Xingqin Lin, and Harpreet Dhillon. An overview of load balancing in HetNets: Old myths and open problems. arXiv preprint arXiv:1307.7779 (2013).

[52] Ning, Zhaolong, Qingyang Song, Yang Huang, and Lei Guo. A channel estimation based opportunistic scheduling scheme in wireless bidirectional networks. Journal of Network and Computer Applications 39 (2014): 61-69.

[53] Ning, Zhaolong, Qingyang Song, and Yao Yu. A novel scheduling algorithm for physical-layer network coding under Markov model in wireless multi-hop network. Computers & Electrical Engineering 39, no. 6 (2013): 1625-1636.

[54] Goudarzi, Shidrokh, Wan Haslina Hassan, Mohammad Hossein Anisi, and Seyed Ahmad Soleymani. MDP-based network selection scheme by genetic algorithm and simulated annealing for vertical-handover in heterogeneous wireless networks. Wireless Personal Communications 92, no. 2 (2017): 399-436.

[55] Sun, C., Stevens-Navarro, E. and Wong, V.W., 2008, May. A constrained MDP-based vertical handoff decision algorithm for 4G wireless networks. In Communications, 2008. ICC'08. IEEE International Conference on (pp. 2169-2174). IEEE, 2008.

[56] IETF, IP Performance Metrics (IPPM) Working Group. [Online].Available: http://www.ietf.org/html.charters/ippm-charter.html.

[57] Eberhart, Russell, and James Kennedy. A new optimizer using particle swarm theory. In Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on, pp. 39-43. IEEE, 1995.

[58] Storn, Rainer, and Kenneth Price. Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. Journal of global optimization 11, no. 4 (1997): 341-359.

[59] Wang, Gai-Ge, Amir H. Gandomi, and Amir H. Alavi. An effective krill herd algorithm with migration operator in biogeography-based optimization. Applied Mathematical Modelling 38, no. 9-10 (2014): 2454-2462.

[60] Ma, Haiping, and Dan Simon. Blended biogeography-based optimization for constrained optimization. Engineering Applications of Artificial Intelligence 24, no. 3 (2011): 517-525.

[61] Mo, Hongwei, and Lifang Xu. Biogeography based optimization for traveling salesman problem. In Natural Computation (ICNC), 2010 Sixth International Conference on, vol. 6, pp. 3143-3147. IEEE, 2010.

[62] Song, Ying, Min Liu, and Zheng Wang. Biogeography-based optimization for the traveling salesman problems. In Third International Joint Conference on Computational Sciences and Optimization (CSO 2010), pp. 295-299. IEEE, 2010.

[63] V. K. Panchal, Parminder Singh, Navdeep Kaur, Harish Kundra, Biogeography based satellite image classification, International Journal of Computer Science and Information Security, vol. 6, pp. 269–274, 2009.

[64] Wang, Gaige, Lihong Guo, Hong Duan, Heqi Wang, Luo Liu, and Mingzhen Shao. Hybridizing harmony search with biogeography based optimization for global numerical optimization. Journal of Computational and Theoretical Nanoscience 10, no. 10 (2013): 2312-2322.

[65] Song, Qingyang, Zhaolong Ning, Shiqiang Wang, and Abbas Jamalipour. Link stability estimation based on link connectivity changes in mobile ad-hoc networks. Journal of Network and Computer Applications 35, no. 6 (2012): 2051-2058.

[66] Tepedelenlioglu, Cihan, and Georgios B. Giannakis. On velocity estimation and correlation properties of narrow-band mobile communication channels. IEEE Transactions on Vehicular Technology 50, no. 4 (2001): 1039-1052.

[67] Kirsal, Yonal, Enver Ever, Altan Kocyigit, Orhan Gemikonakli, and Glenford Mapp. Modelling and analysis of vertical handover in highly mobile environments. The Journal of Supercomputing 71, no. 12 (2015): 4352-4380.

[68] Guideline for evolution of radio transmission technologies for IMT-20 0 0, ITU-R M.1225, 1997.

[69] W.C. Jakes , Microwave mobile communications, IEEE Press, 1994.

[70] Hwang, Ching-Lai, and Kwangsun Yoon. Methods for multiple attribute decision making. In Multiple attribute decision making, pp. 58-191. Springer, Berlin, Heidelberg, 1981.

[71] Khan, Murad, and Kijun Han. A vertical handover management scheme based on decision modelling in heterogeneous wireless networks. IETE Technical Review 32, no. 6 (2015): 402-412.

[72] Nkansah-Gyekye, Yaw, and Johnson I. Agbinya. Vertical handoff decision algorithm for UMTS-WLAN. In Wireless Broadband and Ultra Wideband Communications, 2007. AusWireless 2007. The 2nd International Conference on, pp. 37-37. IEEE, 2007.