Dynamic Target Wireless Network Selection Technique Using Fuzzy Linguistic Variables

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Abstract: Even though various wireless Network Access Technologies (NATs) with different specifications and applications have been developed in the recent years, no single wireless technology alone can satisfy the anytime, anywhere, and any service wireless-access needs of mobile users. A real seamless wireless mobile environment is only realized by considering vertical and horizontal handoffs together. One of the major design issues in heterogeneous wireless networks is the support of Vertical Handoff (VHO). VHO occurs when a multi-interface enabled mobile terminal changes its Point of Attachment (PoA) from one type of wireless access technology to another, while maintaining an active session. In this paper we present a novel multi-criteria VHO algorithm, which chooses the target NAT based on several factors such as user preferences, system parameters, and traffic-types with varying Quality of Service (QoS) requirements. Two modules i.e., VHO Necessity Estimation (VHONE) module and target NAT selection module, are designed. Both modules utilize several "weighted" users' and system's parameters. To improve the robustness of the proposed algorithm, the weighting system is designed based on the concept of fuzzy linguistic variables.

Key words: network access selection; VHO; heterogeneous networks; WLAN; WMAN; WWAN; Techniques for Order Preference by Similarity to Ideal Solution

I. INTRODUCTION

In the recent years, wireless networks have experienced a massive advancement. However, any single type of existing wireless and mobile network such as Wi-Fi, Bluetooth, Universal Mobile Telecommunication System (UMTS) or IEEE 802.16 Worldwide Interoperability for Microwave Access (WiMAX), cannot provide all types of services, e.g., wide-area coverage and high data-rates. In future generation mobile communications systems, an integrated heterogeneous access network is introduced by combing different types of networks with different characteristics, e.g., bandwidth, delay, communication range, speed support, power consumption, security, end-user cost and several other aspects [1]. This convergence of wireless networks provides the Mobile Station (MS) with a greater choice of Network Access Technologies (NATs), which offer different levels of Quality of Service (QoS) and radio characteristics. Significant research work is being done to achieve seamless mobility while an MS moves across these heterogeneous networks and changes it network access using a process, called Vertical Handoff (VHO).

Some previous works dealing with VHO algorithm design are reported in Refs. [2-8]. The Artificial Intelligence (AI) scheme in Ref. [2], which is based on a hybrid of parallel fuzzy-logic-system, multiple-criteria decision

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A new intelligent Vertical Handoff scheme is presented that utilizes MADM technique like TOPSIS and Fuzzy Logic based Linguistic Variables to estimate the necessity of handoff and to determine a new Point of Attachment that can best fulfill the endusers' requirements.

making and Genetic Algorithm (GA), is developed to provide adaptive, flexible, and scalable solution to the VHO decision problem. The decision phase uses three parallel fuzzy-logic subsystems. The normalized outputs of these subsystems along with their importance weights, optimized using GAs, are fed into a multi-criteria decision making system. This system is based on an enhanced version of Simple Multi-Attribute Rate Technique (SMART). The results show an increase percentage of satisfied users. However, the proposed scheme is limited to only four different criteria and does not take into consideration other important decision factor like loading conditions of the network. Furthermore, single-objective GAs are used to optimize each objective weight independently rather than utilizing a multi-objective utilization method to find optimal weights jointly, which could have resulted in an improved performance. A fuzzy multi-criteria VHO algorithm with its parameters enhanced by the use of an inverted 2-layer Multi-Layer Perceptron (MLP) is proposed in Ref. [3]. In the proposed approach, a preliminary selection of candidate networks is performed using Received Signal Strength (RSS) to reduce the complexity of the Fuzzy Logic Controller (FLC). The FLC takes five inputs including RSS and loading-conditions of the current and the target systems, and the velocity of MS. A total of 24 fuzzy handoff rules including general rules, UMTS specific rules, and the Wireless Local Area Network (WLAN) specific rules are created. In the proposed approach a 2-layer MLP, with FLC parameters as inputs and the desired UMTS and WLAN throughput as outputs, is trained and then inverted using a non-linear system. This approach is compared against an algorithm that is based on fixed coverage and load thresholds. However, wireless networks are highly dynamic in nature resulting in varying load conditions and coverage. The authors in Ref. [4] utilize Analytic Hierarchy Process (AHP) for both weight elicitation and network selection processes. RSS is the only criterion that is used to trigger the handoff. This work is extended in Ref. [5] where authors implemented AHP based weight elicitation process along with Techniques for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank the available networks. However, not all the QoS parameters are utilized to make selection decisions. The authors in Ref. [6] provide a scheme, which utilizes AHP for VHO in a WiMAX/WLAN environment. Likewise, this work does not give any consideration to other important parameters such as RSS. A Fuzzy MADM based numerical solution for VHO decisions is introduced in Ref. [7], where imprecise, or fuzzy data in terms of Linguistic Variables is used to specify network parameters and user preferences in the form of weights. These Linguistic Variables are first converted into crisp numbers using a fuzzy number conversion scale and then classical MADM methods like Simple Additive Weighting (SAW) and TOPSIS are applied. The paper provides analysis for only voice and Background traffic types. A utility-based FTOPSIS method emphasizing a balance between performance and energy consumption is provided in Ref. [8]. Fuzzy Linguistic Variables (FLVs) represented as Triangular Fuzzy Numbers (TFNs) are used to determine the weights for the network parameters. The numerical examples provided in this paper considered only two QoS attributes (Bandwidth and Delay).

Most of the existing VHO algorithms, which are based on a single metric, do not exploit the benefits of multi-criteria and the inherent knowledge about the sensitivities of these handoffs. Moreover, while performing VHOs, these algorithms do not take into account the QoS of an ongoing session to maximize end-user satisfaction based on their preferences, location and application contexts. Another problem with the existing algorithms is that the assignment of preference weights for these parameters is done manually. Manual weight assignments do not consider how much of a weight is needed for a certain network parameter, which can lead to a degraded VHO performance. This becomes problematic especially during an ongoing session such as a Voice over IP (VoIP) conversations where achieving a minimum level of QoS is essential. Therefore, in order to guarantee the quality of the currently utilized service, proper weights assignment, especially for QoS-related parameters, is of utmost importance and should be done very carefully. Factors like available network bandwidth, latency, security, usage cost, power consumption, battery status of the MS, and user preferences should be thoroughly considered when performing these handoff decisions.

With the aim of overcoming the aforementioned problems, in this paper, we present a new intelligent VHO scheme, which consists of two modules, namely, VHO Necessity Estimation (VHONE) and NAT selection. Using FLCs, the VHONE module examines the existing conditions of MS's current Point of Attachment (PoA) and estimates the necessity of handoff. In the second module, several parameters of all available candidate networks are utilized to determine a new PoA that can best fulfill the end-user's requirements. Both modules use a weighting mechanism to determine the relative importance of these parameters that are used by the system. FLVs [9-11] are used to design the weighting system, which shows to cope better with the fuzzy nature of network parameters in wireless environments. The second module is designed based on TOPSIS ranking method, which determines the best network for future connection. In this research, we assume four different classes of traffic and our target selection module is designed to adapt to the special requirements of each of these traffic classes. Our scheme is examined by developing a simulation test-bed, which simulates a practical wireless heterogeneous environment with three different networks, i.e., WLAN, Wireless Metropolitan Area Network (WMAN) and Wireless Wide Area Network (WWAN).

The remainder of this paper is organized as follows. In Section II, the proposed scheme is explained. Section III discusses the simulation environment, the performance evaluations, results and comparisons, using different network performance metrics. Finally, concluding remarks are drawn in Section IV.

II. Proposed Scheme

Our proposed VHO algorithm consists of two modules; VHONE, which estimates the necessity of performing the VHO and a NAT selection module based on TOPSIS method. In the first stage of VHONE module, as shown in Figure 1, the parameters from the current PoA are measured. The weights for these parameters are then calculated based on the QoS requirements for each traffic class. Our scheme utilizes a few carefully chosen parameters that are critical to maximize the end-users' satisfaction while performing efficient handoffs. These parameters include network RSS, MS-velocity, distance between the Base Stations (BSs) and MS, network loading-conditions, security provided by the network, service-cost, and QoS parameters including network throughput, latency, jitter, and Packet Loss Ratio (PLR). It is assumed that these parameters are either available to the MS or can be estimated through some mechanism; for example, RSS and QoS related data can be provided to the MS by in-range BSs. Similarly GPS module installed in most MSs are capable of estimating the MS's velocity. Some other estimating techniques are provided in Refs. [12-14]. The distance between the MS and the current PoA plays a critical role in determining the handoff necessity; the increase in distance affects RSS and other critical factors. Hence, an FLC is designed based on the coverage provided by a specific network type. Since the coverage area of the three types of networks are different and the assumption that at the most MS will be connected to one PoA, separate membership functions with different Universe of Discourses (UoDs) are designed based on these network types. This FLC estimate the probability, whether the MS can be served by an available PoA based on its distance with MS. In order to reduce the call dropping probability in a log-normal fading heterogeneous wireless environment, the proposed scheme utilizes Predicted RSS (PRSS) values measured from the networks. These predicted values, obtained using Grey Prediction Theory (GPT), are utilized by the proposed scheme to determine the necessity of a future handoff. In Grey theory, system dynamic model can be represented by $GM(n, h)$, where n is the order of Grey differential equation, and h defines the number of variables. This research work utilizes one of the most popular and widely used Grey prediction models; the $GM(1,1)$ model takes a sequence of n RSS samples, and arranges it into a vector according to $X^{(0)}=\{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}$. The Accumulated Generating Operation (AGO) is utilized to further process these samples due to the possible presence of random noise. The AGO operation produces a first-order AGO sequence given by:

$$x^{(1)}(k)=\sum_{i=1}^{k} x^{(0)}(i); \quad k=1,2,\ldots,n \tag{1}$$

A linear dynamic model is then used to approximate the sequence in $X^{(0)}$ according to:

$$x^{(0)}(k)+ax^{(1)}(k)=b \tag{2}$$

where a (developed parameter) and b (grey input), which can be calculated using the least square approximation, are the coefficients of the differential equation whose solution is given by:

$$x^{(1)}(n+1)=\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-an}+\frac{b}{a} \tag{3}$$

The vector representation of a and b is defined by:

$$c=[ab]^T=(B^T B)^{-1}B^T\gamma_n \tag{4}$$

where,

$$B=\begin{bmatrix} -\frac{1}{2}[x^{(1)}(1)+x^{(1)}(2)] & 1 \\ -\frac{1}{2}[x^{(1)}(2)+x^{(1)}(3)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}[x^{(1)}(n-1)+x^{(1)}(n)] & 1 \end{bmatrix} \tag{5}$$

and

$$\gamma_n=[x^{(0)}(2),x^{(0)}(3),\ldots,x^{(0)}(n)]^T \tag{6}$$

Thus the predictive value of RSS can be obtained by:

$$\tilde{x}^{(0)}(n+1)=\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-an}(1-e^{a}) \tag{7}$$

Results calculated using GPT can help reduce the unnecessary call drops due to the predicted value of weak RSS.

Finally, all these parameters are normalized and in the next stage a handoff factor is calculated, which is later compared to a certain threshold constant for decision regarding the handoff. For simplicity, we assume that the MS is equipped with multiple wireless interfaces and it can connect to different types of networks, but at a given instant of time it is connected to only one network. The types of networks include WLAN, WMAN and WWAN. Note that these three terms are only used to present our scheme in a general manner. However, our scheme can be adapted for any technology, e.g., 4G, LTE-advanced or so-called 5G. If the handoff factor goes above a threshold, the algorithm enters the VHO target selection module, where the target net-

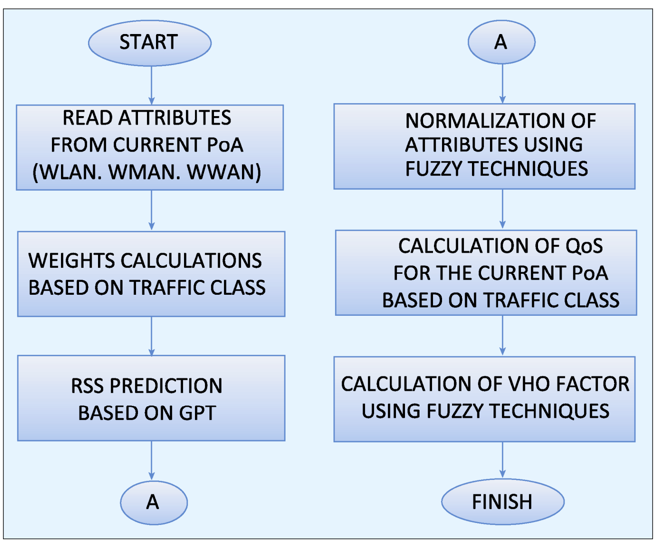

Fig.1 *VHONE module*

work for the future connection is determined. With the exception of distance between the MS and the serving PoA, the same parameters as used in the VHONE module, are also utilized in the NAT selection module to determine the best target network among a list of candidates. Four different FLCs are utilized to calculate the value of VHO factor that is used to determine the necessity of handoffs based on the current conditions of serving PoA. In order to reduce the number of rules and system complexity, three fuzzy logic controllers are combined in a parallel fashion. The outputs of these three FLCs are then fed into the fourth fuzzy logic controller that produces the final VHO factor. Both Sugeno [15] and Mamdani [16] type Fuzzy Inference Systems (FISs)with carefully designed rules are incorporated into these FLCs. This is shown in Figure 2. For more details on the design of our VHONE module, the readers may refer to Ref. [17].

2.1 Weight calculations for system parameters

From a decision making perspective, the end users can specify their needs and preferences by assigning priority weights to each system parameter. Since the goal of our scheme is to maximize end-user's satisfaction, higher weights are assigned to network RSS and QoS. Furthermore, since QoS requirements vary for various types of traffic classes, different weights with respect to these traffic types need to be calculated and assigned, specifically for QoS-related parameters. The proposed scheme considers four different traffic classes with different characteristics and QoS demands as defined by 3GPP TS-23.107 [18]. Note that the assignments and calculations of these weights can be manual or automated. Our proposed scheme is flexible and offers both manual and automated weight calculations using different techniques. Two levels of criteria are considered for the system parameters as shown in Figure 3. The order of preference for level-1 criteria is given by: RSS, QoS, MS-velocity, network-loading, security, and cost; where RSS and QoS are given equal importance. Nonetheless, our scheme is flexible and the order of end-users' preferences may change based on their requirements. The relative importance for the first-level criteria can be assigned by the end user whereas the relative importance for the second-level parameters, i.e., network throughput, latency, jitter and PLR, is defined by our proposed scheme. Different requirements related to the QoS of the four traffic classes are taken into account as well.

In this work, we use the FLVs to design the weights. FLVs are extensively used in calculating the criteria weights in Multi-Attribute Decision Making (MADM) problems [10].

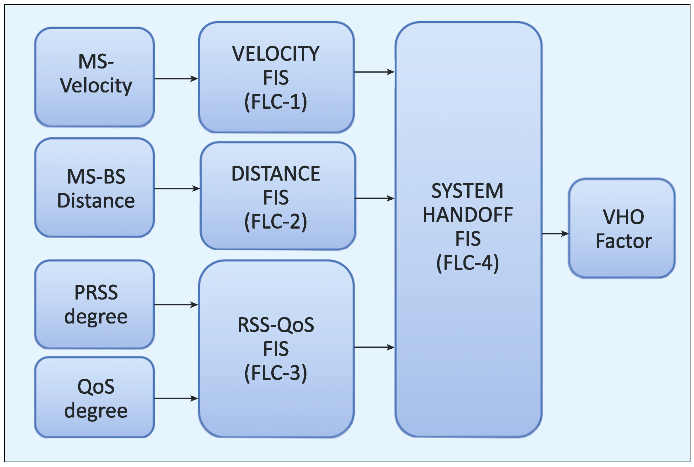

Fig.2 *VHO-factor calculations*

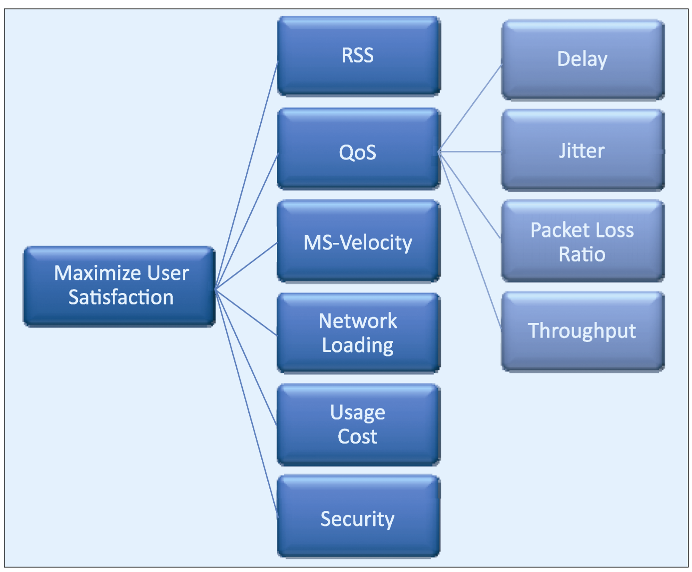

Fig.3 *Hierarchal structure of the parameters*

FLVs are represented using linguistic terms, whose values can be modeled with fuzzy sets. These FLVs can be proven very useful when dealing with complex problems involving uncertainty. For the case of network selection, the uncertainty resides in the vague preferences specified by the end-users. To represent these FLVs, we use the same methodology as proposed in Ref. [11], which is based on the usage of TFNs. These TFNs can be transformed into crisp values as follows:

$$W(\tilde{A})=\frac{1}{6}(l+4m+u) \tag{8}$$

where $\tilde{A}=(l,m,u)$ represents a TFN of fuzzy number $\tilde{A}$. Table I shows TFNs and their corresponding crisp values for different linguistic terms. Table II and Table III show assigned FLVs and their corresponding normalized weights for level-1 and level-2 criteria, respectively, for the conversational traffic class. The weights generated in Tables IV-VI are used to create the interdependence matrix (Table VII) for QoS parameters, which is then multiplied with level-2 criteria weights, to obtain the final weights of the QoS parameters. These final weights are given by:

$$W_{Conv}=\begin{bmatrix} W_{RSS} \\ W_{Qos}\times W_{QoS-Conv-D} \\ W_{Qos}\times W_{QoS-Conv-J} \\ W_{Qos}\times W_{QoS-Conv-P} \\ W_{Qos}\times W_{QoS-Conv-T} \\ W_{Velocity} \\ W_{Nw-Loading} \\ W_{Security} \\ W_{Cost} \end{bmatrix} =\begin{bmatrix} 0.2458 \\ 0.2458\times 0.2501 \\ 0.2458\times 0.0890 \\ 0.2458\times 0.0241 \\ 0.2458\times 0.0712 \\ 0.2034 \\ 0.1525 \\ 0.1017 \\ 0.0508 \end{bmatrix} = \begin{array}{c} \begin{bmatrix} 0.2458 \\ 0.0615 \\ 0.0890 \\ 0.0241 \\ 0.0712 \\ 0.2034 \\ 0.1525 \\ 0.1017 \\ 0.0508 \end{bmatrix} \end{array}\begin{array}{c} R \\ D \\ J \\ P \\ T \\ V \\ L \\ S \\ C \end{array} \tag{9}$$

Table I *Linguistic variables with Triangular Fuzzy Numbers (TFNs)*

Linguistic Variable	Triangular Fuzzy Number (TFN)	Crisp Value
Very Low (VL)	(0.0, 0.0, 0.2)	0.033 3
Low (L)	(0.0, 0.2, 0.4)	0.200 0
Medium (M)	(0.2, 0.4, 0.6)	0.400 0
High (H)	(0.4, 0.6, 0.8)	0.600 0
Very High (VH)	(0.6, 0.8, 1.0)	0.800 0
Excellent (E)	(0.8, 1.0, 1.0)	0.966 7

Table II *Linguistic variables and weights for level-1 criteria, conversational traffic*

Criteria	Linguistic Variable	Normalized Weights
RSS	E	0.245 8
QoS	E	0.245 8
Velocity	VH	0.203 4
Traffic Load	H	0.152 5
Security	M	0.101 7
Cost	L	0.050 8

Table III *Linguistic variables and weights for level-2 criteria, conversational traffic*

Criteria	Linguistic Variable	Normalized Weight
Delay	E	0.353 7
Jitter	E	0.353 7
PLR	H	0.219 5
Throughput	L	0.073 2

Table IV *Linguistic variables and weights with respect to Delay*

Criteria	Linguistic Variable	Normalized Weight
Delay	E	0.707 3
Jitter	M	0.292 7

Table V *Linguistic variables and weights with respect to Jitter*

Criteria	Linguistic Variable	Normalized Weights
Jitter	E	0.617 0
Throughput	H	0.383 0

Table VI *Linguistic variables and weights with respect to PLR*

Criteria	Linguistic Variable	Normalized Weights
Jitter	M	0.184 6
PLR	E	0.446 2
Throughput	VH	0.369 2

Table VII *Linguistic variables interdependence matrix for QoS parameters*

Criteria	Delay	Jitter	PLR	Throughput
Delay	0.707 3	0.000 0	0.000 0	0.000 0
Jitter	0.292 7	0.617 0	0.184 6	0.000 0
PLR	0.000 0	0.000 0	0.446 2	0.000 0
Throughput	0.000 0	0.383 0	0.369 2	1.000 0

Similar procedure is followed to calculate the weights for other traffic classes. The final weights for all four traffic classes are shown in Table VIII.

2.2 NAT selection module

Our NAT selection module is designed using a TOPSIS ranking algorithm. TOPSIS [19] is an MADM ranking algorithm, designed to measure the relative efficiency of the available alternatives based on certain criteria. One of the reasons for its popularity is that it requires limited subjective inputs from decision makers, which happens to be the preference weights, assigned to different criteria. The principle behind this algorithm is very simple; the chosen alternative should be as close to the ideal solution as possible and as far from the negative-ideal solution as possible. The ideal solution is a composite of the best performance values, for each parameter, exhibited by any alternative. The negative-ideal solution is the composite of the worst performance values. The distance between each alternative and these performance values is measured in the Euclidean sense to decide relative closeness to the ideal solution. Note that this distance is affected by the decision maker's subjective preferences for each criterion. The steps for TOPSIS ranking procedure are given as follows:

1) *Decision Matrix Construction*: A $m \times n$ decision matrix containing the ratings of each alternative with respect to each criterion is created as:

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \end{array} \tag{10}$$

where A_m is the mth alternative and C_n is the nth criterion. Each element d_{ij} of the decision matrix represents the performance rating of the alternative A_i with respect to the criterion C_j.

2) *Decision Matrix Normalization*: Decision matrix is normalized based on the following equation:

$$rij = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d_{ij}}}; i = 1,2,...,n,\ j = 1,2,...,n \tag{11}$$

where r_{ij} is the normalized value of element d_{ij}.

3) *Weighted Normalized Decision Matrix Construction*: This matrix is constructed by multiplying each element r_{ij} with its associated weight w_j, as follows:

$$v_{ij} = r_{ij} \times w_j \tag{12}$$

4) *Calculation of Positive & Negative Ideal Solution*: The positive and negative ideal solutions, A^+ and A^-, respectively, are defined as:

$$\begin{aligned} A^+ &= (v_1^+, v_2^+, \ldots, v_n^+) \\ &= \{(\max_i v_{ij} \mid j \in C_B), (\min_i v_{ij} \mid j \in C_C)\} \end{aligned} \tag{13}$$

$$\begin{aligned} A^- &= (v_1^-, v_2^-, \ldots, v_n^-) \\ &= \{(\min_i v_{ij} \mid j \in C_B), (\max_i v_{ij} \mid j \in C_C)\} \end{aligned} \tag{14}$$

where C_B and C_C denote the sets with benefit and cost criteria, respectively.

Table VIII *Weights for four different traffic classes calculated using linguistic variables*

Traffic Type	RSS	QoS				Velocity	Loading	Security	Cost
		Delay	Jitter	PLR	Throughput				
Conversational	0.245 8	0.061 5	0.089 0	0.024 1	0.071 2	0.203 4	0.152 5	0.101 7	0.050 8
Streaming	0.245 8	0.013 5	0.055 2	0.034 2	0.142 8	0.203 4	0.152 5	0.101 7	0.050 8
Interactive	0.245 8	0.071 0	0.057 5	0.037 1	0.080 2	0.203 4	0.152 5	0.101 7	0.050 8
Background	0.245 8	0.019 7	0.035 6	0.024 8	0.165 7	0.203 4	0.152 5	0.101 7	0.050 8

5) *Calculation of Separation between Alternatives & Ideal Solutions*: The separation (distance) between each alternative from the positive ideal (S_i^+) and negative ideal solutions (S_i^-) is calculated as follows:

$$S_i^+ = \sqrt{(v_{ij} - v_i^+)^2};\ i = 1,2\ldots,m,\ j = 1,2,\ldots,n \tag{15}$$

$$S_i^- = \sqrt{(v_{ij} - v_i^-)^2};\ i=1,2,\ldots,m,\ j = 1,2,\ldots,n \tag{16}$$

6) *Calculation of Relative Closeness to the Ideal Solution*: This step involves calculating the relative closeness (C_i) to the ideal solution, which is defined as:

$$C_i = \frac{S_i^-}{S_i^- + S_i^+};\quad i=1,2,\ldots,m \tag{17}$$

7) *Ranking of the Alternatives*: The ranking of the alternative is performed by sorting the values of relative closeness C_i, in descending order. The best alternative has the highest value of C_i.

As part of the target network selection scheme, MATLAB code is implemented to perform the selection of the best network among the other available candidates, using a modified version of the above mentioned TOPSIS algorithm.

III. Performance Evaluation

This section begins by providing numerical examples using a scenario based approach in order to verify and validate the usability of different aspects of our scheme. Later, we present our simulation test-bed along with the performance evaluation of our VHO scheme in a dynamic heterogeneous wireless environment, where a single MS moving in a straight path is simulated.

3.1 Numerical example

We first present an exemplary scenario to show the performance of our VHO scheme, without considering any dynamic aspect of a real wireless environment. We assume that the MS is currently watching a recorded webcast (streaming) using his/her own WLAN (Scenario 1) Later, this user leaves home for work and starts walking toward the nearest bus stand while watching the same webcast (Scenario 2) This results in an increased distance between WLAN-AP and MS and consequently, the RSS starts to become weaker. The parameter sets for two scenarios are presented in Table IX. Note that, the GPT predicted an undetectable RSS based on the collected samples. Based on these parameter sets, the overall handoff factor that the VHONE calculates comes out to be 0.25 and 0.85 for Scenario1 and Scenario 2, respectively. Since 0.85 for Scenario 2 is greater than the handoff threshold (set as 0.75), the module will trigger the handoff and execute the target selection module to find the best available network that can support the continuity and quality of the currently utilized service. The MS, then steps in a bus that starts to move with a relatively higher velocity than the walking user (Scenario 2).

Table IX *Parameter set for numerical example*

Parameters	Scenario 1	Scenario 2
Current PoA	WLAN	WLAN
Current Traffic Class	Streaming	Streaming
Weight Scheme	AHP	AHP
Velocity (m/s)	0 (Low)	1(Low)
MS-PoA Distance (m)	10 (Near)	85 (Far)
RSS Samples (dbm)	-58.5, -55.3, -57.6, -59.8	-90.5, -92.7, -97.3, -98.9
PRSS using GPT (dbm)	-62.21 (High)	-102.63 (Undetectable)
Delay (ms)	100 (Low)	120 (High)
Jitter (ms)	10 (Low)	20 (High)
PLR (loss per 10^6 bytes)	3 (Low)	4 (Medium)
Throughput (Mb/s)	130 (High)	30 (Low)

As the user is walking towards the bus stand, the handoff target network selection scheme senses the availability of three different networks. The parameter values for these three networks, presented in Table X, are then fed into the target network selection module and normalized to produce their corresponding membership values based on whether the parameters are benefit or cost type. A graphical representation of the normalized parameter values at the MS-speed of 5 m/s are shown in Figure 4. The rankings for all network types utilizing TOPSIS with FLV weighting scheme in combination with different speeds of MSs are presented in Figures 5-7. We observe that the preferred network is WLAN for slower moving MS (Figure 5) and WWAN for MS moving with higher speed (Figure 7). However, Figure 5 shows a choice competition between WLAN and WMAN for MS moving with a velocity of 2 m/s. A similar competition can be observed between WMAN and WWAN for MS moving with 5 m/s. This can be observed from Figure 6.

Table X *Parameter set for available networks in-range (numerical example)*

Parameters	WLAN	WMAN	WWAN
PRSS (dbm)	-114.05	-137.40	-116.10
Delay (ms)	130	20	10
Jitter (ms)	27	5	4
PLR (loss per 10^6 bytes)	3	4	3
Throughput (Mb/s)	70	60	1.5
Network-Load (%)	20	30	40
Security (1-10)	1	5	7
Cost (1-10)	3	4	7
MS-Velocity (m/s)		2	

3.2 Simulation environment

The VHONE and TOPSIS based NAT selection modules are implemented in MATLAB and evaluated using a comprehensive test-bed, developed based on the concept of RUNE [20]. RUNE is a special purpose simulator for wireless networks. Three types of co-existing networks, i.e., WLANs, WMANs, and WWANs, based on a cellular concept are considered according to Figure 8. The WLAN is defined with 27 cells with a radius of 100 meters each. The WMAN and WWAN are defined with 12 cells, each with a radius of 375 and 750 meters, respectively. The standard hexagonal shape with Omni-directional antennas is considered for all cells. For the propagation model, we consider the path loss,

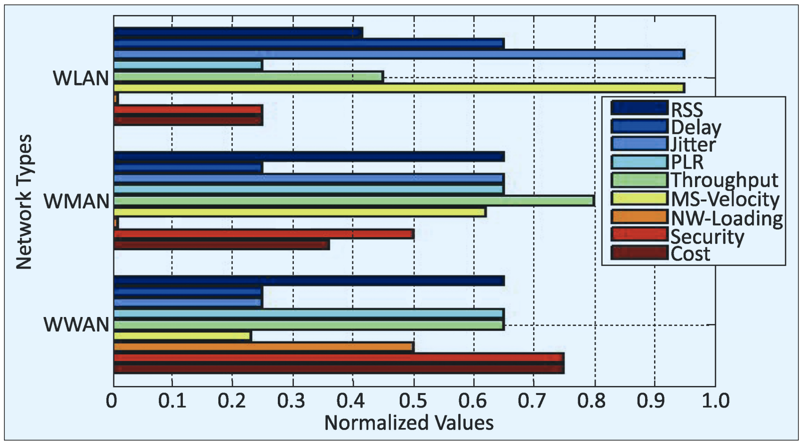

Fig.4 *Normalized network parameters (Velocity = 5 m/s)*

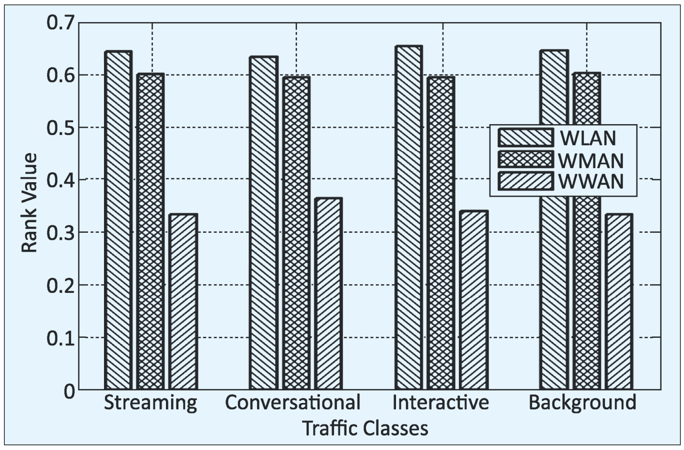

Fig.5 *TOPSIS ranking of networks based on traffic classes and TFN weighting (Velocity = 2 m/s)*

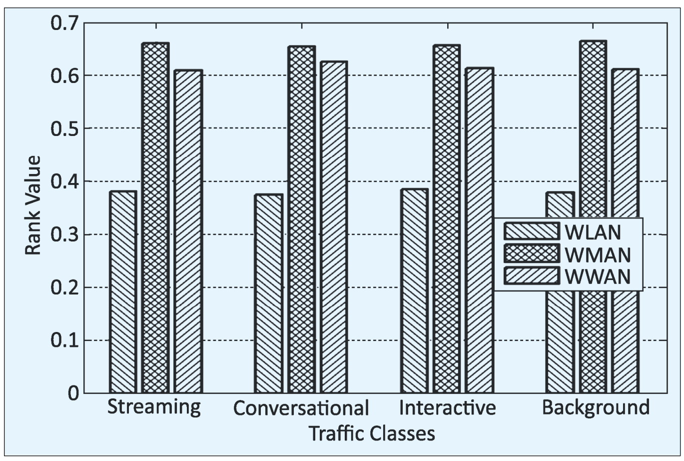

Fig.6 *TOPSIS ranking of networks based on traffic classes and TFN weighting (Velocity = 5 m/s)*

shadow fading and Rayleigh fading. For the performance evaluation, we consider a single user scenario, where an MS travels in a straight line with different speed and passes

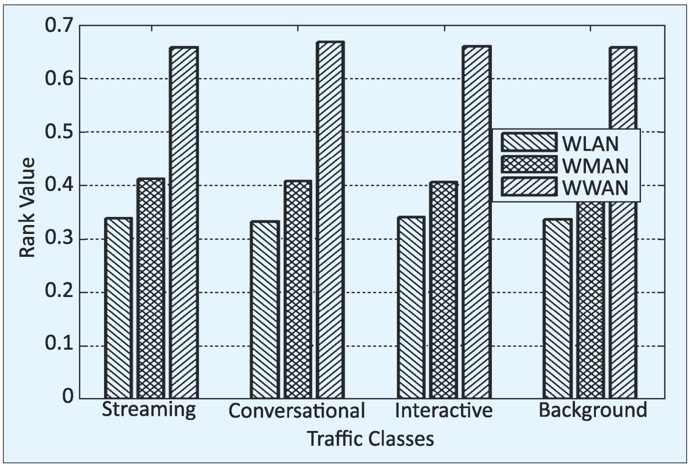

Fig.7 *TOPSIS ranking of networks based on traffic classes and TFN weighting (Velocity = 10 m/s)*

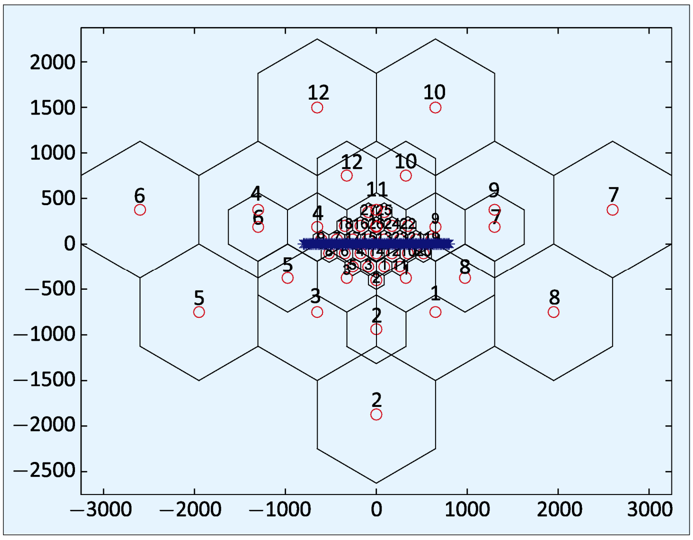

Fig.8 *Network topology*

through the coverage of several cells located within the three networks. The considered numerical values for the networks' parameters are illustrated in Table XI.

3.3 Single-user scenario

In this scenario (Figure 8), we calculate the percentage of time that a single user is connected to each network type, while moving along a straight path. Figures 9-12 show the percentage of connections preferred by MS towards a preferred network type, as selected by our TOPSIS-FLV scheme for the Conversational, Interactive, Background, and Streaming traffic classes, respectively. These percentages are obtained for an MS with a speed of 0-10 m/s. It can be observed from these figures that TOPSIS-FLV scheme shows a clear choice of network connectivity preferences for slower, medium and higher speed MS; with minor differences, the percentages of connectivity towards a preferred wireless network for different traffic classes are almost the same, based on parameters listed in Table XI. A 100% preference towards WWAN for the MS with higher speeds contrasting a 98% connectivity preference for WLAN for slower speeds MS can be observed for all traffic classes. For all types of traffic classes, the preferred network is WLAN for MS-speed between 0-3 m/s. Our scheme shows a connectivity preference towards WMAN when the MS is moving with a speed of 3-6 m/s. At higher speeds (6-10 m/s), the choice is WWAN.

Table XI *Simulation parameters*

Parameters	WLAN	WMAN	WWAN
Cell Shape	Hexagonal with Omni-directional Antennas		
Mean Velocity (m/s)	0-10		
Thermal Noise Floor (dBm)	-118		
Standard deviation for fading (db)	6		
Fading Correlation (downlink)	0.5		
Fading Correlation distance (m)	20		
Average Number of Calls per Cell	1-10		
Min. RSS to connect (dBm)	-110	-160	-150
Attenuation at 1 m distance (db)	-40	-55	-28
Path Loss Exponent	3.3	4	4
Delay (ms)	130	30	10
Jitter (ms)	30	10	1
PLR (per 10^6 bytes)	5	4	2
Throughput (Mb/s)	140	50	0.2
Security (1-10)	5	5	5
Cost (1-10)	2	4	7

3.4 Multi-user scenario

In multi-user scenario, a random number of

MSs joins the system based on a Poisson arrival rate and the connection duration is modeled based on an exponential distribution. A mobility model similar to Ref. [20] is considered where new MSs are distributed uniformly in a cellular and layered heterogeneous wireless environment. The direction and speed of each MS are updated randomly based on a specific correlation with the previous values. In order to evaluate our proposed scheme, several metrics, such as average outage probability, average new call blocking probability, average handoff blocking probability and average handoff rate, are considered. The performance of our scheme is compared against an existing algorithm that is based on RSS threshold and network load balancing. Evaluations are based on the maximum number of arrived calls (10) in each cell with multiple MSs moving randomly at the average speeds of 1 m/s, 5 m/s, and 9 m/s. The results shown in Figures 13-16 are based on conversational traffic class. The TOPSIS based network selection scheme shows significant performance improvement over existing RSS and load balancing based scheme. Figure 13 shows the outage probability for different values of average call arrival per cell. It is observed that for MSs moving with slower speed and with maximum number of calls per cell, the outage probability offered by our scheme is around 19% as compared to RSS with 31%. Similarly, at higher speeds, the outage probability is around 40%, which shows about 9% improvement over RSS. The average handoff rate is presented in Figure 14. Once again, our scheme demonstrates a superior performance when compared against the reference algorithm. An improvement of 23% when compared against RSS based scheme can be noticed. These handoff rates are calculated for an average call arrival rate of 10 per cell and with MSs' speed of 9 m/s. This improvement over the existing algorithm shows that our scheme is performing handoff necessity estimation and target selection in a more intelligent and

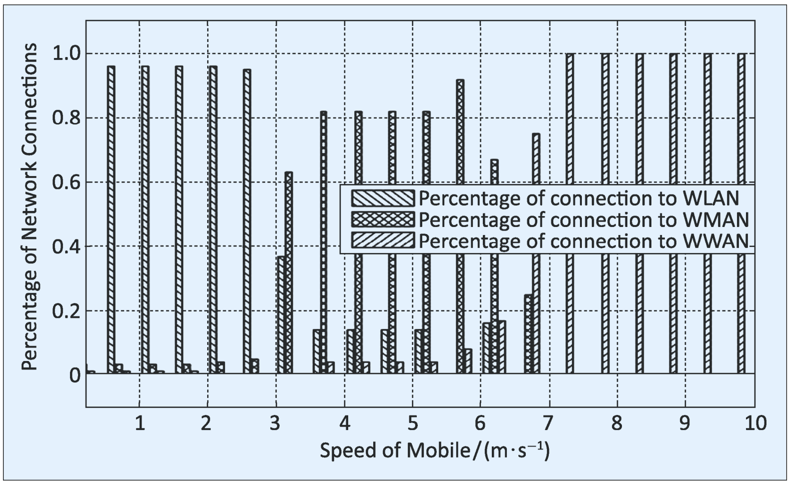

Fig.9 *Percentage of Network-Connection for TOPSIS-FLV per different MS speeds, Conversational Traffic*

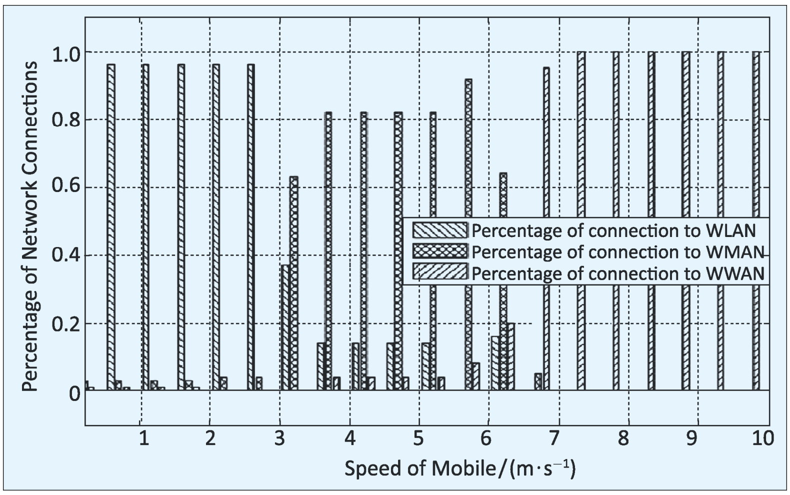

Fig.10 *Percentage of Network-Connection for TOPSIS-FLV per different MS speeds, Interactive Traffic*

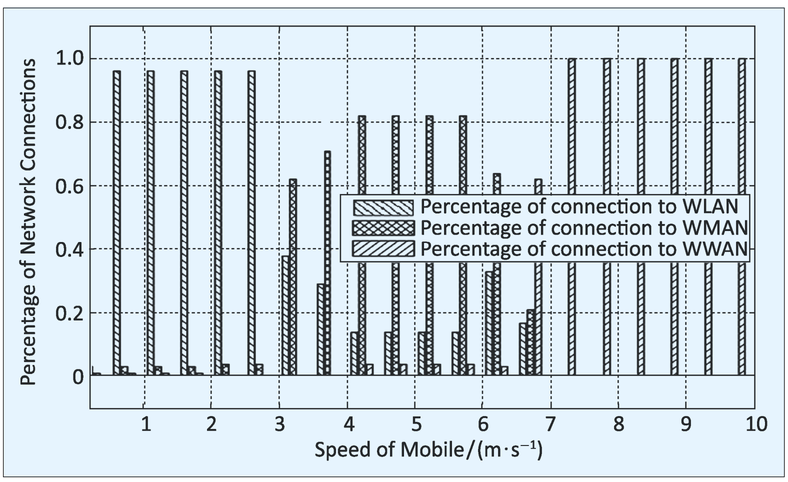

Fig.11 *Percentage of Network-Connection for TOPSIS-FLV per different MS speeds, Background Traffic*

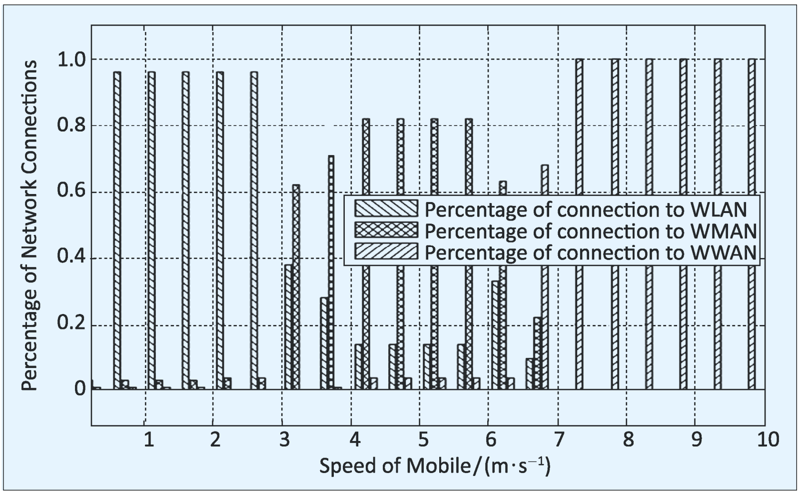

Fig.12 *Percentage of Network-Connection for TOPSIS-FLV per different MS speeds, Streaming Traffic*

efficient manner. Figure 15 shows the handoff blocking probability using our proposed scheme as the target network selection algorithm. For MSs moving with any speed and for any numbers of average calls arrival per cell, the reference algorithm performs better than our proposed algorithm. Figure 16 shows the RSS based scheme performing better than our proposed scheme based on new call blocking probability metric. Table XII provides the aforementioned evaluations, comparing all the four traffic classes including, Conversational, Background, Streaming, and Interactive. Table XIII shows the average percentage of connections to each of the three networks and for different MSs' speeds of 1 m/s, 5 m/s and 9 m/s for Conversational traffic class. A common trend can be observed from these figures where WWAN is consistently given higher preference as compared to WMAN, and WLAN. This is true for any mobile speed and any number of average system calls per cell. WMAN and WLAN are given second and third preferences, respectively. This is because Conversational traffic class requires a low value of delay and jitter and according to the chosen parameters listed in Table VIII, WWAN provides the lowest values of these parameters, followed by WMAN and WLAN. At an average call arrival rate of 10, a distribution of connections among the three available networks can also be observed. Based on the characteristics of the Conversational traffic class, our scheme still assigns more calls to WWAN as it offers better overall QoS for the Conversational traffic class.

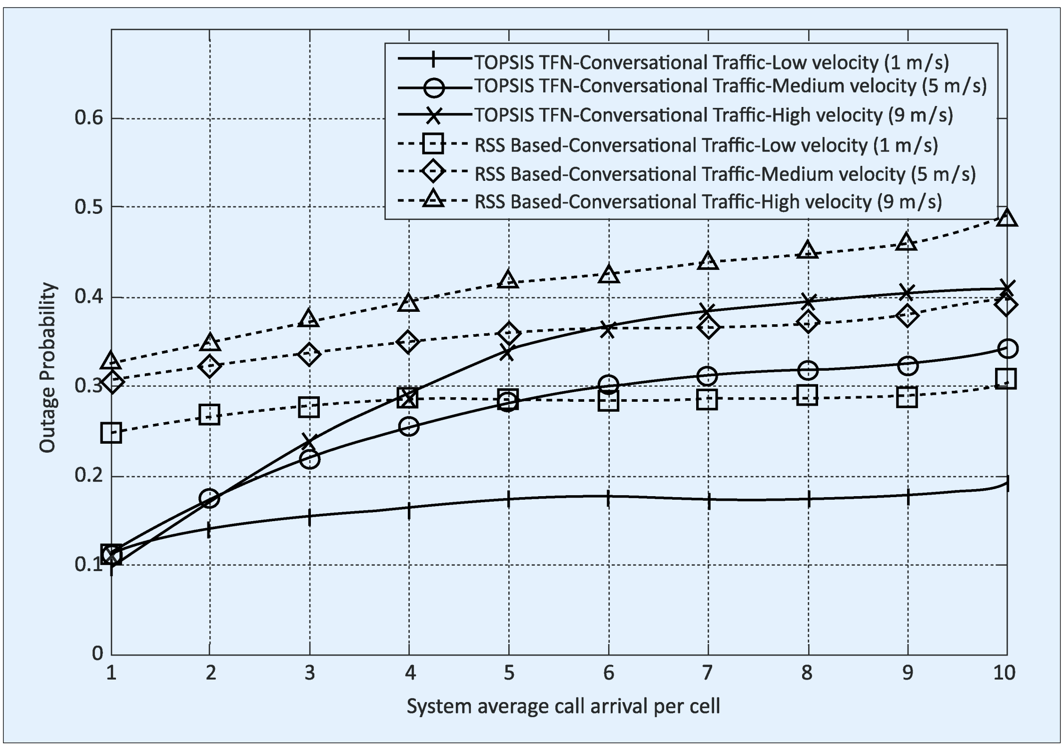

Fig.13 *Outage Probability for Conversational Traffic using TOPSIS*

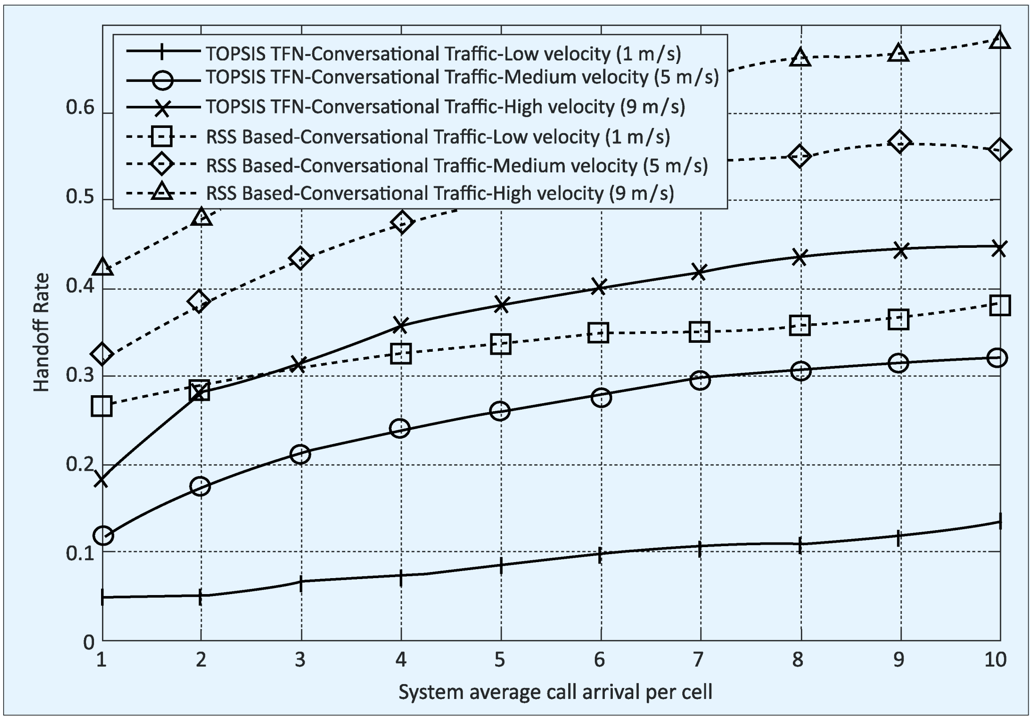

Fig.14 *Handoff rate for Conversational Traffic using TOPSIS*

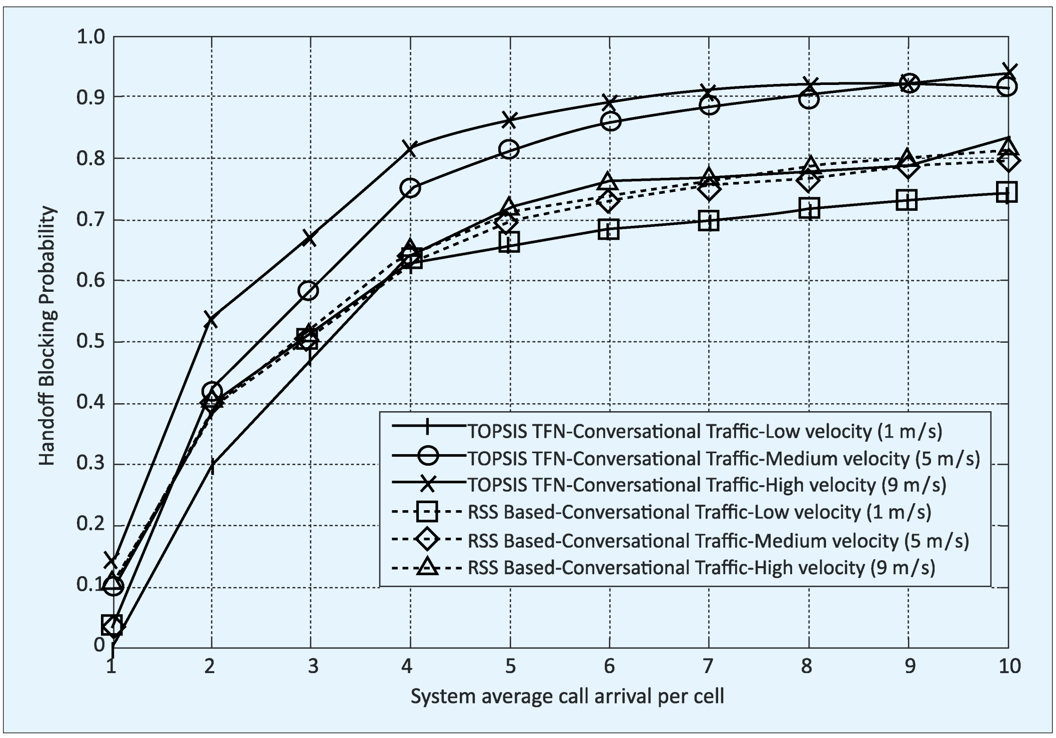

Fig.15 *Handoff Blocking Probability for Conversational Traffic using TOPSIS*

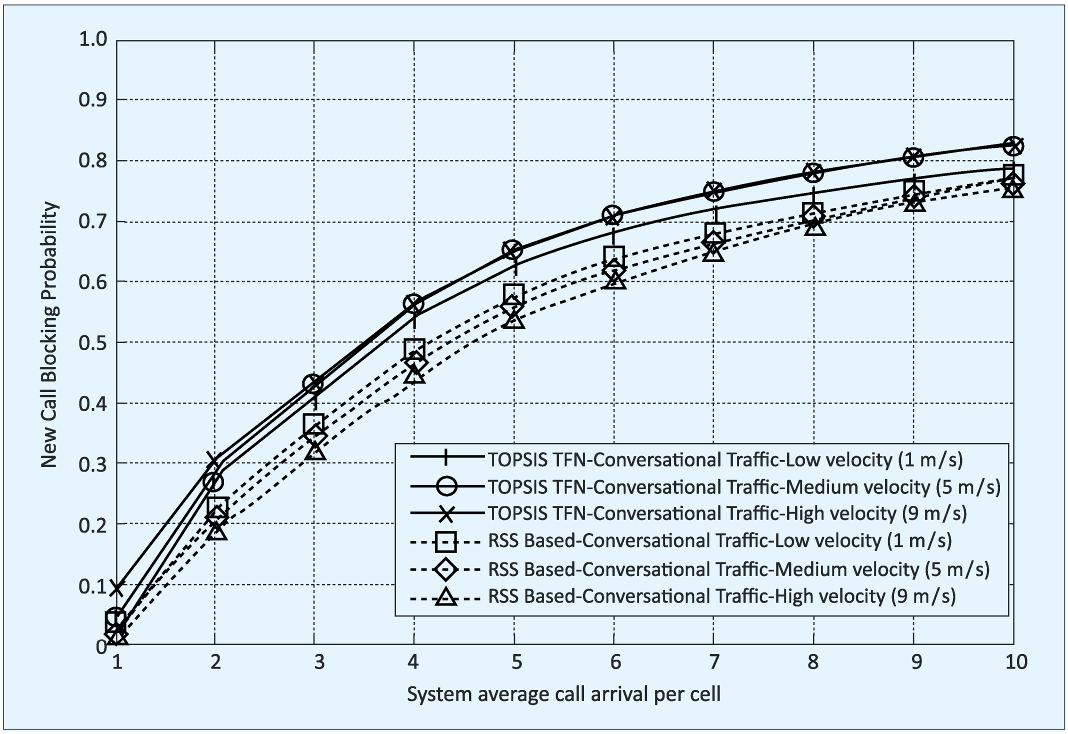

Fig.16 *New Call Blocking Probability for Conversational Traffic using TOPSIS*

Table XII *Performance comparison for different traffic classes*

	Average Outage Probability (%)			New Call Blocking Probability (%)			Handoff Blocking Probability (%)			Average Handoff Rate (%)		
Speed (m/s)	1	5	9	1	5	9	1	5	9	1	5	9
Streaming	19	33	44	86	89	88	90	89	88	16	30	39
Background	17	32	42	87	88	88	93	88	89	16	29	40
Interactive	16	30	42	87	89	88	93	92	90	15	29	42
Conversational	16	32	40	84	86	88	90	86	88	15	28	38

Table XIII *Network connections*

		Percentage of Network Connections (%)								
	Speed (m/s)	1			5			9		
	Call Arrival	1	5	10	1	5	10	1	5	10
RSS	WLAN	14	22	28	10	25	29	9	26	30
	WMAN	24	30	28	26	29	27	27	27	28
	WWAN	62	48	44	64	46	44	64	47	42
Conversational	WLAN	8	16	23	3	5	12	2	8	12
	WMAN	18	30	29	19	36	34	24	33	34
	WWAN	74	54	48	78	59	54	74	59	54
Streaming	WLAN	8	15	23	4	7	14	2	11	15
	WMAN	18	31	29	19	35	34	23	30	31
	WWAN	74	54	48	77	58	52	75	59	54
Background	WLAN	8	16	23	4	7	16	2	12	17
	WMAN	18	31	29	19	33	32	23	30	31
	WWAN	74	53	48	77	60	52	75	58	52
Interactive	WLAN	7	16	26	3	6	14	2	9	16
	WMAN	18	31	28	19	35	34	24	32	31
	WWAN	75	53	46	78	59	52	74	59	53

IV. CONCLUSION

A VHO algorithm with two modules, namely, VHONE and NAT Selection, was proposed. The Fuzzy Logic based VHONE module determines whether a handoff is necessary by taking into consideration the PRSS values provided by the current PoA, the degree of the provided QoS based on the requested traffic class (conversational, streaming, background, and interactive), and the speed of the vehicle including the MS direction of mobility. The target selection module utilizes FLVs to weight different system parameters, in addition to a TOPSIS ranking algorithm to select the best target network. It was observed that our VHO scheme intelligently chooses the preferred network based on the speed of MS, for four different traffic classes. WLAN is preferred network for slower moving MS, whereas for medium and fast moving MS, our scheme shows high preference towards WMAN and WWAN, respectively.

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