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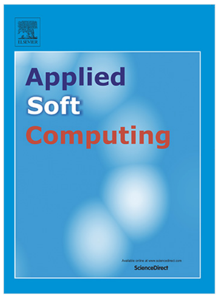

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A Hybrid Intelligent Model for Network Selection in the Industrial Internet of Things

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A B S T R A C T

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. The findings shown that the MDP-BBO algorithm is able to outperform other algorithms in terms of number of handoffs, bandwidth availability, and decision delays. Our algorithm displayed better expected total rewards as well as a reduced average account of handoffs compared to current approaches. Simulation results obtained from Monte-Carlo experiments prove validity of the proposed model.

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.

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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 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 novel optimized algorithm with the benefit of two current approaches that address the requirements stated above. The novelty of our approach lies in the hybridization of Markov decision process and biogeography-based optimization algorithm.

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 networks (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. Such limitations have motivated us to create intelligent algorithms that prevent slow and high computing linked to direct search methods thus lowering the time of computation. Motivated by these observations, we have proposed an efficient algorithm to perform intelligent decision-making during the vertical handover process. Since the importance of high latency, packet loss and signaling cost problems during handover process are undeniable, the lack of an effective vertical handover decision (VHD) algorithm, which could select the most optimal access network for handover, is sensible. The complexity of calculating the many parameters in VHD algorithms is another problem. Moreover, it has been shown that the use of adaptive behavior has not been fully investigated. Moreover, a well-established algorithm for a VHD algorithm is critically required that would both create a hybrid VHD algorithm which uses forms of intelligence for making decisions via the utilization of mixed heuristic techniques and be able to robustly adapt to the various conditions when the need arises given the dynamic changes that keep occurring in the wireless environment.

Compared with existing efforts, our main contributions can be summarized as follows: a) we use MDP to establish the radio access technology (RAT) selection's probability; b) we use the BBO to determine the best RAT using the described multi-point algorithm in the heterogeneous network; c) we construct a simulation to evaluate our proposed method, and results show that our method can outperform mobile terminal VHO effectively in the heterogeneous network. Improvements in connectivity through our novel designed model serve users with a high level quality of service across different conditions. The proposed model can support different range of applications such as transportation safety applications, voice and data connections applications, conversational and streaming applications. The primary objective of Intelligent Transportation System (ITS) is to provide safety to human lives and improve the efficiency of the transportation system. To achieve this goal, ITS converges remote sensing and communication technologies. Moreover, demand for voice, data and multimedia servces, while moving in car, increase the importance of broadband wireless systems in ITS.

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 caused 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 [31] 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 [31]. Wang et al. [32] 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 [33-35]. 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 [36], 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 [30] using the similar prediction method [37]. 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 [38], 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. [39] 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 [40], designing an algorithm and protocol that takes into account the QoS parameters when the end user is receiving IPTV [41] and scheming depending on the requirements of the IPTV client [42]. 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) [43]. There have been evaluations on the workings of the proposed scheme against the TOPSIS [44] and grey relational analysis (GRA) [45] decision-making model.

Researchers in [46] 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 SEFI-SA 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 [46] introduced an algorithm using the Genetic Algorithms (GAs) to get a higher level of performance compared to the SEFI-SA. 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.

The above related works show important results of comparison of artificial intelligence mechanisms as initial finding of this research. Based on comparison, hybrid approach reduces network selection time and improves mobile QoS. Ongoing research is required to build novel hybrid approach that is able to provide optimal outcomes but without too much complication, with a certain level of intelligent and adaptive characteristics to manage uncertainties and to meet the robust mobile environment.

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.

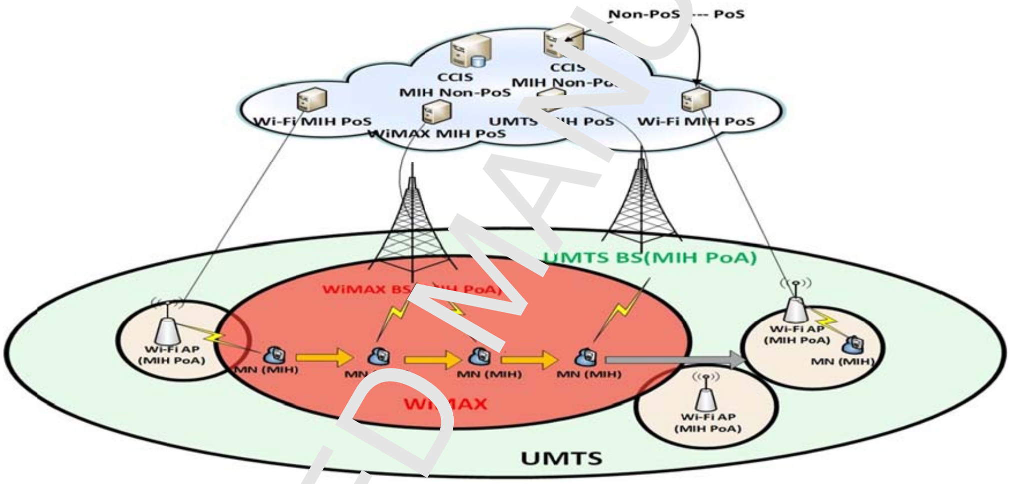


Fig. 1. Heterogeneous wireless networks.

There are two factors that 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 [47].

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 [48]. 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 [49] 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 [50]:

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

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 [51], these probabilities are also defined as:

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

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 $N_{\text{Mobile input/output}}$.

$T = \{1, 2, \ldots, N\}$ 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 of 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 $P\ [s' \mid s, a]$. 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 = ($\delta_1, \delta_2, \dots, \delta_N$) represents the sequence for the decision rule that is utilized at all the decision epochs.

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.
$P_{WiMAX} \vert P_{WiFi}[t]$	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.
$P_{WiFi}[t+1]$	$P_{WiFi} \vert P_{WiMAX}[t+1]P[t] + (1 - P_{WiMAX} \vert P_{WiFi}[t+1])P_{WiFi}[t]$
$P_{WiMAX}[t+1]$	$P_{WiMAX} \vert P_{WiFi}[t+1]P[t] + (1 - P_{WiFi} \vert P_{WiMAX}[t+1])P_{WiMAX}[t]$
$P_{WiMAX}[t]$	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.
$P_{LTE} \vert P_{WiMAX}[t]$	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.
$P_{WiMAX}[t+1]$	$P_{WiMAX} \vert P_{LTE}[t+1]P[t] + (1 - P_{LTE} \vert P_{WiMAX}[t+1])P_{WiMAX}[t]$
$P_{LTE}[t+1]$	$P_{LTE} \vert P_{WiMAX}[t+1]P[t] + (1 - P_{WiMAX} \vert P_{LTE}[t+1])P_{LTE}[t]$
$P_{LTE}[t]$	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.
$P_{WiFi} \vert P_{LTE}[t]$	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.
$P_{LTE}[t+1]$	$P_{LTE} \vert P_{WiFi}[t+1]P[t] + (1 - P_{WiFi} \vert P_{LTE}[t+1])P_{LTE}[t]$
$P_{WiFi}[t+1]$	$P_{WiFi} \vert P_{LTE}[t+1]P[t] + (1 - P_{LTE} \vert P_{WiFi}[t+1])P_{WiFi}[t]$

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 $P\ [S' \vert s, a]$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 [52]:

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

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:

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

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], $f_b(s,a)$ represents the function for bandwidth whereas $f_d(s,a)$ 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:

$$S' = [j, b_1', d_1', p_1', th_1', be_1', c_1', sec_1', j_1', \ldots, b_M', d_M', p_M', th_M', be_M', c_M', sec_M', j_M'] \tag{15}$$

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:

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

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

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

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 services as described by the Internet Engineering Task Force IP Performance Metrics Working Group [53]. 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 $\mathrm{B^m}$,and $\mathrm{D^m}$, $\mathrm{P^m}$, 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.

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.

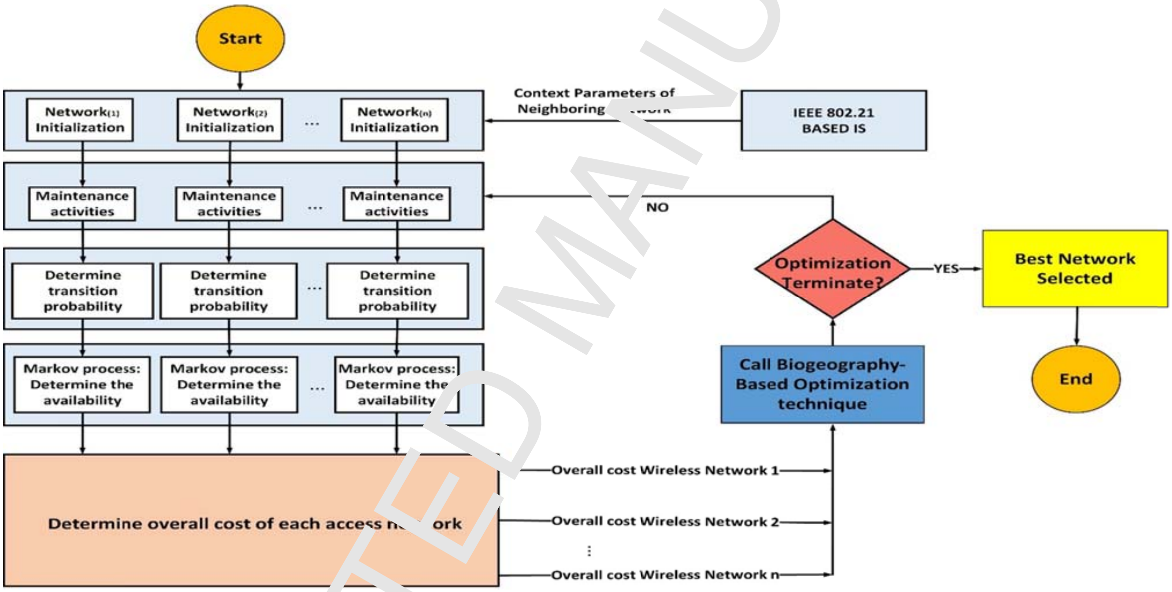


Fig. 2. Hybrid model of BBO with MDP to select the best network

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 [54-56].

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 [57] involving such as the Traveling Salesman Problem [58-59], classification of satellite images [60], 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, 61] 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].

In the MDP-BBO algorithm, the species geographic distribution of genes was mapped to determine the solution to the problem. The position of each gene represents a possible solution to the optimization problem and the habitats' rates of immigration and emigration correspond to the quality (cost) of the associated solution. Therefore, the deployment of the wireless networks in the sensed area (each solution of the deployment problem) refers to a habitat in the algorithm. The quality of the network, for example the total coverage area, corresponds to the cost value (habitat' rate) of the solution. Table 3 shows the basic concepts of MDP-BBO.

Table 3. Mapping table for the proposed MDP-BBO algorithm

Concept	**Refers to**
Available network	Available Habitats
Cost value of network	Habitats' rates of immigration and emigration
Set of mobile nodes	Group of gene candidate
Best network	Best Habitat
Quality of network	Quality of island habitats

The proposed algorithm is applied over the multi-point decision making (MDP) module to optimize the weight coefficients, so that the best network is selected. The conventional biogeography based optimization consisted of major two steps namely migration and mutation. In traditional BBO, mutation is a varying operator that randomly changes the values at one or more search positions of the selected species. We proposed a new mutation mechanism based on MDP process which is employed to increase the exploration ability in search space. In our proposed model no changes are made in the migration part so as to maintain the exploitation ability.

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
End if
Best Cost = ***Choose****(Best Costs)*
End

Standard Pseudo Code for Migration

For $i = 1$ *to* NP ***do***
    Select H_i with probability based on λ_i
    If H_i is selected **Then**
        For $j = 1$ to NP **do**
            Select H_j with probability based on μ_j
            If H_j is selected **Then**
                Randomly select a *SIV(s)* from H_j
                Copy them *SIV(s)* in H_j
            End if
        End for
    End if
End for

Standard Pseudo Code for Mutation

For $i = 1$ *to* NP ***do***
    Use λ_i *and* μ_i *to compute the probability* P_i
    Select SIV $H_i(j)$ *with probabi;lity* $\propto P_i$
    If $H_i(j)$ *is selected* ***Then***
        Replace $H_i(j)$ *with a randomly generated SIV*
    End if
End for

6. Results and discussion

We utilized MATLAB and OMNET++ to evaluate network performance. We utilized MATLAB ++ to implement all algorithms in the pre-processing steps. OMNET++ is a well-designed, component-based, modular and open-architecture simulation environment with strong GUI support and an embeddable simulation kernel. 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 4 and 5 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 [62-64]. 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.

Table 4. 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	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	3.84 x 106	

					the wireless links	

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 [65] 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 [66] is used with the decorrelation length of 50 m and the Rayleigh fading is applied using a Jakes spectrum model.

Table 5. 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	[illegible] 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

We selected utility functions-based approaches for comparison such as TOPSIS, GRA, FMADM and SEFISA. Several assessments exist based on the workings of the proposed scheme versus the TOPSIS [41, 42] 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 [68]. 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 [67].

Table 6 provides the sample data set of considered users with the constraint parameters fixed namely bandwidths, packet loss, delay, throughput, cost of bit error rate, security, and jitter which are used for RAT selection process (1000 users were considered). Firstly, the entire proposed algorithmic approach was rum in MATLABR2014 environment and executed in Intel Core2 Duo Processor with 2.27 GHz speed and 2.00 GB RAM. Then, the codes and modules are programmed and translated into C++ code to implement into the OMNET++.

Table 6. Sample dataset of mobile users for input parameters (B, P, D, TH, BER, S and J)

S. no	WiMAX							WiFi							UMTS						
	B	P	D	TH	BER	S	J	B	P	D	TH	BER	S	J	B	P	D	TH	BER	S	J
1	4.5	0.8	5.8	6.6	1.7	0.9	5.4	0.9	1.2	9.6	5.7	1.7	0.7	6.7	8.9	1.6	8.5	7.3	1.8	0.8	8.7

2	3.8	0.9	5.5	6.1	1.6	0.8	4.2	0.8	1.4	8.9	5.5	1.4	0.8	6.4	8.3	1.5	7.6	6.9	1.7	0.9	9.1
3	5.5	0.7	6.1	7.2	1.5	0.9	5.1	0.7	1.3	9.4	5.1	1.8	0.8	6.3	8.1	1.7	[illegible]	7.1	1.9	0.8	7.9
4	4.3	0.8	5.9	6.8	1.8	0.7	5.5	0.8	1.2	9.1	4.9	1.7	0.9	5.9	7.9	1.6	8.5	7.5	1.5	0.9	8.1
5	3.6	0.7	5.5	6.3	1.5	0.8	4.1	0.8	1.4	8.9	5.5	1.4	0.8	6.4	8.1	1.7	8.2	7.1	1.9	0.8	7.9
6	3.8	0.9	5.5	6.6	1.7	0.9	4.2	0.6	0.8	1.4	8.9	5.5	1.4	0.8	8.9	1.6	8.5	7.3	1.8	0.8	8.7
7	5.5	0.7	6.1	7.2	1.5	0.9	5.1	0.7	1.3	9.4	5.1	1.8	0.8	6.3	8.1	1.7	[illegible]	7.1	1.9	0.8	7.9
8	4.3	0.8	5.9	6.8	1.8	0.7	5.5	0.8	1.2	9.1	4.9	1.7	0.9	5.9	7.9	1.6	8.5	7.5	1.5	0.9	8.1
9	3.4	0.8	5.9	6.1	1.6	0.8	4.2	0.6	1.5	9.1	4.5	1.9	0.7	5.8	7.4	[illegible]	8.9	7.4	1.9	0.8	8.8
10	3.8	0.9	5.5	6.6	1.7	0.9	4.2	0.8	1.4	8.9	5.5	1.8	0.8	6.3	8.1	[illegible]	[illegible]	7.1	1.9	0.8	7.9
And so on up to 100 users																					

For the considered data samples of 100 users with the sample data set as shown in Table 6 to start with proposed MDP process was applied and the MDP-BBO output for the respective input parameters are computed. The outputs from the MDP are sent to the BBO algorithm (MDP-BBO module) to select the best RAT for heterogeneous network. The proposed approach targets fast movement of the MN and solves the dynamic decision-making issues efficiently. The simulation parameters of three access networks are shown in Table 7.

Table 7. Sample dataset of

WLAN Access Point Parameters	**Value**
Transmission Power	0.027 W
Receiving Threshold	1.17557e-10 W
Throughput	0.3733550
Carrier Sensing Threshold	1.05813 e-10 W
Coverage Radius	150 meters
Radio Propagation Model	Two-Ray Ground
Frequency	2.4 GHz
WiMAX Parameters	**Value**
Transmission Power	30 W
Receiving Threshold	3e-11 W
Carrier Sensing Threshold	2.4 e-11 W
Coverage Radius	1500 meters
Radio Propagation Model	Two-Ray Ground
Antenna Type	Omni Antenna
Code Rate	1/2
PHY Mode	256 OFDM
Maximum Data Rate	1882 Kbps
UMTS Parameters	**Value**
Coverage	All Simulation Area
Maximum Data Rate	384 Kbps

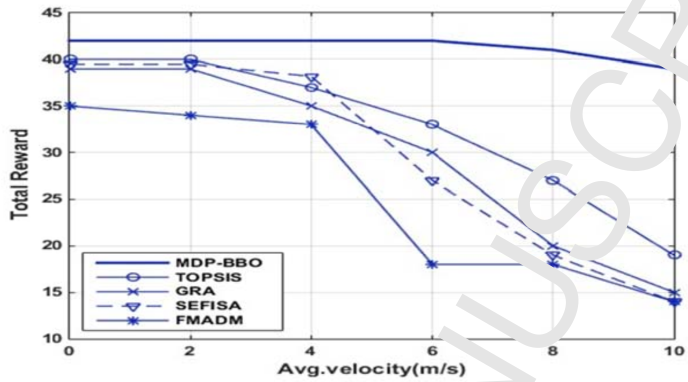
The working of the proposed scheme is tested in both smaller and larger coverage area networks. The movement of different number of MTs have been considered ranging from 10 to 100 with variable speed in three different networks, i.e. cellular, WiMAX, and WiFi. The MT performed several handovers between these networks.

We have conducted performance comparisons between our algorithm MDP-BBO and other algorithms structured in the literature, namely SEFISA [46] and FMADM [69]. In a study by Jaraiz-Simon et al. [46], 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. SEFISA is selected for comparison because it is a heuristic proposition based on the Simulated Annealing (SA) algorithm and SA is a probabilistic technique for approximating the global optimum of a given function. In addition, the FMADM is a multiple attribute decision making algorithm that selects a suitable wireless access network during the vertical handover process. The findings show that the proposed mechanism has better performance in comparison to the SEFISA, TOPSIS, GRA and FMCDM algorithms according to the metrics based on number of handover, failed HO, number of packets loss, throughput and handover latency.

To show the limits of using previous models to select an access network and to motivate the need of optimized selection method to improve seamless handover, several experiments are simulated using OMNET++ that support the MIH modules implemented by INET/NAT. To compare MDP-BBO and original MIH results, the same topology of simulation is used which cited in Fig. 1. The traffic used has a constant bit rate (CBR), which allows for calculating the amount of packet loss.

It also could be used to simulate voice traffic. Packet size is always constant at 1500 bytes and the throughput is determined by varying the interval of sending packet during simulation.

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 researcher 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.

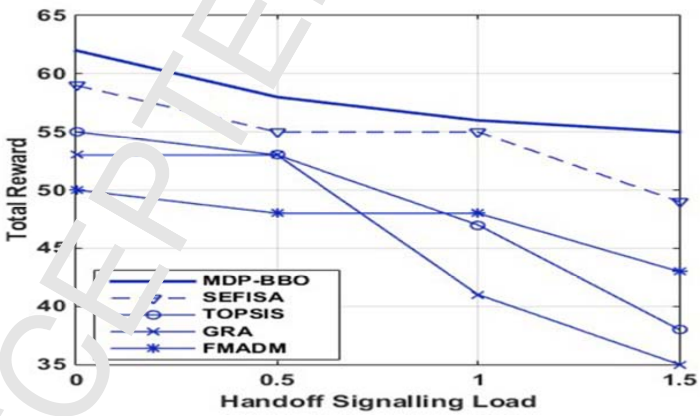


Fig. 4. Comparisons of average numbers of HOs under various signaling loads

The handoff rates in the proposed scheme in comparison between the MDP-BBO, SEFISA, TOPSIS, GRA and FMADM are demonstrated in Fig. 5.

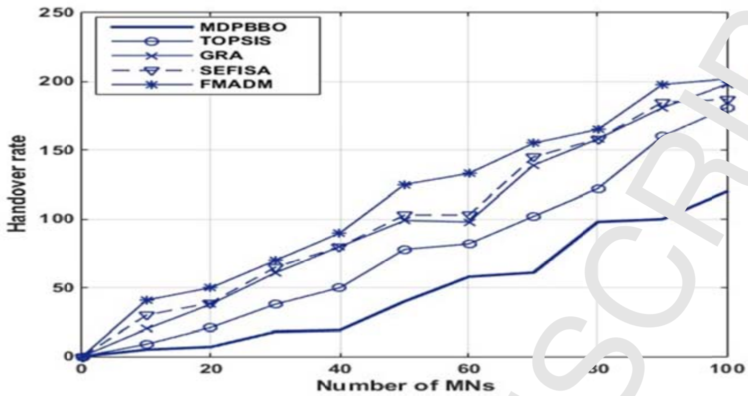


Fig. 5. Analysis of handoff rates

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. As shown in Figure 5.12, regardless of number of nodes, the network selection methods including TOPSIS, GRA, SEFISA and FADM have very close results and these similarities grow by increasing the number of nodes. One of the reasons which can be identified when observing the simulation is the non-suitable handover triggering caused by the RSS in the GRA and TOPSIS. Despite of other method, MDP-BBO has lower number of handover. The reason for this effect is that proposed model integrates the MIH model, data rate threshold values, the MDP and the cost functions to an MDP-BBO handover decision algorithm.

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. Also, GRA, TOPSIS select the best network with more time to process, which loads the network with a high number of packets. Also, in RSS-based approach, handover initiating is based on RSS threshold and RSS degradation during handover leads to increase false handover trigger alarms. This in turn causes high packet loss. 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.

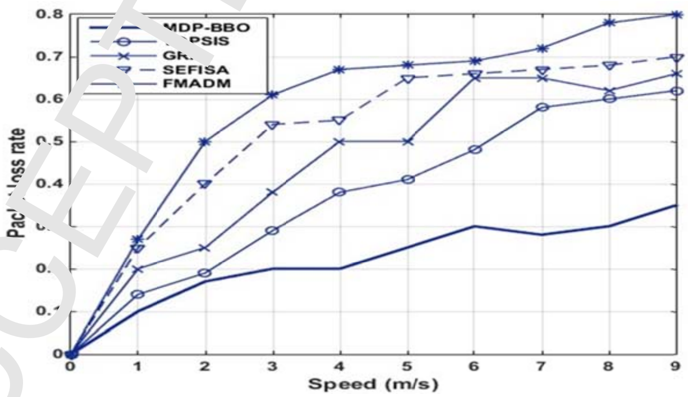


Fig. 6. Packet losses during handovers

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. 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.

Initially, a short period of time is required to trigger MDP-BBO, after which the average success rate of packet delivery in MDP-BBO is increased over simulation time dramatically, even though initially the throughput experienced by the mobile node is continuous without any interruption when the MDP-BBO decision solution was employed. This is because the MDP-BBO selects the best network in a lower level of loss of packets and low delay in handover due to optimized network selection, thus increasing the throughput. The loss of packets affects throughput in an indirect manner. Other approaches have high packet loss and as such offer low gains in throughput mainly because of non-suitable handovers. Delays in handovers and time taken for data redirecting also influence the throughput. Hence, since the MDP-BBO uses MIH protocol for supporting QoS and for managing connectivity issues, there is also high throughput in the MN. Fig. 7. shows the throughput gain comparison in the proposed scheme, GRA, and TOPSIS decision models.

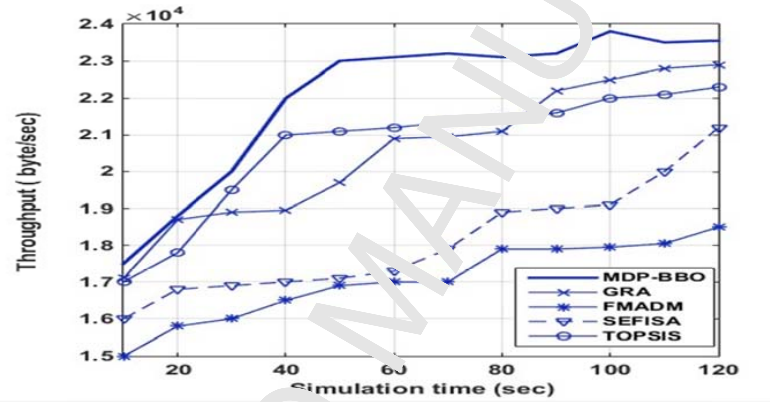


Fig. 7 Throughput gains

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). The modification made in the mutation part with MDP increases the exploration ability. Thus the proposed MDP-BBO results in a balanced exploration and exploitation ability of algorithm.

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.

From the simulation results presented in Fig.9, it is not surprising the handover delay increases in the hybrid MDP-BBO algorithm assisted MIH and other methods 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 framework achieves a lower delay for audio and video applications of 30%, compared to a traditional simple scenario. In this experiment, simulation results show that this research can improve the QoS of a real-time application by integrating MDP-BBO algorithm to make an accurate decision.

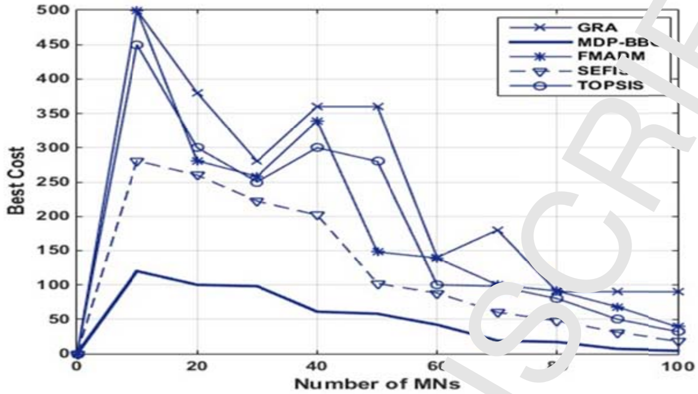


Fig. 8. Best costs

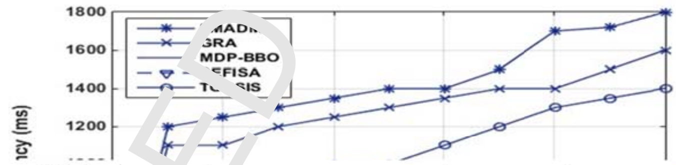


Fig. 9. Handover latency vs Mobile speed

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.

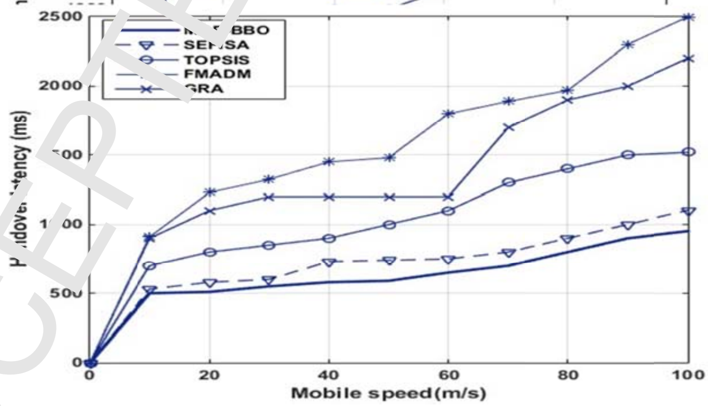
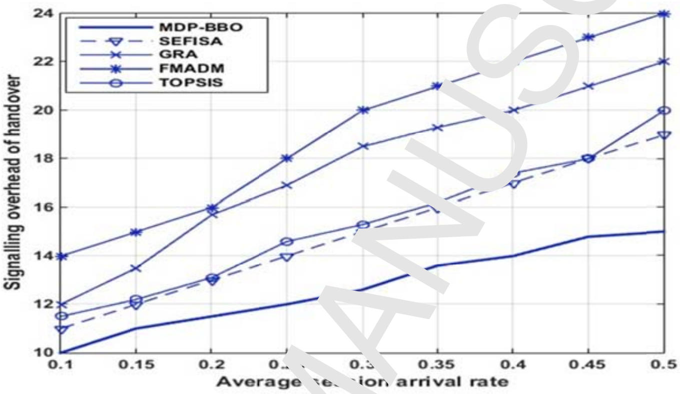


Fig. 10. Handover latency vs. Mobile nodes densities

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 10 Mbps. 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 trucking 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.

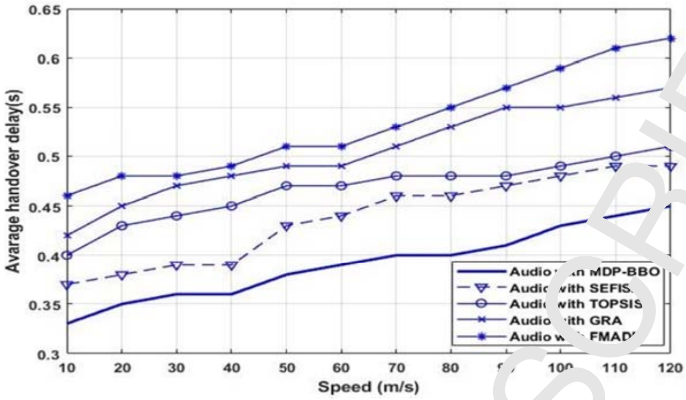


Fig. 12. Handover delays for audio versus moving speed of MNs

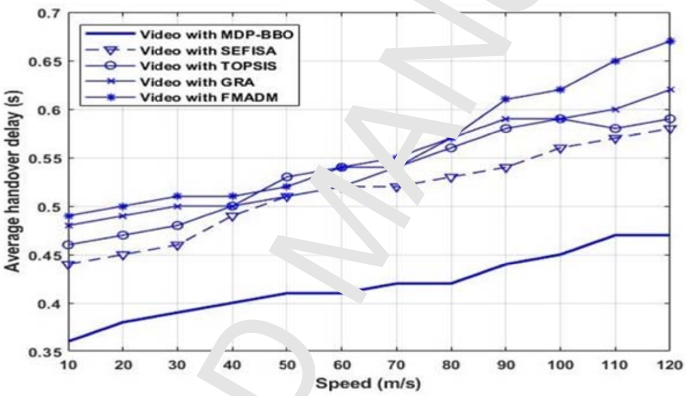


Fig. 13. Handover delays for video versus moving speed of MNs

Calculating the computation time (CT) taken for algorithm completion is especially necessary in the real-time applications when VHO decision algorithm should quickly select the best network during VHO process. In this study, the stopwatch timer functions, tic and toc, are used to calculate the computation time. Invoking tic starts the timer, and the next toc reads the elapsed time in MATLAB. The CPU time returns the total CPU time (in seconds). The line graph compares the average of computation times in the MDP-BBO, SEFISA, TOPSIS, GRA and FMADM in 30 runs. When comparing the data resulting from the plot, the average time needed for SEFISA calculation is approximately 0.6 (s). TOPSIS and GRA have high computation time of about 0.85 (s), 0.87 (s). The FMADM has highest computation timeabout 0.9 (s). In contrast, MDP-BBO has the lowest computation time of 0.43 (s). Figure 14 shows changes in the computation time between the MDP-BBO, SEFISA, TOPSIS, GRA and FMADM methods.

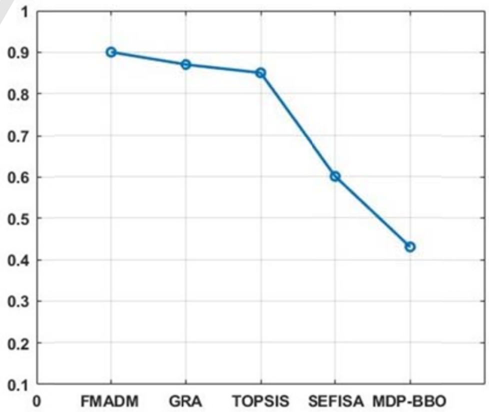


Fig. 14. Average of computation time

The computational time taken for determining the best networ for the given heterogeneous network is reduced to half the time in comparison with that of the methods available in the literature.

Several comparisons were performed between the MDP-BBO, SEFISA, TOPSIS, GRA and FMADM. The FMADM has the highest rate of handovers as compared to other models. The TOPSIS and GRA have the same rates of handover and MDP-BBO has better performance in terms of handover rate which helps mobility management. Generally, SEFISA, TOPSIS, GRA and FMADM models have shortcomings: they are usually not possible to make right VHO decisions timely because of high packet loss, high latency and low throughput gains. Another unfortunate practical problem is the high volume of calculations for finding the criteria weight for evaluation.

We compare the performance of our proposed model with the existing techniques using Monte-Carlo simulations [43]. In Monte-Carlo experimentation for a given velocity (v) and the given value of probability of handover failure (Pf) or probability of unnecessary handover (Pu) the threshold value (M or N) is obtained using the above threshold Eqs. (19 and 21).

$$P_f = \begin{cases} P_r[M < T \leq \tau_i] = \int_M^{\tau_i} f_T(t)dt, & 0 < T \leq \frac{2a}{v} \\ 0, & otherwise \end{cases} \quad (19)$$

We can achieve the value of M for an acceptable level of probability of failure by following formula (20):

$$M = \frac{2a[\tan[\arctan\left(\frac{vt_i}{\sqrt{4a^2 - v^2\tau_i^2}}\right) - \frac{\pi P_f}{2}]}{v\sqrt{1+k_f^2}} \ , \ 0 < M \leq \tau_i \quad (20)$$

$$P_u = \begin{cases} P_r[N < T \leq \tau_T] = \int_N^{\tau_T} f_T(t)dt, & 0 < T \leq \frac{2a}{v} \\ 0, & otherwise \end{cases} \quad (21)$$

We obtain the value of N to keep probability of unnecessary handover within desired bounds by following formula (22):

$$N = \frac{2a[\tan[\arctan\left(\frac{vt_T}{\sqrt{4a^2 - v^2\tau_T^2}}\right) - \frac{\pi P_u}{2}]}{v\sqrt{1+k_u^2}} \ , \ 0 < N \leq \tau_T \quad (22)$$

As per Monte-Carlo rule the experiment is repeated very large number of times and finally we obtain the experimental value of the probability of handover failure or unnecessary handover by dividing the failed or unnecessary attempts with the total number of handover attempts. For each value of v the experiment is repeated until the results are stabilized and a clear pattern has emerged. The threshold values for other models are obtained in exactly the same fashion using their derived relationship and their assumed probability distributions of their models. The experiments are performed using the same methodology and results are obtained and compared. The lowest speed and highest speed considered are 5m/s and 35m/s respectively. This is due to the fact that WLAN has a small coverage radius. The coverage radius of WLAN is assumed to be 50m. Also, we assumed the total latency for hand-into and hand-out of WLAN is about T = 2 s. So the maximum dwell time above 25 m/s speed is less than the sum of handover latencies which would guarantee always unnecessary handover. Results of Monte-Carlo simulation are presented in Figs. 15 and 16 for probability of handover failure and probability of unnecessary handover, respectively.

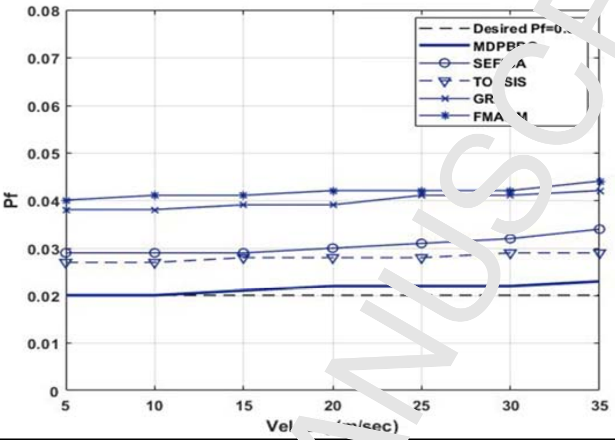


Fig. 15. Probability of handover failure

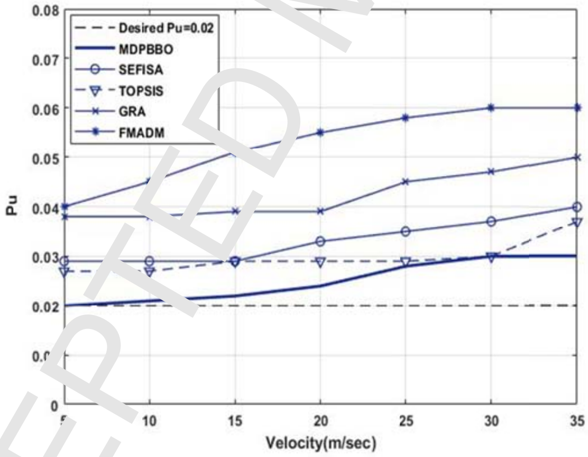


Fig. 16. Probability of unnecessary handover

Monte-Carlo simulation results validate our model and show better performance than other comparable approaches. In maintaining the handover failure probability for our proposed model, the percentage deviation from the desired level is 0% for the lowest observed velocity and remains less than 7%, while the deviation in the other models ranges from 2 to 25% and 100 to 125% for the same range of velocity. Likewise, for maintaining the probability of unnecessary handover within desired bounds the improvement provided by our proposed model is roughly of the same order. From the graphs, we observe that as the velocity of the MN increases, the probability of unnecessary handover and handover failure increases and deviates from the designed level. This indicates that speed has an impact on the calculation of threshold values, which are obtained using this probabilistic model. This is because high mobility makes it difficult to maintain the connection between the MT and target network during the handover period and thus reduces the probability of a successful handover.

Table 8 shows root mean square error (RMSE) for the models under consideration. The RMSE is a statistical tool that shows how the models deviate from the predefined benchmark value of 0.02. In both cases, the error for the proposed model of P_f and P_U was minimal.

Table 8. Values of RMSE for the models

Model	FMADM	GRA	TOPSIS	S[illegible]FISA	MDP-BBO
P_f's RMSE	0.01367	0.01243	0.00506	0.0046[illegible]	0.00054
P_U's RMSE	0.01784	0.01073	0.00729	0.0050[illegible]	0.00152

We can found that the efficiency of our model in accordance with the failure close to the benchmark value. The efficiency of the proposed model for a benchmark value of 0.02 was 98.85%.

In summary, the simulation results prove the effectiveness of the proposed approach as follows:

- This proposed algorithm reduces the call dropping probability as well as the signaling and processing cost by considering the velocity of the MT
- Many unnecessary handoffs are prevented.
- The rate of handoff and signaling overhead have been decreased significantly and the packet loss is minimized
- The throughput and performance in terms of precision and cost function. have been improved
- The proposed work improves the QoS of real-time applications

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, throughput, 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.

Acknowledgements

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Highlights

- This works proposes a hybrid intelligent model for network selection in Industrial Internet of Things.
- The proposed 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 the input to the BBO process
- The BBO determines the best radio access technology (RAT) using the described multi-point algorithm in the heterogeneous networks.