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COOPERATIVE MULTICRITERIA HANDOVER MANAGEMENT FOR RELIABLE V2I COMMUNICATION AND IMPROVED QoS IN OVERLAYED HETEROGENEOUS NETWORK ENVIRONMENT

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Abstract: Providing uninterrupted wireless connectivity to vehicles has posed a significant challenge in the context of Vehicle–to–Infrastructure (V2I) communications especially in heterogeneous network environments. This limitation primarily arises due to the constrained infrastructure of vehicular networks. Solutions like Wireless Access for Vehicular Environment (WAVE) protocol and On–Board Units (OBUs) have aimed to expand network capacity and enhance communication between vehicles and infrastructure. However, significant network resources are spent on selecting appropriate target networks during handover in heterogeneous networks. To address issues like incorrect handover network selection and handover delays, researchers have proposed various multi–criteria decision making (MCDM) techniques to choose the optimal candidate cell within HetNet environment. Nevertheless, a majority of these solutions do not account for variations in criteria weights during handoff decisions, which impacts the efficient utilization of resources in V2I communications. To mitigate the problem of incorrect network selection during handover, this study introduces a V2I Multicriteria based Handover Algorithm (mV2I–MHA), considering network parameters such as cost, bandwidth, packet loss ratio, and packet latency. The algorithm's performance was evaluated using MATLAB R2020a. The obtained results were compared with an existing algorithm where it demonstrated a significant improvement of 27.6% in throughput and a reduction in packet loss rates.
Keywords: Handover, Multi–Criteria Decision–Making, Packet Loss, Throughput, Vehicle–to–Infrastructure, OBUs

1. INTRODUCTION

According to [1], vehicular communication technology facilitates interaction among diverse vehicles, infrastructure components, and other devices. Common types of vehicular communication encompass vehicle–to–vehicle (V2V) communication, vehicle–to–infrastructure (V2I) communication, and vehicle–to–everything (V2X) communication. In V2V communication, vehicles directly exchange wireless information through On–Board Units (OBUs) without relying on roadside infrastructure (RSUs). Conversely, in V2I communication, vehicles communicate wirelessly between in–built OBUs and fixed RSUs. While V2X communication includes the sharing of information between vehicles and other things that can communicate, like roadside infrastructure, pedestrians, networks, and the cloud. [2]. Modern times have witnessed a surge in the desire for wireless applications and services., driven by the imperative to access information regardless of location or time constraints. Consequently, wireless communication networks are now under pressure to deliver faster data rates [3]. Furthermore, the increasing prevalence of time–aware applications in vehicular networks, including those related to mobility, road safety, infotainment, and environmental concerns, has intensified the requirement for increased data capacity and wider bandwidth. Consequently, the need for continuous connectivity in moving vehicles with low latency and high packet delivery ratio is essential. Ensuring uninterrupted application usage and service provision for vehicles in a dynamically changing vehicular network, characterized by varying speeds and node densities, is challenging. V2I communication often experiences drawbacks such as high delays, packet losses, or low throughput. To maintain quality of service (QoS) for vehicles with continuous connections, the installation of RSUs is the initial step [2]. However, excessive RSU deployment is impractical due to installation and maintenance costs. This approach can lead to interference issues. The subsequent step is to enable vehicles to connect to diverse networks (heterogeneous networks) [2].

In spite of the numerous benefits offered by V2I applications, establishing continuous connections for moving vehicles remains a significant difficulty in V2I communications. Present vehicular network systems fall short in terms of adequate coverage, hindering the ability of people in vehicle to connect to the internet while in motion. As a response to this challenge, new standards have been developed like WAVE. WAVE uses IEEE802.11p technology at the MAC and physical layers to enable better wireless connectivity for vehicles. However, this protocol faces challenges such as scalability issues, communication delays, and limited coverage area [4]. Addressing these challenges has led to the deployment of a multi–tier

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

heterogeneous network arrangement with different cell sizes, leveraging the capabilities of 5G networks [3].

The vehicle manufacturing industry efforts have led to the incorporation of Wireless communication technologies like LTE, Wi–Fi, UMTS and WiMAX, within vehicles' built–in OBUs. This integration aims to tackle scalability challenges and enhance vehicle communication systems [2]. However, a notable challenge arises in the form of increased frequent yet unnecessary handovers [5], which can significantly impact QoS in V2I communications across heterogeneous networks.

In urban multi–tier heterogeneous network environments, effective Vehicle–to–Infrastructure (V2I) communication hinges on the seamless execution of rapid (horizontal and vertical) and smooth transitions between large–scale and small–scale cellular networks. This includes handovers among various small–scale networks to guarantee uninterrupted mobility and communication. Existing research on handovers in heterogeneous networks primarily focuses on slow–moving vehicle users with specific performance criteria [6]. In such environments, handovers consume substantial network resources, resulting in increased network latency [7]. This research introduces a modified QoS–aware multi–criteria handover decision–making algorithm (mV2I–MHA). This algorithm chooses the suitable cell for transition depending on specific performance criteria to ensure uninterrupted connectivity for end–users, thereby simplifying smooth transition processes for V2I communications across overlayed diverse networks. The rest of this study can be summarized as follows: Section 2 outline an overview of studies on multi–tier and multi–radio access network handover. Section 3 outlines the materials and methods adopted in this research paper. The results obtained are discussed in section 4, while section 5 serves as the conclusion for this study.

2. REVIEW OF SIMILAR WORK

The review of similar works is very important because it outlines the amount to which research has gone in the resolution of the problem of multi–tier and multi–radio access network handover. It outlines the tools and approaches employed by other researchers and the problem they encountered in obtaining the results they achieved. It then helps in the decision–making of the tool and the approach to be taken to obtain better results. Similar literature that are relevant to the research area are reviewed in this section. [8] introduced an enhanced vertical handover decision algorithm grounded in mobile, equal, and network priorities to amplify Quality of Service within heterogeneous network settings. The heterogeneous network encompassed WLAN, LTE, and WiMAX components.

The algorithm harnessed TOPSIS to ascertain the relative weights of multiple criteria, including mobile speed, Received Signal Strength, cost, and network occupancy. Their proposed algorithm underwent implementation in NS–2, and simulation outcomes demonstrated that the approach yielded superior throughput and reduced packet loss for network decision–making when juxtaposed with the conventional network decision algorithm. Nonetheless, an increase in the ratio between mobile speed and the cost function led to heightened network signaling load and affected the network decision process adversely. [9]

Introduced an approach using Multi–Criteria Decision Making (MCDM) principles, integrating Modified Grey Relational Analysis (E–MGRA) and Fuzzy Analytic Hierarchy Process (FAHP) for handover decision–making in Heterogeneous Networks (HetNet). Criteria included security, delay, network availability, packet loss, cost, energy, and jitter. Advocated for an "Always–Suitable–Connection" (ASC) approach. Simulations reduced handover delay and frequency for four traffic classes, but practical implementation might increase computational time and costs, potentially impacting network selection, handover failure rates, and QoS. [10] used a Multi–Criteria Decision Making technique in choosing the best candidate node based on service requirements like bandwidth, latency, and cost. The technique outperformed other V2I handover algorithms but had limitations in handling imprecision and subjectivity in network selection due to AHP. In 2020, Pacheco et al. introduced Skip–HoVe, a handover algorithm for video in dense vehicular networks. It uses skipping–based handovers to reduce ping–pong effects, predicts vehicle mobility, and employs AHP for cell selection. Simulations showed better video quality but had limitations in mobility prediction and criteria weighting. Network–wide performance impact was not analyzed [11]. In [12] the authors embraced a multi–criteria approach using both fuzzy (FTOPSIS) and non–fuzzy (TOPSIS) techniques for ranking networks in heterogeneous wireless environments. The goal was to enhance network performance, QoS, and service diversity.

They used Fuzzy Analytic Hierarchy Process (FAHP) to assign weights to performance parameters. FTOPSIS outperformed TOPSIS in specific traffic classes, reducing ping–pong effects and blocking probability.

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

However, it led to more handovers at high mobile user speeds. The work of [13] Implemented AHP–FVikor technique for selecting the best target network in vehicular communication to maintain uninterrupted connectivity and meet QoS requirements. It used a two–stage fuzzy logic–based process, considering factors like RSS and vehicle velocity, as well as criteria such as cost, jitter, bandwidth, and delay using AHP. Compared to other methods like SAW and VIKOR, it reduced handovers and delay. However, it's important to acknowledge that the proposed approach exhibited slightly increased delay compared to SAW due to overhead considerations. [14] described a priority–based strategy called H2ATF to reduce handovers, improve data rates, and minimize ping–pong effects. It used Analytic Hierarchy Process (AHP), TOPSIS, and fuzzy logic to prioritize base stations based on SINR, RSRP, RSRQ, and speed. While it reduced handovers and ping–pong effects. However, it is essential to note that the proposed scheme did exhibit a higher handover failure rate due to AHP's inherent uncertainty compared to some other algorithms. The work of [15] introduced a framework for optimal placement of Roadside Units (RSUs) in Vehicle–to–Infrastructure (V2I) systems, using AHP, entropy, and VIKOR. Criteria included cost, Packet Loss Ratio (PLR), and Ratio of Intersection Area (RIA). It didn't consider bandwidth in Vertical Handover (VHO) and thus underutilized network resources. Various methods aim to enhance Quality of Service (QoS) in V2I networks, considering factors like network load, mobile speed, RSS, cost, and more. Common goals include reducing unnecessary handovers and improving packet delivery, but challenges include delays, computational complexity, and signaling loads. Nonetheless, certain approaches might be face with challenges such as extended handover delays, heightened computational time and expenses, compromised system performance, and elevated network signaling loads. Similarly, in the work of [26], the authors introduced a fuzzy logic–based vertical handover algorithm for heterogeneous wireless networks, showing advantages over traditional methods in simulations. However, the study had limitations, including a focus on two hypothetical networks and a fixed low vehicle speed of 30 km/h. While Patil and Patil introduced a fuzzy logic–based vertical handover method for heterogeneous wireless networks. It has three phases: decision, network selection, and execution. Simulation results showed improvement but suggested adding more criteria like signal strength and delay in [27]. And In [28] the authors discussed a method for vehicle network selection in LTE–A heterogeneous networks, addressing challenges like unwanted handovers. Their approach uses vehicle mobility data to identify optimal networks and showed improved handover success in simulations, but it doesn't consider target network resource availability.

In summary, these investigations offer valuable insights into the hurdles and possibilities tied to enhancing QoS in V2I communication within multi–tier heterogeneous networks. Further exploration and advancements in this domain are imperative to formulate more potent and efficient techniques that can ensure high–quality communication within these intricate network environments.

3. MATERIALS AND METHODS

The suggested mV2I–MHA technique for choosing a more acceptable candidate network for HO was tested using MATLAB R2020a as the testing tool. On an HP Pavilion laptop, this simulation was run. The next sub–sections outline the approaches taken into consideration for FAHP modification, splicing of the mFAHP and SAW, and the pseudocode for the created algorithm. The Simple Additive Weighting (SAW) and Fuzzy Analytic Hierarchy Process (FAHP), which are MCDM techniques are additionally discussed to give context to the hybridization of mFAHP and the SAW technique in this paper.

Simple Addictive Weighting

Simple Additive Weighting is one of the simplest MCDM techniques which is derived from average assigned weights [16]. It is also known as Weighted Sum Model (WSM). SAW determines the score of each alternative by simple mathematical product operations of the normalized decision matrix and the assigned weights of importance. The final ranking of the alternatives is computed by the comparison of the weighted products of the alternatives and then ranked in order of preference, where the network alternative with the maximum weight product performance score is ranked as the optimal network [17]. SAW is performed utilizing the subsequent procedures.

Given a decision matrix problem, A, the set of b alternatives, which are the candidate RATs at the time of handover is represented as [10]:

$$b = (b_1, b_2, b_3, \dots, b_m) \quad (1)$$

The set of criteria, z, denotes the application requirements. The requirements adopted in the work of [10] are the guaranteed bandwidth, packet latency, packet loss ratio and service cost provided by various network.

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

$$z = (z_1, z_2, z_3, \dots, z_n) \tag{2}$$

To achieve optimal decision making in a Multi–Criteria Decision Making (MCDM) problem, MCDM analysis is used. The MCDM problem is generally represented as [18]:

$$\mathbf{A} = (b \times z) \tag{3}$$

where A signifies the decision matrix, b represents the alternative RATs, and z represents the criterion.

Step 1: Constructing the decision matrix [10]:

$$\mathbf{A} = \begin{array}{c c} & \begin{array}{cccc} z_1 & z_2 & z_3 \cdots & z_n \end{array} \\ \begin{array}{c} b_1 \\ b_2 \\ \cdot \\ \cdot \\ \cdot \\ b_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & x_{13} & x_{1n} \\ x_{21} & x_{22} & x_{23} & x_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ x_{m1} & x_{m2} & x_{m3} & x_{mn} \end{bmatrix} \end{array} \tag{4}$$

Step 2: Creating a standardized decision matrix for both benefit factors and the cost factors. According to [19] and [18], the appropriate representation of the Min–Max method used to normalize the decision matrix element, $\bar{\mathbf{A}}_{ij}$ for the benefit criteria is given as follows:

$$\bar{\mathbf{A}}_{ij} = \frac{x_{ij}}{x_j^{max}}, \quad i = 1,2,3, \dots, m, \quad j = 1,2,3, \dots, n \tag{5}$$

where x_j^{max} is a criteria parameter with high value, which is the maximum entry of the j^{th} column in $\mathbf{A}$. In this case, the criterion is the guaranteed bandwidth and x_{ij} denotes the performance score of the i^{th} alternative in terms of j^{th} criterion.

Similarly, for the cost criteria, the low values of these parameters are optimal. These values are obtained using equation (6).

$$\bar{\mathbf{A}}_{ij} = \frac{x_j^{min}}{x_{ij}}, \quad i = 1,2,3, \dots, m, \quad j = 1,2,3, \dots, n \tag{6}$$

where x_j^{min} represent the minimum entry of the j^{th} column in A.

Step 3: Calculate each SAW rank index, B_{SAW}^{i} of the i^{th} alternative utilizing equation (7) and equation (8) the total of W_j equals unity [10, 18].

$$B_{SAW}^{i} = \sum_{j=1}^{n} W_j A_{i,j} \tag{7}$$

$$\sum_{j=1}^{n} W_j = 1 \tag{8}$$

Where, W_j represents the weight of a criterion i.

Step 4: Compute the score of each alternative

$$B_{SAW}^{i*} = \sum_{j=1}^{n} B_{SAW_j}^{i}, \qquad i=1, 2, 3, \dots, n \tag{9}$$

Step 5: Obtaining the suitable (Y) option.

$$Y = \max_{i=1}^{n} B_{SAW}^{i*} \tag{10}$$

Fuzzy Analytic Hierarchy Process

The classical AHP method is a technique for analyzing complex decisions [19]. This classical AHP algorithm is designed to mimic the behavior of humans to make choices. To achieve this, the algorithm generally considers a hierarchical process to analyze the decision–making process [20]. This algorithm generally considers the decision–making process in layers, which are the goal/target layer, criterion layer, and the alternatives/solution layer. In general, the criterion would be accessed by the goal, while each alternative would be accessed by each criterion to select from the candidate options and settle for the target option that is optimal for the alternatives [21]. In the work of [10], the application of the AHP process breaks the decision–making of the V2I–MHA into three hierarchical levels as well. At the goal/target, a target network is considered from the candidate networks available in a multitier HetNet; the criterion level on the other hand primarily considers the GB, PLR, PL, and cost, while the OBUs in the vehicles are the alternatives.

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

As highlighted in the work, the OBU (alternatives) accesses the criterion of each candidate network to select the target network optimal for the vehicles, regardless of upward or downward HO. However, the perception of humans to make decisions are not deterministic, for in most cases, there are situations of uncertainty in our preferences [20]. To account for this uncertainty, fuzzy set theory is used, to further model the AHP decision–making process to model scenarios that are more pragmatic to our environments [22], or as in the case of this research, the selection of the appropriate target network. The fuzzy AHP technique is an enhanced analytical approach derived from the conventional AHP, integrating elements of fuzzy logic and linguistic variables. Fuzzy logic plays a crucial role in addressing uncertainties in decision–making scenarios and in handling imprecise data definitions [9]. Using this approach introduces a range of values between the logical [0, 1], crisp logic found in the AHP. As stated in the work of [10], the criterion varies between operators (that is, the constituents of the HetNet). This variation expands the ambiguities during the process of making decisions necessary in choosing target network. A mathematical representation of the Fuzzy AHP (FAHP) process which is represented in [23] includes decomposing the problem into hierarchical framework demonstrated in Figure 1.

Step 1: Decomposing the problem into the hierarchical structure for ranking the decision criteria consists of three levels.

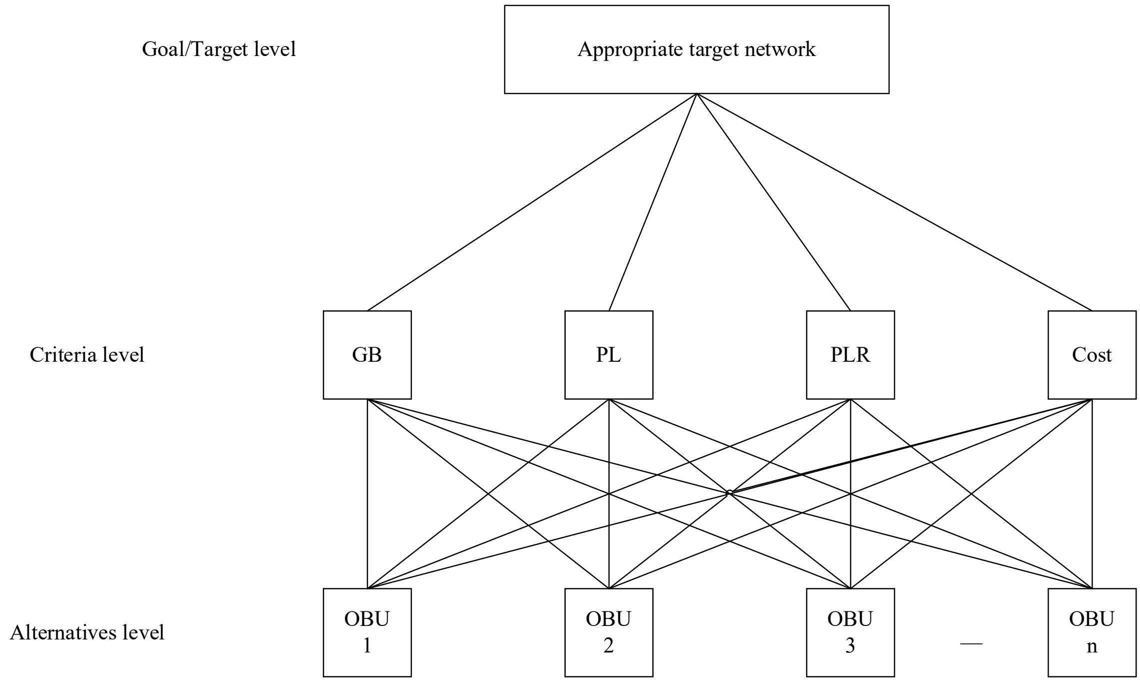

Figure. 1: Hierarchical Structure for V2I Handover Decision

Step 2: Calculating the fuzzy pairwise comparison matrix which can be obtained with the help of scale of relative importance using Triangular Fuzzy Numbers (TFN) to convert the linguistic variables which are crisp numeric values to fuzzy numbers using equation (11).

$$\mu_M(x_{ij}) = \begin{cases} \dfrac{x_{ij} - l_{ij}}{m_{ij} - l_{ij}}, & l_{ij} \le x_{ij} \le m_{ij} \\ \dfrac{x_{ij} - u_{ij}}{m_{ij} - u_{ij}}, & m_{ij} \le x_{ij} \le u_{ij} \\ 0, & x_{ij} < l \text{ or } x_{ij} > u_{ij} \end{cases} \tag{11}$$

Here, ‘l’ represents the lowest value, ‘m’ signifies the most frequent or central value, and ‘u’ stands for the highest value.” Thereafter the fuzzy pairwise comparison matrix is represented as:

$$\mathbf{A} = (x_{ij}) = \begin{array}{c} \\ z_1 \\ z_2 \\ \vdots \\ z_n \end{array} \begin{array}{c} \begin{array}{cccc} z_1 & z_2 & \cdots & z_n \end{array} \\ \begin{bmatrix} 1 & (l_{12}, m_{12}, u_{12}) & \dots & (l_{1n}, m_{1n}, u_{1n}) \\ \left(\frac{1}{u_{21}}, \frac{1}{m_{21}}, \frac{1}{l_{21}}\right) & 1 & \dots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ \left(\frac{1}{u_{n1}}, \frac{1}{m_{n1}}, \frac{1}{l_{n1}}\right) & \left(\frac{1}{u_{n2}}, \frac{1}{m_{n2}}, \frac{1}{l_{n2}}\right) & \dots & 1 \end{bmatrix} \end{array} \tag{12}$$

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

Step 3: Computing the synthetic fuzzy extent with respect to i[th] alternative using equation (13)

$$S_i = \frac{\sum_{j=1}^{n} x_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}} \tag{13}$$

$\sum_{j=1}^{n} x_{ij}$ and $\frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}}$ in equation (13) are obtained using the fuzzy aggregation process of n extent analysis for fuzzy pairwise comparison matrix as shown below:

$$\sum_{j=1}^{n} x_{ij} = \left(\sum_{j=1}^{n} l_j, \sum_{j=1}^{n} m_j, \sum_{j=1}^{n} u_j\right) \tag{14}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij} = \left(\sum_{i=1}^{n} l_j, \sum_{i=1}^{n} m_j, \sum_{i=1}^{n} u_j\right) \tag{15}$$

$$\frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}} = \left(\frac{1}{\sum_{i=1}^{n} l_j}, \frac{1}{\sum_{i=1}^{n} m_j}, \frac{1}{\sum_{i=1}^{n} u_j}\right) \tag{16}$$

Step 4: To compare the fuzzy numbers, the likelihood of $M_2 \geq M_1$ is calculated as:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) \tag{17}$$

$$V(M_2 \geq M_1) = \begin{cases} 1, & \text{if } M_2 \geq M_1 \\ 0, & l_1 \geq u_2 \\ \dfrac{(l_1 - u_2)}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases} \tag{18}$$

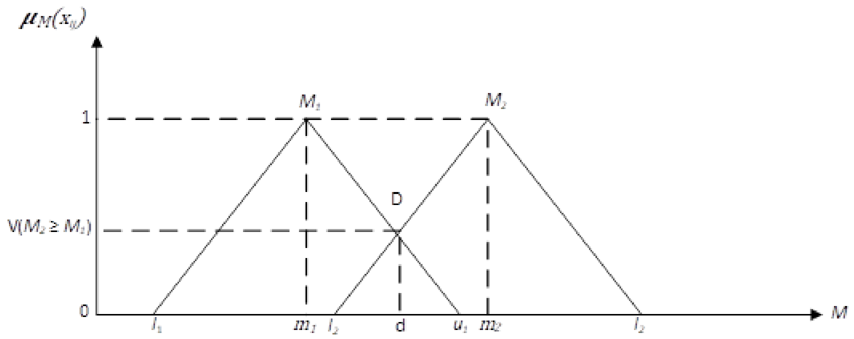

Figure 2: Membership Function of the TFN Showing Intersection Between μ_{M_1} and μ_{M_2} [23]

Where d represents the maximum intersection point D between μ_{M_1} and μ_{M_2} illustrated in Fig. 2. M_1 and M_2 are convex fuzzy numbers represented as $M_1 = (l_1, m_1, u_1)$, $M_2 = (l_2, m_2, u_2)$.

Step 5: Calculating the minimum degree of possibilities: Initially, the likelihood of a convex fuzzy number surpassing k other convex fuzzy numbers, including convex fuzzy number M and k additional convex fuzzy numbers M_i (i = 1, 2, 3, …, k) is obtained using equation (19).

$$V(M \geq M_1, M_2, \dots, M_k) = MinV(M \geq M_i), \quad i = 1, 2, \dots, k \tag{19}$$

Step 6: Normalization of the weight vectors: To normalize the weight vectors, assuming that

$$d'(B_i) = MinV(M_i \geq M_k) \text{ for } k = 1, 2, \dots, n; k \neq i \tag{20}$$

where B_i = (i = 1, 2, …, n) are n attributes

Hence, the normalized weight vectors are obtained in equation (21) using equation (22), where the weight vectors are real numbers.

$$W = (d(B_1), d(B_2), \dots, d(B_n))^T \tag{21}$$

$$W = \frac{W'}{\sum_{i=1}^{n} d'(B_i)} \tag{22}$$

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

Modification of Fuzzy Analytic Hierarchy Process

As shown in [24] for developing the FEA of FAHP, in the conventional FEA approach, to elimination or correct the possible wrong decision by assigning zero weights and reduce the higher computational complexity associated with the FEA method, the magnitude value evaluation of triangular fuzzy numbers is introduced as defined in equation (23) [25]

$$\mathrm{Mag}(S_i) = \frac{1}{2}\int_0^1 \left(\left(\bar{A}(\alpha) + \underline{A}(\alpha) + \mathrm{core}\,(\bar{A}) + \mathrm{core}\,(\underline{A})\right) f(\alpha)\right) d\alpha \tag{23}$$

where $f(\alpha)$ is defined as a differentiable, non–negative and a function on the interval [0,1] that does not decrease, and $f(0) = 0, f(1) = 1$ and $\int_0^1 f(\alpha)d\alpha$. The α – cut of fuzzy number A is given as,

$$A(\alpha) = \{x \in | \mu_A(x) \geq \alpha\}, \alpha \in [0,1] \tag{24}$$

where A(α) is defined as a convex subset within set U.

The boundaries of the α–cut A are specified as follows,

$$\bar{A}(\alpha) = \{x \in | \mu_A(x) \geq \alpha\}, \tag{25}$$

$$\underline{A}(\alpha) = \{x \in | \mu_A(x) \geq \alpha\}, \tag{26}$$

Hence,

$$\bar{A}(\alpha) = u \tag{27}$$

$$\underline{A}(\alpha) = l \tag{28}$$

The core of a fuzzy number A comprises the element x with a membership grade of 1. In other words,

$$\mathrm{core}\,(A) = \{x \mid \mu_A(x) = 1\} \tag{29}$$

If A is defined as fuzzy triangular number represented as $A = (l, m, u)$ then,

$$\mathrm{core}\,(\bar{A}) = \mathrm{Sup}\{x \mid \mu_A(x) = M_A\} = m \tag{30}$$

$$\mathrm{core}\,(\underline{A}) = \inf\{x \mid \mu_A(x) = M_A\} = m \tag{31}$$

To obtain the values of the magnitude $\mathrm{Mag}(S_i)$ of the triangular fuzzy number and the normalized weight values the following steps are used:

Step A. For each fuzzy number, equation (32) is applied to calculate the magnitude $\mathrm{Mag}(S_i)$. Step B. The normalization of $\mathrm{Mag}(S_i)$. is determined using equation (34) to obtain the weights. Simplifying equation (23); in this work, the fuzzy numbers are normal, therefore, $M_{S_i} = 1$. Furthermore, $\mathrm{core}\,(\bar{S_i}) = \mathrm{core}\,(\underline{S_i}) = m$, because of the fuzzy triangular number. Substituting these values into equation (23), the magnitude $\mathrm{Mag}(S_i)$ hence, can be rewritten as:

$$\mathrm{Mag}(S_i) = \frac{1}{2}\int_0^1 ([(u-(u-m)\alpha) - (l+(m-l)\alpha) + 2m]\alpha)d\alpha \tag{32}$$

$$\mathrm{Mag}(S_i) = \frac{l + 10m + u}{12}, i = 1, \dots, n. \tag{33}$$

Hence,

$$W = \frac{\mathrm{Mag}(S_i)}{\sum_{j=1}^{n} \mathrm{Mag}(S_i)} \tag{34}$$

The normalized weight vectors (W) in equation (34) are real numbers generated adopting the above step A and step B.

Handover Process for the mV2I–MHA

As elucidated in the handover stages in [10], for both existing and the developed technique. In the downward network selection process, the UE initiates an ANDSF request, receiving a list of small cell networks from the ANDSF server. This list, acquired during the information gathering phase, guides the UE's decision in the subsequent V2I–MHA decision phase. Based on ongoing application needs, the UE chooses an appropriate target small cell for handover. If none meet requirements, it stays with the serving macrocell base station. Similar steps occur for upward network selection, with the potential addition of a call event initiation. Here, the UE identifies the best target network for call needs, potentially transitioning from small cell to macrocell based on application demands.

System Model

The vehicle velocity is modeled using continuous time and continuous–state random walk model, where the vehicle speed is represented as a stochastic process, described by a set of differential equation in equation (35).

$$dv(t) = a(t)dt + \sigma(t)dW(t) \tag{35}$$

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

Where,
$dv(t)$ is the change in the vehicle speed at a given time t
$a(t)$ is defined as the acceleration of the vehicle
$\sigma(t)$ is the standard deviation of the noise in the speed
and $dW(t)$ is the Wiener process.

The acceleration of the vehicle can be modeled as a stochastic process that takes into account the uncertainties and randomness in the driving environment, such as road conditions and traffic congestion. By using this type of model, it is possible to simulate the movement of a vehicle in a more realistic way and take into account real–world factors that may impact the speed of the vehicle. This information can then be used in vertical handover decisions in vehicular communication to choose the best suited destination network considering the speed and other quality of service needs of the running application as depicted in the mV2I–MHA framework in Figure 4.

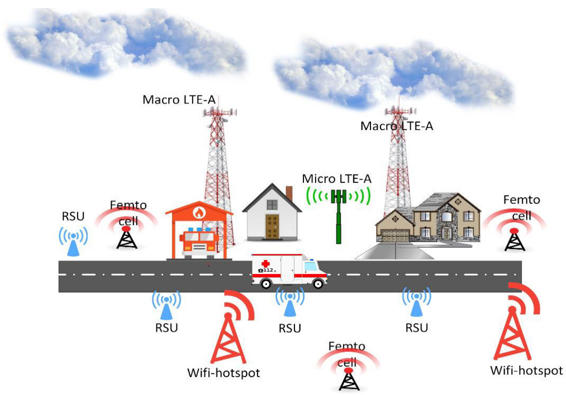

Figure 4: mV2I–MHA Conceptual Framework

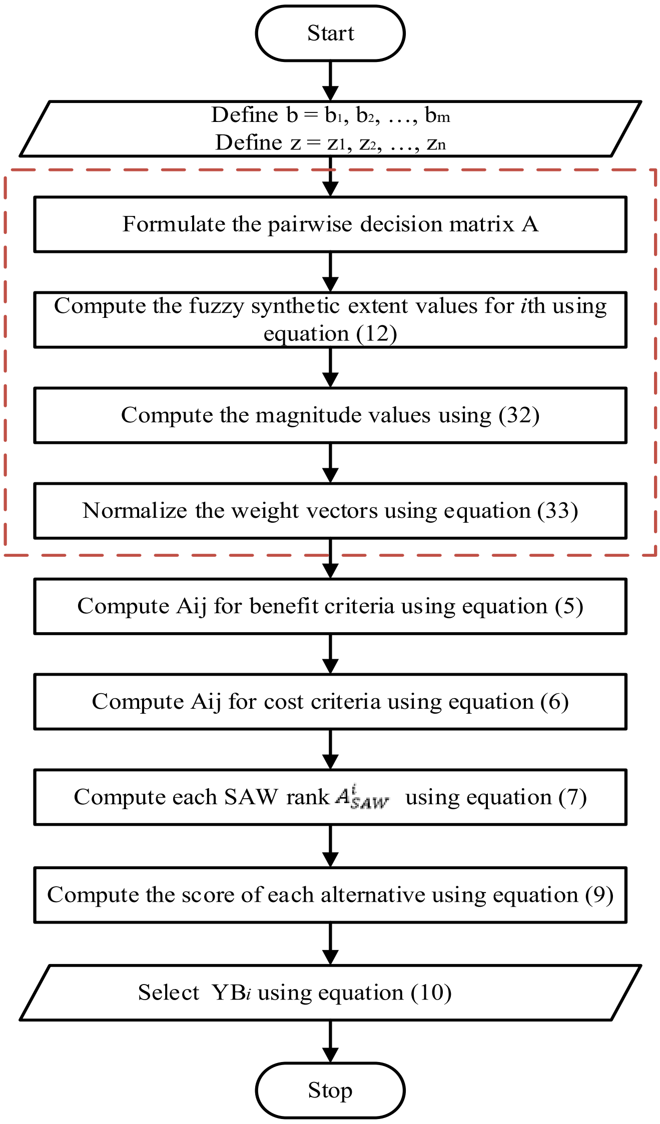

Figure 3: mV2I–MHA Handover Decision Process

Table 1 shows the simulation parameters of the developed algorithm.

Table 1: Simulation Parameters [4]

S/N	Parameter	Values
1	Network area (m*m)	1000 * 1000
2	Transmit power of LTE–A macro/SAP	0.5W/0.1W
3	LTE–A macro/SAP gain	14dBi/5dBi
4	WiFi SAP (IEEE 802.11p) transmit power	0.05W
5	Vehicle speed (Km/h)	20 – 140
6	Path loss	$L = (40(1 - 4 * 10^{-3}\Delta hb)\log 10\, R - 18\log 10\, \Delta hb + 21\log 10\, f + 80)$ dB
7	Radio propagation	Large–scale propagation
8	log–normal shadow fading	10 dB
9	LTE–A Channel bandwidth	1.4 MHz
10	Mobility	Vector based trajectory
11	Simulating time	600s

4. RESULTS AND DISCUSSION

To measure the performance of the network in relation to packet loss and throughput, the simulation was carried out employing MATLAB R2020a. The results of mV2I–MHA from the graphs obtained were compared with the results of the existing V2I–MHA algorithm in terms of Packet loss and throughput. The discussion of the results obtained are delineated hereunder.

The chart in Figure 5 represents the packet loss of the five different application profiles. Packet loss occurs when data packets are lost or dropped during transmission between the mobile device and the network. Packet loss can lead to degraded communication performance, retransmissions, and reduced overall user

ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665

experience. Concerning packet losses, Figure 5 illustrates that the mV2I–MHA solution, as suggested, has achieved a decrease in packet losses, with reductions for application profiles of around 5.5% for maximum quality, 7% for voice, 6% for video, 34% for general and 37% for service cost compared to existing work.

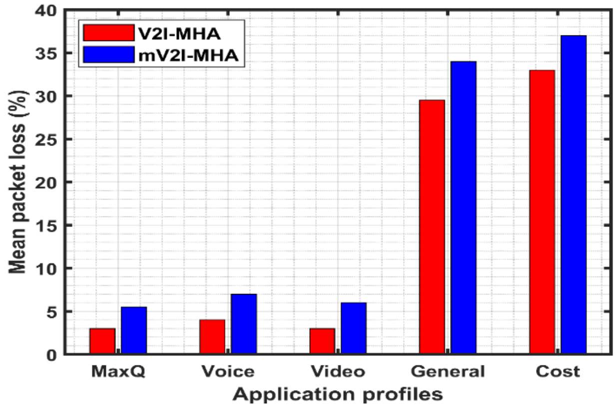

Figure 5: Packet Loss Comparison of mV2I and V2I–MHA

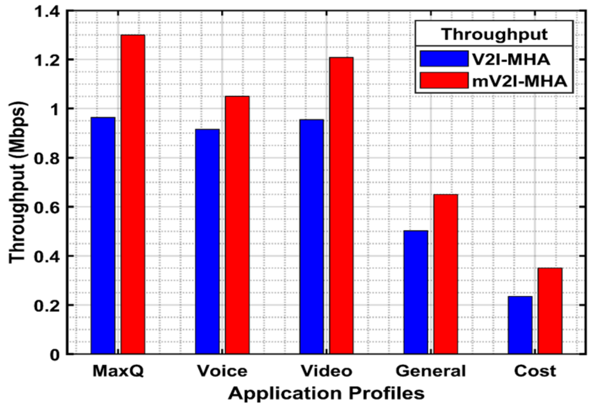

Figure 6: Throughput Comparison of mV2I–MHA and V2I–MHA

Figure 6 presents a chart of simulation throughput of the five different application profiles where The Maximum Quality (MaxQ) and video profiles obtained the highest throughput values of the total required throughput, while the voice profile achieved significant lower value as a result of its lower priority on bandwidth. The general profile recorded just half of the necessary data transfer rate as it did not prioritize services. The Service cost application profile yielded the lowest recorded throughput with the lowest priority, as this profile prioritizes low service costs over better handover performance.

The average throughput for the mV2I–MHA and V2I–MHA as shown in Table 4.4, the results indicate that relative to the five different application profiles for mV2I–MHA and V2I–MHA, the average throughput of the mV2I–MHA increased by 27.6%. This means that the average throughput of the mV2I–MHA is better than the V2I–MHA by 27.6%. In other words, the proposed algorithm has improved the network QoS throughput compared to the V2I–MHA scheme.

5. CONCLUSION

In a multiple layer diverse network setting, the issue of incorrect network selection during handover presents a hurdle, leading to delays in handover process and diminished overall network efficiency. This research project has made enhancements to a multi–criteria algorithm for decision–making during handovers, known as mV2I–MHA. The aim is to effectively choose the most suitable or ideal target network for seamless handover within integrated multi–tier heterogeneous networks. The mV2I–MHA selects the optimal candidate network based on available bandwidth, packet latency, packet loss ratio and cost satisfying the QoS requirements of five different application profiles for possible handover. Developing this modified handover decision algorithm, the throughput increased and the packet loss reduced with an improved QoS in the network. The handover decision algorithm was achieved by utilizing mFAHP–SAW technique for assigning weights to the network criteria and selecting the best target cell. For validation and comparison of the modified algorithm, the results obtained were evaluated with an existing algorithm in terms of the throughput and packet loss. Results showed that the developed algorithm had a 27.6% network throughput improvement, increasing it from 0.7142 to 0.9116 Mbps and a achieved a decrease in packet losses, with reductions for application profiles of around 5.5% for maximum quality, 7% for voice, 6% for video, 34% for general and 37% for service cost compared to the existing algorithm. Future works would consider exploring machine learning techniques like deep neural networks, random forests, or support vector machines to further examine the performance on the datasets and improve the approach in selecting the optimal target network for handover.

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ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN–L 1584 – 2665