

A Dynamic Weighting of Attributes in Heterogeneous Wireless Networks Using Fuzzy Linguistic Variables

Abolfazl Mehbodniya[†], Faisal Kaleem[‡], Kang K. Yen[‡] and Fumiayuki Adachi[†]

[†]Tohoku University, Sendai, Japan

[‡]Florida International University, Miami, FL, USA

Email: mehbod@mobile.ecei.tohoku.ac.jp {kaleemf, yenk}@fiu.edu adachi@ecei.tohoku.ac.jp

Abstract—Even though different wireless Network Access Technologies (NAT) with different specifications and applications have been developed, no single wireless technology can satisfy the anytime, anywhere, and any service wireless access needs of mobile users. A real seamless 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 user with a multi-interface terminal changes connection 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 the several factors such as user preferences, system parameters and QoS requirements for different traffic classes. Two modules i.e., VHO Necessity Estimation (VHONE) module and target NAT selection module, are designed. Both modules function based on weighting the different users' and system's parameters. To improve the robustness of our algorithm, the weighting system is designed based on the concept of fuzzy linguistic variables.

Keywords-Network Access Selection; Vertical Handoff; Heterogeneous Networks; WLAN; WMAN; WWAN; TOPSIS

I. INTRODUCTION

In the recent years, wireless networks have experienced a huge 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 combining 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 its network access using a process, called Vertical Handoff (VHO). Most of the existing VHO algorithms, which are based on single metric such as Received Signal Strength (RSS), 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. Factors like available network bandwidth, latency, security, usage cost, power consumption, battery status of the MS, and user preferences should be thoroughly considered while performing these handoff decisions. Previous works mostly related to our research are reported in [2] and [3]. The Artificial Intelligence (AI) scheme in [2], which is based on a hybrid of parallel fuzzy-logic-system, multiple-criteria decision 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, which utilizes 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 doesn't 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 [3]. In the proposed approach, a preliminary selection of candidate networks is performed using 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. In this paper, we present an intelligent VHO scheme, which

consists of two modules, namely, VHO Necessity Estimation (VHONE) and NAT selection. The VPHONE module examines the existing conditions of MS's current Point of Attachment (PoA) to estimate the necessity of handoff using a FLC. In the second module, different parameters of all available candidate networks are utilized to determine a new PoA which can best fulfill the end-user's requirements. Both modules use a weighting mechanism to determine the relative importance of different parameters in the system. Fuzzy Linguistic Variables (FLVs) [4] 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 the Techniques for Order Preference by Similarity to Ideal Solution (TOPSIS) ranking method, which determines the best network for future connection. We assume four different classes of traffic in this research and our target selection module is designed to adapt to the special requirements of each traffic class. 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 VPHONE module is explained. Section III presents the details of our weighting procedure for system parameters. Section IV explains our NAT selection module. Section V discusses the simulation environment and the numerical results. Finally, concluding remarks are drawn in section VI.

II. VPHONE MODULE

In the first stage of VPHONE module, the parameters from the current PoA are measured and then the weight for each parameter is calculated, characterized on the specifications of 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 available to the MS through some mechanism; for example, GPS module installed in most MSs are capable of estimating the MS's velocity. In order to reduce the call dropping probability in a lognormal fading heterogeneous wireless environment, the proposed scheme utilizes predicted RSS values measured from the networks. These predicted values, obtained using Grey Prediction Theory (GPT), are utilized by the proposed scheme to determine if a future handoff is necessary or not. 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 $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\}$. The Accumulated Generating Operation (AGO) is utilized to

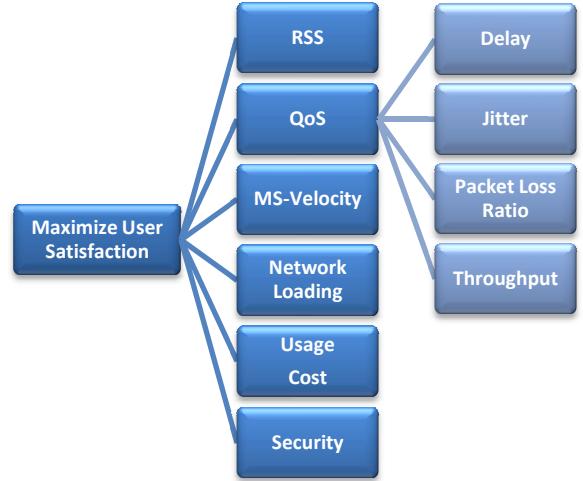


Figure 1: Hierarchical Structure of the Parameters

further process these samples due to the possible presence of random noise. The AGO operation produces a first-order AGO sequence given by.

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

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

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

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

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

The vector representation of a and b is defined by

$$c = [a \ b]^T = (B^T B)^{-1} B^T \gamma_n \quad (4)$$

where,

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

and

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

Thus the predictive value of RSS can be obtained by

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

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 about 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 here we use these three terms to present our scheme in a general manner. However, our scheme can be adapted for any technology, e.g., 4G, LTE-advanced or

Table 1: Linguistic Variables with Triangular Fuzzy Numbers (TFNs)

Linguistic Variable	Triangular Fuzzy Number (TFN)	Crisp Value
Very Low (VL)	(0.0, 0.0, 0.2)	0.0333
Low (L)	(0.0, 0.2, 0.4)	0.2000
Medium (M)	(0.2, 0.4, 0.6)	0.4000
High (H)	(0.4, 0.6, 0.8)	0.6000
Very High (VH)	(0.6, 0.8, 1.0)	0.8000
Excellent (E)	(0.8, 1.0, 1.0)	0.9667

Table 2: Linguistic Variables and Weights for Level-1 Criteria, Conv. traffic

Criteria	Linguistic Variable	Normalized Weights
RSS	E	0.2458
QoS	E	0.2458
Velocity	VH	0.2034
Traffic Load	H	0.1525
Security	M	0.1017
Cost	L	0.0508

Table 3: Linguistic Variables and Weights for Level-2 Criteria, Conv. traffic

Criteria	Linguistic Variable	Normalized Weight
Delay	E	0.3537
Jitter	E	0.3537
PLR	H	0.2195
Throughput	L	0.0732

Table 4: Linguistic Variables and Weights with respect to Delay

Criteria	Linguistic Variable	Normalized Weight
Delay	E	0.7073
Jitter	M	0.2927

Table 5: Linguistic Variables and Weights with respect to Jitter

Criteria	Linguistic Variable	Normalized Weights
Jitter	E	0.6170
Throughput	H	0.3830

Table 6: Linguistic Variables and Weights with respect to PLR

Criteria	Linguistic Variable	Normalized Weights
Jitter	M	0.1846
PLR	E	0.4462
Throughput	VH	0.3692

so-called 5G. If the handoff factor goes above a threshold, the algorithm enters the VHO target selection module, where the target network 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 VHOME module, are also utilized in the NAT selection module to determine the best target network among a list of candidates. For details on the design of our VHOME module, the readers may refer to [5].

III. 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 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 [6]. 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 1. 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 [7]. 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 FLVs, we use the same methodology proposed in [4], which is based on the usage of Triangular Fuzzy Numbers (TFNs). These TFNs can be transformed into crisp values as follows

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

where $\tilde{A} = (l, m, u)$ represents a TFN of fuzzy number \tilde{A} . Table 1 shows TFNs and their corresponding crisp values for different linguistic terms. Table 2 and Table 3 show assigned FLVs and their corresponding normalized weights for level-1 and level-2 criteria for the conversational traffic class, respectively. The weights generated in Tables 4-6 are used to create the interdependence matrix (Table 7) of QoS parameters, which is multiplied with the weights for level-2 criteria to obtain the weights of QoS parameters. The final weights are given by

$$W_{Conv} = \begin{bmatrix} W_{RSS} \\ W_{QoS} \times W_{QoS-Conv-D} \\ W_{QoS} \times W_{QoS-Conv-J} \\ W_{QoS} \times W_{QoS-Conv-P} \\ W_{QoS} \times W_{QoS-Conv-T} \\ W_{Velocity} \\ W_{Nw-Loading} \\ W_{Security} \\ W_{Cost} \end{bmatrix} = \begin{bmatrix} 0.2458 \\ 0.2458 \times 0.2501 \\ 0.2458 \times 0.0890 \\ 0.2458 \times 0.0241 \\ 0.2458 \times 0.0712 \\ 0.2034 \\ 0.1525 \\ 0.1017 \\ 0.0508 \end{bmatrix} = \begin{bmatrix} 0.2458 \\ 0.0615 \\ 0.0219 \\ 0.0060 \\ 0.0715 \\ 0.2034 \\ 0.1525 \\ 0.1017 \\ 0.0508 \end{bmatrix} \begin{matrix} R \\ D \\ J \\ P \\ T \\ V \\ L \\ S \\ C \end{matrix} \quad (9)$$

Similar procedure is followed to calculate the weights for other traffic classes. The final weights for all four traffic classes are shown in Table 7.

Table 8: Weights for four different traffic classes calculated using Linguistic Variables

Traffic Type	RSS	QoS				Velocity	Loading	Security	Cost
		Delay	Jitter	PLR	T.put				
Conversational	0.2458	0.0615	0.0890	0.0241	0.0712	0.2034	0.1525	0.1017	0.0508
Streaming	0.2458	0.0135	0.0552	0.0342	0.1428	0.2034	0.1525	0.1017	0.0508
Interactive	0.2458	0.0710	0.0575	0.0371	0.0802	0.2034	0.1525	0.1017	0.0508
Background	0.2458	0.0197	0.0356	0.0248	0.1657	0.2034	0.1525	0.1017	0.0508

IV. NAT SELECTION MODULE

Our NAT selection module is designed using a TOPSIS ranking algorithm. TOPSIS [8] 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:

$$D = \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ A_1 & \left[\begin{array}{cccc} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{array} \right] \\ A_2 \\ \vdots \\ A_m \end{bmatrix} \quad (10)$$

where A_m is the possible alternatives and C_n is the criteria. 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:

$$r_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^m d_{ij}}} \quad i = 1, 2, \dots, m \quad j = 1, 2, \dots, n \quad (11)$$

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:

$$v_{ij} = r_{ij} \times w_j \quad (12)$$

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

$$A^+ = (v_1^+, v_2^+, \dots, v_n^+) = \{(\max_i v_{ij} | j \in C_B), (\min_i v_{ij} | j \in C_C)\} \quad (13)$$

$$A^- = (v_1^-, v_2^-, \dots, v_n^-) = \{(\min_i v_{ij} | j \in C_B), (\max_i v_{ij} | j \in C_C)\} \quad (14)$$

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

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

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

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

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

$$C_i = \frac{s_i}{s_i + s_i^+} \quad i = 1, 2, \dots, m \quad (17)$$

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

V. PERFORMANCE EVALUATION

In this section, first the numerical examples using a scenario based approach is provided 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.

A. Numerical Example

In this section we bring some numerical examples 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, while walking. Later this MS steps in a bus that starts to move with a relatively higher velocity than the walking user. Although, RSS and some other parameters do not remain constant and changes rapidly due to the dynamic nature of wireless networks, we

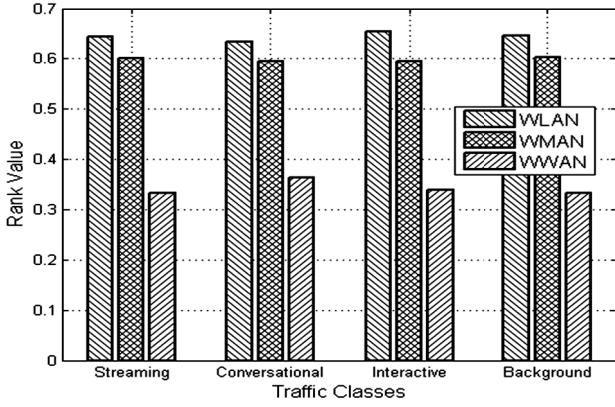


Figure 2: TOPSIS Ranking of Networks based on Traffic Classes and TFN weighting (Velocity = 2 m/s)

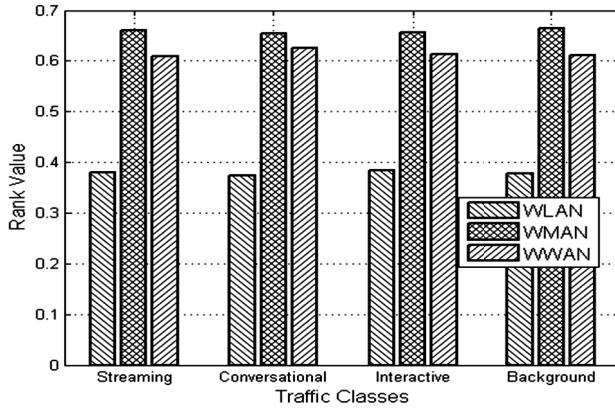


Figure 3: TOPSIS Ranking of Networks based on Traffic Classes and TFN weighting (Velocity = 5 m/s)

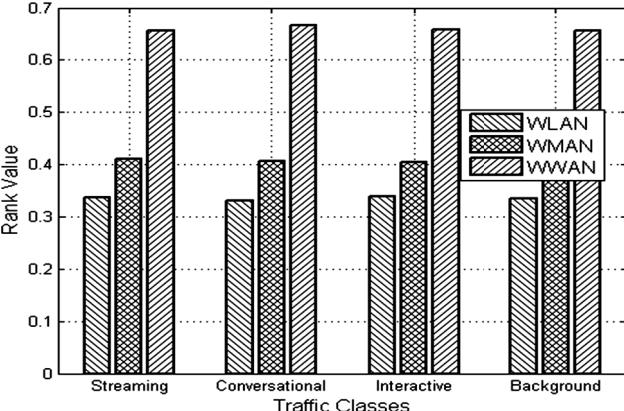


Figure 4: TOPSIS Ranking of Networks based on Traffic Classes and TFN weighting (Velocity = 10 m/s)

Table 9: Network Parameters

	WLAN	WMAN	WWAN
Delay (ms)	130	30	10
Jitter (ms)	30	10	1
PLR (per 10 ⁶ bytes)	5	4	2
Throughput (Mbps)	140	50	0.2
Security (1-10)	5	5	5
Cost (1-10)	2	4	7

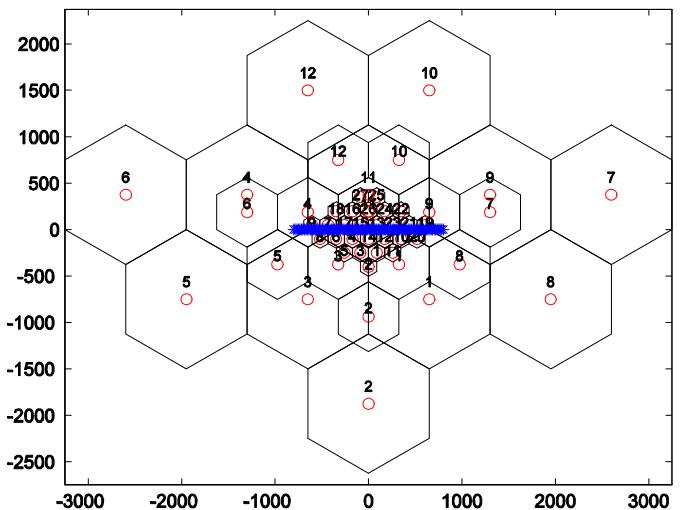


Figure 5: Network Topology

will keep these values constant just to observe the effects of velocity on the network selection process. The rankings for all networks utilizing TOPSIS with FLV weighting scheme and different speeds of MSs are presented in Figures 2-4. We observe that the preferred network is WLAN for slower moving MS and WWAN for MS moving with higher speed. However, Figure 2 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 3.

B. Simulation Environment

The VPHONE and TOPSIS based NAT selection modules are implemented in MATLAB and evaluated using a comprehensive test-bed developed based on the concept of RUNE [9]. RUNE is a special purpose simulator to simulate wireless networks. Three types of co-existing networks, i.e., WLANs, WMNs, and WWNs, based on a cellular concept are considered according to Figure 5. The WLAN is defined with 27 cells with a radius of 100 meters each. The WMN and WWN 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, 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 through the coverage of several cells located within the three networks. The considered numerical values for the networks' parameters are illustrated in Table 9.

C. Simulation Results

Figures 6-9 show the percentage of connections towards a preferred network 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

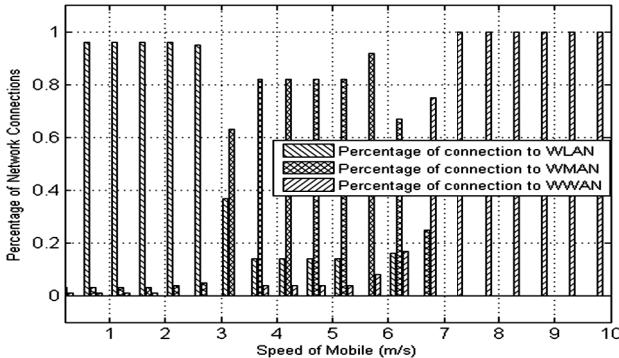


Figure 6: Percentage of NW-Connection for TOPSIS-FLV per different MS speeds, Conversational Traffic.

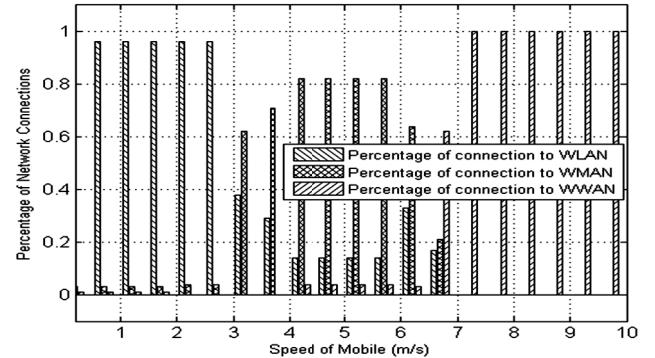


Figure 8: Percentage of NW-Connection for TOPSIS-FLV per different MS speeds, Background Traffic.

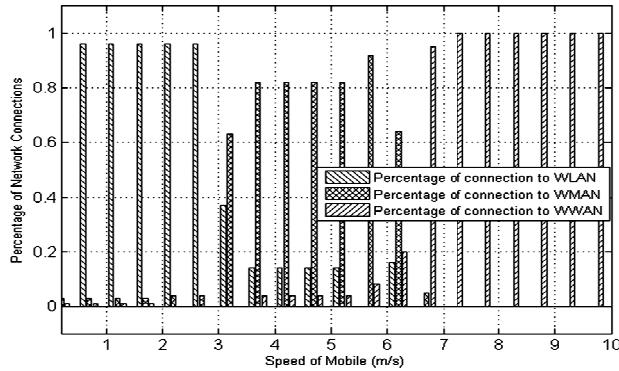


Figure 7: Percentage of NW-Connection for TOPSIS-FLV per different MS speeds, Interactive Traffic.

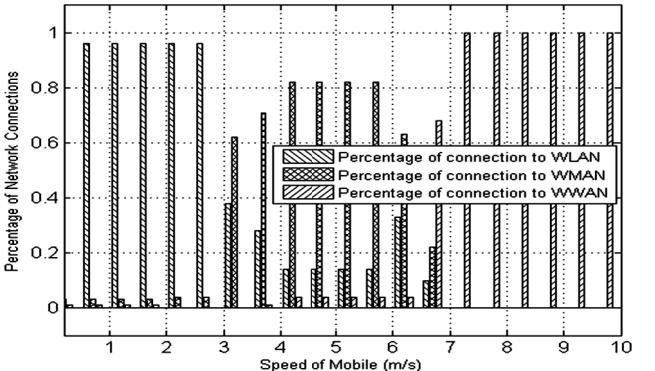


Figure 9: Percentage of NW-Connection for TOPSIS-FLV per different MS speeds, Streaming Traffic.

these figures that TOPSIS-FLV scheme shows a clear choice of network connectivity preferences at slower, medium and higher speeds; 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 9. 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 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.

VI. CONCLUSIONS

A vertical handoff (VHO) Algorithm with two modules, namely, VHO Handoff Necessity Estimation (VHONE), and Network Access Technology (NAT) Selection, were proposed. The Fuzzy Logic based VHONE module determines whether a handoff is necessary by taking into consideration the predicted RSS values provided by the current Point of Attachment (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 Fuzzy Linguistic Variables (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.

REFERENCES

- [1] B. V. Quang, R. V. Prasad and I. Niemegeers, "A Survey on Handoffs — Lessons for 60 GHz Based Wireless Systems," *IEEE Communications Surveys & Tutorials*, vol. 14, pp. 64-86, 2012.
- [2] M. Alkhawiani and A. Ayesh, "Access network selection based on fuzzy logic and genetic algorithms," *Advances in Artificial Intelligence*, vol. 8, pp. 1:1-1:12, January, 2008.
- [3] S. Horrich, S. Ben Jamaa and P. Godlewski, "Neural networks for adaptive vertical handover decision," in Proc 5th International Symposium on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks and Workshops(WiOpt '07), 2007, pp. 1-7.
- [4] D. Yong, "Plant location selection based on fuzzy TOPSIS," *The International Journal of Advanced Manufacturing Technology*, vol. 28, pp. 839-844, 2006.
- [5] Faisal Kaleem, "VHITS: Vertical Handoff Initiation and Target Selection in a Heterogeneous Wireless Network", PhD Dissertation, Florida International University, 2012
- [6] J. Rinne, "3GPP Specification Details, TS 23.107," .
- [7] H. Lin and W. Chang, "Order selection and pricing methods using flexible quantity and fuzzy approach for buyer evaluation," *Eur. J. Oper. Res.*, vol. 187, pp. 415-428, 2008.
- [8] T. Gwo-Hshiung and H. Jih-Jeng, *Multiple Attribute Decision Making: Methods and Applications*. 2011.
- [9] J. Zander and S. Kim, *Radio Resource Management in Wireless Networks*. Artech House, 2001.