Evaluation of RAT Selection in Heterogeneous Wireless Networks Using the WASPAS Multi-Criteria Decision-Making Technique

Department & University
Department of Electrical Engineering
University of Cape Town

Course Code & Name
EEE4121F - Mobile and Wireless Networks

Author's Name
Manare Rammutla - RMMMAN003

June 7, 2025

Declaration

1. I know that plagiarism is wrong. Plagiarism is to use another's work and pretend that it is one's own.
2. I have used the IEEE convention for citation and referencing. Each contribution to, and quotation in, this report from the work(s) of other people has been attributed, and has been cited and referenced.
3. This report is my own work.
4. I have not allowed, and will not allow, anyone to copy my work with the intention of passing it off as their own work or part thereof.

ME RAMMUTLA

June 7, 2025

Manare Rammutla

Date

Contents

0.1 Task 1: Literature Review

0.1.1 Introduction

The evolution of wireless technologies has led to the emergence of Heterogeneous Wireless Networks (HWNs), which integrate multiple Radio Access Technologies (RATs) such as Wi-Fi, LTE, 5G, and others. This integration aims to deliver seamless connectivity, broader coverage, and higher quality of service (QoS) to users in dynamic environments [2]. As shown in Figure 1, HWNs support diverse services and applications ranging from high-speed internet access to real-time multimedia and IoT-based solutions. However, the coexistence of multiple RATs introduces challenges in network selection and vertical handover (VHO), which involves switching between different technologies rather than within the same type (i.e., horizontal handover) [3].

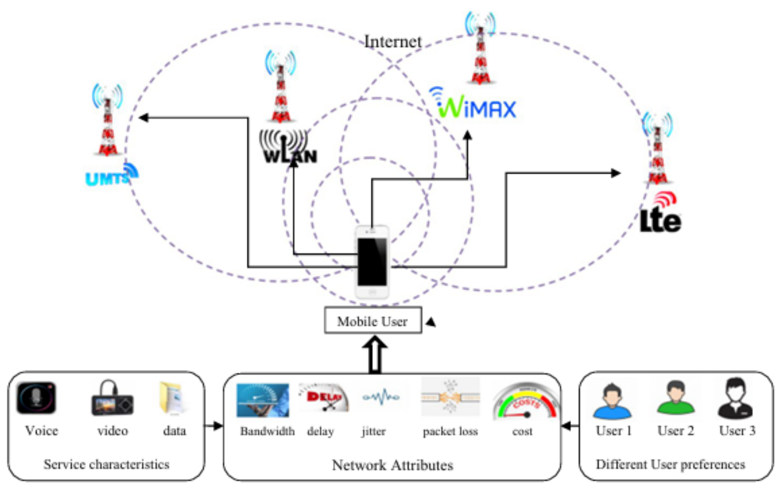


Figure 1: Scenario with HWNs for network selection [1]

To address these challenges, the *Always Best Connected* (ABC) paradigm advocates intelligent and context-aware decision-making mechanisms. These mechanisms must evaluate a range of dynamic criteria, including signal strength, available bandwidth, latency, cost efficiency, and user mobility [4]. Traditional decision strategies are increasingly being replaced or supplemented by Multi-Attribute Decision-Making (MADM) frameworks and Artificial Intelligence (AI) methods [1]. These advanced techniques promise improved handover performance, minimized service disruption, and user-centric adaptability in next-generation wireless networks.

0.1.2 Evolution of RAT Selection Techniques

Initial network selection strategies were based on Received Signal Strength (RSS), suitable for homogeneous networks but ineffective in HWNs due to their inability to incorporate QoS and user-centric considerations [2]. As network demands evolved, RSS-only approaches led to excessive handovers and suboptimal connectivity [7]. To address these shortcomings, advanced selection frameworks were introduced. Więcek et al. [7] proposed a multi-RAT orchestration strategy using edge computing to allocate network resources efficiently. Hsu et al. [5] developed a Weighted Sum Model (WSM) for dynamic RAT selection using multiple QoS attributes such as delay, cost, and signal quality.

Further reviews by Zhou et al. [10] and Stanic et al. [3] highlight the adoption of layered and hybrid decision architectures, including hierarchical models and multi-tier optimization methods. These techniques enhance the adaptability and robustness of decision-making processes under dynamic and heterogeneous network conditions.

0.1.3 MADM and AI-Based Decision Frameworks

MADM methods such as the Weighted Sum Model (WSM), Analytic Hierarchy Process (AHP), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) offer structured frameworks for evaluating trade-offs among conflicting criteria.

WSM [5] assigns weights to each criterion and computes a weighted sum to rank alternatives. It is computationally efficient and suitable for real-time decisions, but assumes linearity among attributes and lacks the ability to resolve conflicting preferences.

AHP [12] decomposes the decision problem into a hierarchy and uses pairwise comparisons to derive the relative importance of each criterion. While effective in managing subjective inputs and complex decisions, it can be prone to inconsistency and is often time-consuming.

TOPSIS [9] ranks alternatives based on their geometric distance from an ideal solution. It is well-suited for handling quantitative criteria and conflicting objectives, but is sensitive to normalization techniques and assumes linear relationships among criteria.

Abdelli et al. [6] extended MADM frameworks with value constraints to increase realism and adaptability in practical network environments.

On the AI front, Abdullah et al. [1] proposed a double hierarchy linguistic neural network as illustrated in Figure 2, capable of handling user preference uncertainty. Zia et al. [8] introduced cross-layer predictive models that enhance QoS reliability in IoT settings through AI-driven anticipation of network behavior. Bendaoud [11] used user mobility data to support predictive handover decisions, improving stability and reducing latency.

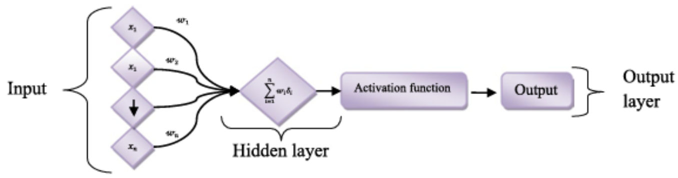


Figure 2: Artificial neural network [1]

0.1.4 Comparative Strengths and Limitations

MADM techniques provide interpretability, low computational complexity, and structured trade-offs among multiple decision criteria, making them ideal for resource-constrained environments. However, they are less adaptable to fast-changing network contexts. Conversely, AI techniques offer strong adaptability and prediction capabilities but are often computationally intensive and require large volumes of training data [4].

Hybrid decision-making models, which integrate AI's learning and adaptive capabilities with the transparency and structure of MADM, are emerging as effective solutions [1, 12].

0.1.5 Challenges and Future Outlook

Key challenges include the sensitivity of MADM techniques to network dynamics and the limited generalizability of AI models when exposed to unseen environments [4,6]. Standardized benchmarking frameworks remain underdeveloped, limiting comparative analysis [3]. Furthermore, issues such as energy efficiency, privacy, and cybersecurity are often overlooked [8, 11]. Future research should focus on secure, scalable, and standardized hybrid models that integrate real-time adaptability and user-centric optimization.

0.1.6 Evaluation of Methods

Table 1: Evaluation of Network Selection Methods in Heterogeneous Wireless Networks

Method	**Criteria Evaluated**	**Strengths**	**Weaknesses**
Fuzzy MADM with Context-aware Decision [1]	Network resources, user context, QoS, delay	Manages uncertainty effectively; enhances adaptability	Computationally expensive; requires expert tuning
Weighted Sum Model (WSM) [5]	Signal strength, delay, cost, throughput	Simple; real-time suitability	Limited to linear trade-offs; lacks conflict resolution
Analytic Hierarchy Process (AHP) [12]	Multi-criteria: delay, cost, reliability	Handles hierarchical criteria well; supports subjective input	Time-consuming; prone to inconsistency in comparisons
TOPSIS [9]	Delay, cost, bandwidth	Effective with quantitative criteria; good ranking clarity	Sensitive to normalization; assumes ideal/anti-ideal reference
Double Hierarchy Linguistic Neural Network [1]	Signal strength, cost efficiency, user preferences	Captures user uncertainty; dynamically adaptable	High training overhead; unsuitable for low-resource devices
Cross-layer Predictive AI [8]	Latency, QoS history, resource availability	Proactive; suitable for IoT dynamics	Demands data; high model complexity

0.1.7 Conclusion

The evolution of network selection methods in HWNs—from RSS-based approaches to structured MADM and adaptive AI models—highlights significant advancements in addressing QoS challenges. Techniques such as WSM, AHP, and TOPSIS offer transparency and feasibility in constrained settings, while AI models introduce adaptability and predictive capabilities. Despite these gains, issues like generalization, computational cost, and lack of standardization persist. Hybrid models that combine the strengths of both MADM and AI represent a promising path toward scalable, real-time, and user-centric network management.

0.2 Task2: RAT Selection in Heterogeneous Wireless Networks

0.2.1 Available RAT and their supported calls

RAT	Supported Calls & Services
4G LTE	Voice over LTE (VoLTE), Video calls, Data, Messaging
5G	Ultra-fast mobile broadband, Enhanced Mobile Broadband (eMBB), Internet of Things (IoT), Smart Cities, Autonomous Vehicles, Industrial Automation, AR/VR applications, Ultra-low latency services, High-definition video streaming.
3G	circuit-switched voice, SMS/MMS, packet-switched Internet data, video calling, multimedia streaming, and basic location-based services.

Table 2: Available RATs and Supported Calls

0.2.2 RAT selection criteria

- **Signal Strength (dBm) –** Measure th connection stability and quality
- **Data Rate (Mbps) –** Determines the speed of data transmissions
- **Cost ($/GB) –** Represents the monetary cost incurred per gigabyte of data transferred over the network.

0.2.3 The decision matrix

Table 3: Decision–matrix values before normalisation [13]

RAT	Signal Strength(dBm)	Data Rate (Mbps)	Cost ($/GB)
3 G	-85	5	3.5
4 G LTE	-65	55	4.5
5G	-55	100	7

To enable consistent normalization, the Signal Strength values were converted to absolute values as shown in Table 4 below. This is necessary because Signal Strength in dBm is expressed as a negative number, with stronger signals having values closer to zero (e.g. -55 dBm), and weaker signals having larger negative values (e.g. -85 dBm).

Table 4: Decision–matrix values before normalisation [13]
Signal strength (dBm) was converted to absolute values

RAT	|Signal Strength(dBm)|	Data Rate (Mbps)	Cost ($/GB)
3 G	85	5	3.5
4 G LTE	65	55	4.5
5G	55	100	7

The given decision matrix can be formulated as:

$$M = \begin{bmatrix} & C_1 & C_2 & C_3 \\ R_1 & 85 & 5 & 3.5 \\ R_2 & 65 & 55 & 4.5 \\ R_3 & 55 & 100 & 7 \\ \end{bmatrix}$$

The set of weights that a user can assign to a RAT-selection criterion is 9 levels as follows: 1,2,3,4,5,6,7,8,9.Level 1 represents the lowest priority while 9 represents the highest priority.

0.3 Task 3: The heterogeneous wireless network to be evaluated using diagram

Figure 3 below represents a Heterogeneous Wireless Network (HetNet), showing the integration of multiple Radio Access Technologies (RATs) that provide internet access to user devices.

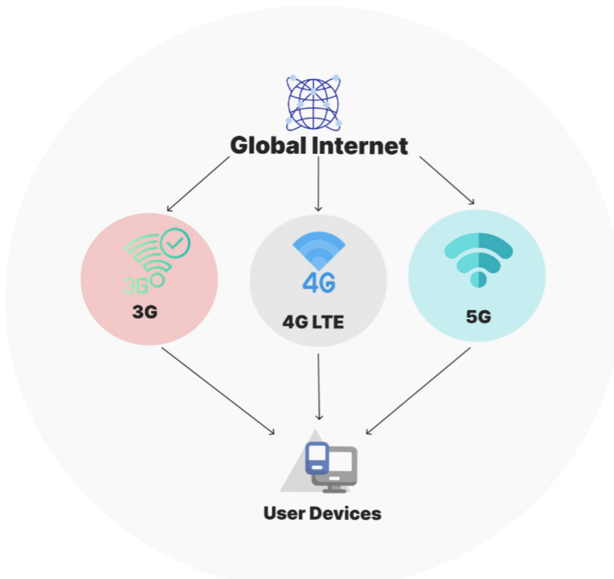
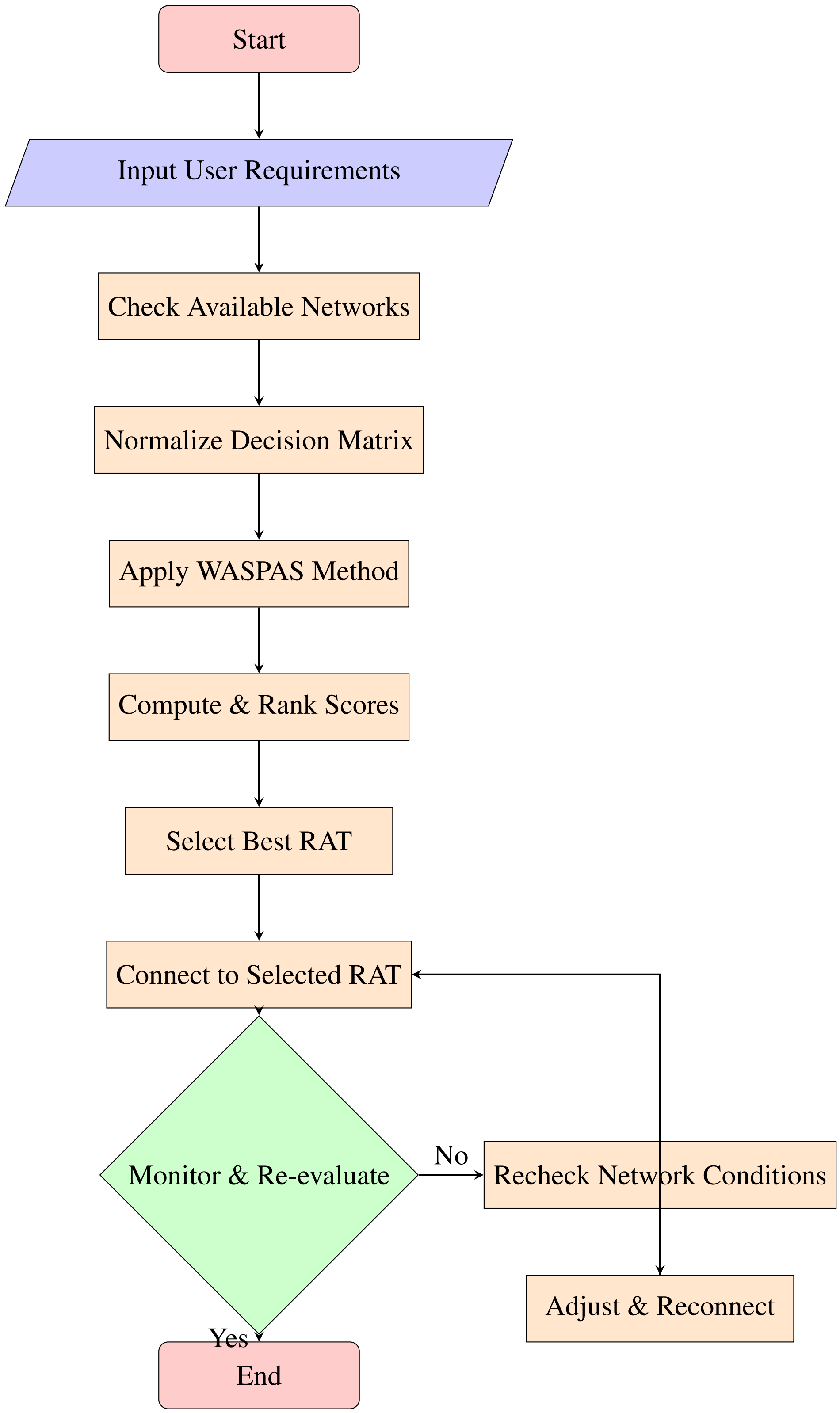


Figure 3: The heterogeneous wireless network to be evaluated

Key Relationships

- The **Global Internet** connects to multiple RATs (3G, 4G LTE, 5G) as gateways.
- Each **RAT** independently provides internet access to user devices.
- **User devices** can dynamically switch between RATs for optimal connectivity.

0.4 Task4: Flowchart for RAT Selection in HetNets



0.5 Task 5: Normalization of the Decision Matrix in the WASPAS Multi-Criteria Decision-Making Technique

Normalization Equations

For a decision matrix $X = [x_{ij}]$ with $i = 1, 2, ..., m$ alternatives and $j = 1, 2, ..., n$ criteria:

- For **Benefit criteria** (higher is better):

$$\bar{x}_{ij} = \frac{x_{ij}}{\max_i(x_{ij})}$$

- For **Cost criteria** (lower is better):

$$\bar{x}_{ij} = \frac{\min_i(x_{ij})}{x_{ij}}$$

Where:

- $\bar{x}_{ij}$ is the normalized value of x_{ij}.
- $\max_i(x_{ij})$ is the maximum value of criterion j.
- $\min_i(x_{ij})$ is the minimum value of criterion j.

The given decision matrix contains different types of criteria. To normalize it properly, we first classify them into benefit and cost criteria:

Note: Taking the absolute value allows us to represent Signal Strength on a positive scale, where lower values correspond to stronger signals. After this conversion, Signal Strength behaves as a cost criterion: smaller absolute dBm values indicate better performance. Accordingly, it was normalized using the min/current approach typically used for cost criteria. This ensures that the normalization correctly reflects the desirability of stronger signals in the RAT selection process.

- **Benefit Criteria (Higher is Better):**
  - C_2 - Data Rate (Mbps)
- **Cost Criteria (Lower is Better):**
- C_1 - | signal strength(dBm) |
- C_3 - Cost($/GB)

Normalization Calculations

Given the raw decision matrix:

$$D_{\text{raw}} = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & C_2 & C_3 \end{array} \\ \begin{bmatrix} 85 & 5 & 3.5 \\ 65 & 55 & 4.5 \\ 55 & 100 & 7 \end{bmatrix} \end{array}$$

Column-wise Maxima

$$\min(\text{Signal Strength}) = 55$$

$$\max(\text{Data Rate}) = 100$$

$$\min(\text{Cost }) = 3.5$$

Normalized Matrix

$$D = \begin{bmatrix} \frac{55}{85} & \frac{5}{100} & \frac{3.5}{3.5} \\ \\ \frac{55}{65} & \frac{55}{100} & \frac{3.5}{4.5} \\ \\ \frac{55}{55} & \frac{100}{100} & \frac{3.5}{7} \\ \end{bmatrix} = \begin{bmatrix} 0.65 & 0.05 & 1.00 \\ \\ 0.85 & 0.55 & 0.78 \\ \\ 1.00 & 1.00 & 0.50 \\ \end{bmatrix}$$

0.6 Task 6: Ranking of Available RATs for Vertical Handoff

In heterogeneous wireless networks, choosing the optimal Radio Access Technology (RAT) during a new or vertical handoff is critical. The WASPAS (Weighted Aggregated Sum Product Assessment) method enables multi-criteria decision-making by combining the Weighted Sum Model (WSM) and the Weighted Product Model (WPM):

$$S_i = \lambda \cdot \sum_{j=1}^{n} w_j x_{ij} + (1-\lambda) \cdot \prod_{j=1}^{n} x_{ij}^{w_j} \tag{1}$$

Where:

- S_i is the WASPAS score for RAT i
- x_{ij} is the normalized value of RAT i for criterion j
- w_j is the normalized weight of criterion j
- $\lambda \in [0,1]$ balances WSM and WPM

Example Calculation

Let the normalized decision matrix be:

$$\begin{bmatrix} 0.65 & 0.05 & 1.00 \\ 0.85 & 0.55 & 0.78 \\ 1.00 & 1.00 & 0.5 \\ \end{bmatrix}$$

Assuming user weights $w = [0.3, 0.4, 0.3]$ and $\lambda = 0.5$, we compute the WASPAS scores as follows:

3G

$$\text{WSM} = 0.3 \cdot 0.65 + 0.4 \cdot 0.05 + 0.3 \cdot 1.00 = 0.515$$

$$\text{WPM} = 0.65^{0.3} \cdot 0.05^{0.4} \cdot 1.00^{0.3} \approx 0.1859$$

$$S_{3G} = 0.5 \cdot 0.515 + 0.5 \cdot 0.1859 = 0.3505$$

4G LTE

$$\text{WSM} = 0.3 \cdot 0.85 + 0.4 \cdot 0.55 + 0.3 \cdot 0.78 = 0.709$$

$$\text{WPM} = 0.85^{0.3} \cdot 0.55^{0.4} \cdot 0.78^{0.3} \approx 0.6688$$

$$S_{4G} = 0.5 \cdot 0.709 + 0.5 \cdot 0.6688 = 0.6889$$

5G

$$\text{WSM} = 0.3 \cdot 1.00 + 0.4 \cdot 1.00 + 0.3 \cdot 0.5 = 0.85$$

$$\text{WPM} = 1.00^{0.3} \cdot 1.00^{0.4} \cdot 0.5^{0.3} \approx 0.8122$$

$$S_{5G} = 0.5 \cdot 0.85 + 0.5 \cdot 0.8122 = 0.8311$$

Final Ranking

$$\text{5G (0.8311)} > \text{4G LTE (0.6889)} > \text{3G (0.3505)}$$

Thus, 5G is the optimal RAT for vertical handoff in this scenario based on the given criteria and weight configuration.

Methodology

In this project, the WASPAS (Weighted Aggregated Sum Product Assessment) method was implemented in Python to analyze RAT selection decisions under varying priority weights and sensitivity to the λ parameter. The analysis was performed on a normalized decision matrix consisting of three RATs (3G, 4G-LTE, and 5G) and three selection criteria: Signal Strength (dBm), Data Rate (Mbps), and Cost ($/GB). The normalized matrix was derived from the original decision matrix after applying appropriate normalization methods.

Two key experiments were conducted.

First, a criterion-impact analysis was performed to evaluate how changing the priority assigned to a specific criterion influences RAT selection decisions. In this experiment, four priority levels were defined: Low, Moderate, High, and No priority . These were implemented using predefined weight intervals for the selected criterion, corresponding to the ranges [1,3], [4,6], [7,9], and [1,9], respectively. For each run, one criterion was assigned a weight randomly sampled from its assigned priority range, while the other two criteria were assigned random weights between 1 and 9. The resulting weight vector was normalized to sum to 1. This process was repeated for each of the three criteria, with each criterion taking its turn to receive priority. For each priority level and each criterion, 2000 simulations were performed (500 per level), and in each simulation, the WASPAS scores for the three RATs were computed as per equation 1

For this analysis, $\lambda = 0.5$ was used. The RAT with the highest score was recorded in each simulation, and selection frequencies were visualized using bar charts.

Secondly, a sensitivity analysis on λ was conducted to examine how varying the λ parameter influences RAT selection outcomes. In this experiment, λ was varied across five values: 0, 0.25, 0.5, 0.75, and 1. For each value of λ, random weight vectors were generated uniformly for all three criteria, normalized to sum to 1. Again, 2000 simulations were performed in total, with selection frequencies recorded and plotted to observe the effect of λ on the decision behavior.

Both experiments were implemented in Python using NumPy for computation and Matplotlib for visualization. The use of randomized weights allowed for robust simulation of various user preference scenarios, while varying λ and criterion priorities provided insight into how different configurations affect optimal RAT selection in heterogeneous wireless networks.

0.7 Task 7:Effect of Signal Strength Weight on RAT Selection

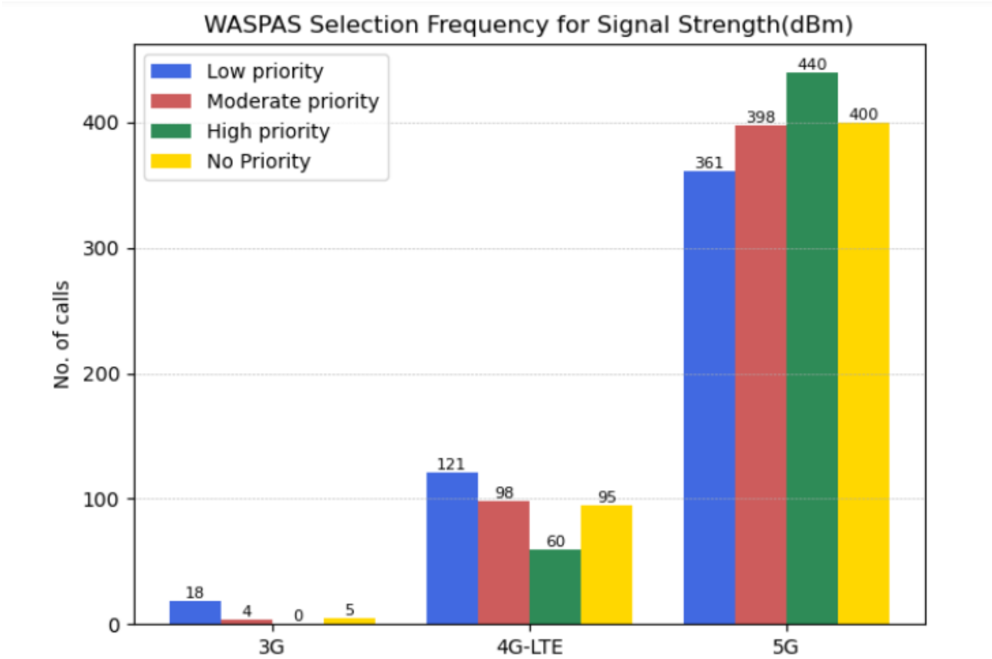


Figure 4: Effect of Signal Strength Weight on RAT Selection

Table 5: WASPAS Selection Frequency for Different Signal Strength Priorities

RAT	Low Priority	Moderate Priority	High Priority	Full Priority
3G	18	4	0	5
4G LTE	121	98	60	95
5G	361	398	440	400

The bar chart in Figure 4 illustrates the effect of varying the priority (weight) assigned to the first RAT-selection criterion, Signal Strength (dBm), on RAT-selection decisions during new or vertical handoff calls in the heterogeneous wireless network.

At low priority, the contribution of Signal Strength to the WASPAS score is relatively small. Other criteria, such as Data Rate and Cost, have a stronger influence on the selection outcome. In this scenario, 5G remains the dominant selection with 361 calls due to its strong overall performance. 4G-LTE is selected 121 times, while 3G receives 18 selections. This distribution reflects the influence of secondary criteria when Signal Strength is not prioritized.

As the priority of Signal Strength is increased to moderate, its influence on the WASPAS score grows. Since 5G has the best normalized Signal Strength (1.0), increasing its weight further enhances its competitiveness. As a result, 5G selections rise to 398, while 4G-LTE selections decrease to 98. 3G is selected only 4 times, as its poor Signal Strength increasingly penalizes its score.

At high priority, where Signal Strength heavily dominates the WASPAS score, 5G becomes the clear choice with 440 selections. 4G-LTE declines to 60 selections, while 3G is not selected at all, as its weak Signal Strength cannot be compensated by performance in other criteria.

When no priority is assigned (weights fully randomized), 5G remains the most selected RAT with 400 calls. 4G-LTE receives 95 selections, and 3G records 5 selections. This distribution again shows that when the criteria weights are balanced, the strong overall performance of 5G leads to its consistent selection.

These selection shifts are explained by the structure of the WASPAS method. As the weight assigned to Signal Strength increases, RATs with stronger Signal Strength gain a greater advantage in their overall scores. Conversely, RATs with poor Signal Strength, such as 3G, become progressively less competitive. The combined additive and multiplicative components of WASPAS ensure that when Signal Strength is heavily weighted, it dominates the selection outcome.

In conclusion, increasing the priority assigned to Signal Strength results in a clear shift in RAT selection toward RATs with stronger signal quality, particularly 5G. This is consistent with real-world expectations, where applications that require stable and reliable connectivity would prioritize networks with superior Signal Strength.

0.8 Task 8: Effect of Data Rate Weight on RAT Selection

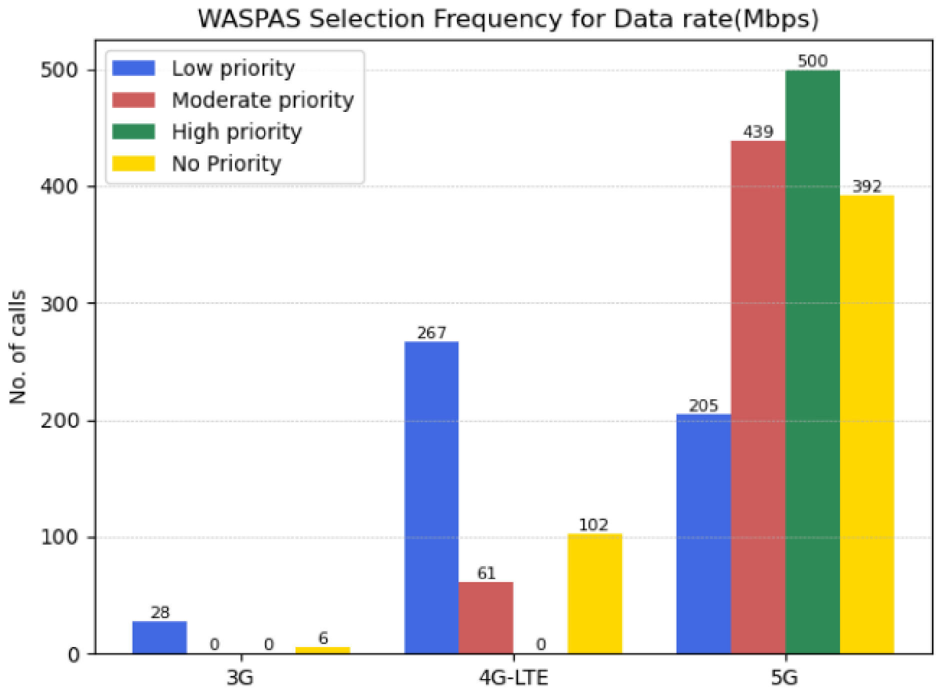


Figure 5: Effect of data rate weigh on RAT selection

Table 6: WASPAS Selection Frequency for Different Data-rate Priorities

RAT	Low Priority	Moderate Priority	High Priority	Full Priority
3G	28	0	0	6
4G LTE	267	61	0	102
5G	205	439	500	392

The bar chart in Figure 5 shows the effect of varying the priority (weight) assigned to the second RAT-selection criterion, Data Rate (Mbps), on RAT-selection decisions during new or vertical handoff calls in the heterogeneous wireless network.

At low priority, the influence of Data Rate on the WASPAS score is limited. Other criteria, such as Signal Strength and Cost, have a greater impact on the selection outcome. In this scenario, 4G-LTE performs well due to its balanced performance across criteria and is selected 267 times. 5G receives 205 selections, while 3G, despite its poor Data Rate, gains 28 selections because Cost and Signal Strength are contributing more heavily.

When the priority of Data Rate increases to moderate, its contribution to the WASPAS score becomes more significant. Since 5G has the best normalized Data Rate (1.0), increasing the weight on this criterion strongly favors 5G. As a result, 5G selections rise sharply to 439, while 4G-LTE selections drop to 61. 3G is no longer selected at this level, as its low Data Rate is now penalized more strongly.

At high priority, where Data Rate is the dominant factor in the WASPAS score, 5G completely dominates the selection, being chosen in all 500 cases. Neither 4G-LTE nor 3G is selected at this level, as they are unable to compete on Data Rate when this criterion is strongly weighted.

When no priority is assigned (weights fully randomized), 5G remains the most selected RAT with 392 calls, reflecting its strong overall performance. 4G-LTE receives 102 selections, while 3G gains a small number of selections (6), again showing that when weights are more balanced, secondary criteria such as Cost may allow weaker RATs to occasionally be selected.

The observed selection shifts are a direct result of how the WASPAS method integrates weighted criteria. As the weight assigned to Data Rate increases, RATs with superior throughput capabilities gain an increasing advantage in their overall scores. Conversely, RATs with poor Data Rate performance, such as 3G, become uncompetitive. The combined additive and multiplicative components of WASPAS ensure that even when one criterion is dominant, other criteria still contribute under lower priority scenarios.

In conclusion, increasing the priority assigned to Data Rate strongly favors RATs with high throughput, particularly 5G. This aligns with real-world expectations, where applications that require fast data transmission, such as video streaming and cloud gaming, would naturally prioritize networks offering the best Data Rate performance.

0.9 Task 9: Effect of Cost Weight on RAT Selection

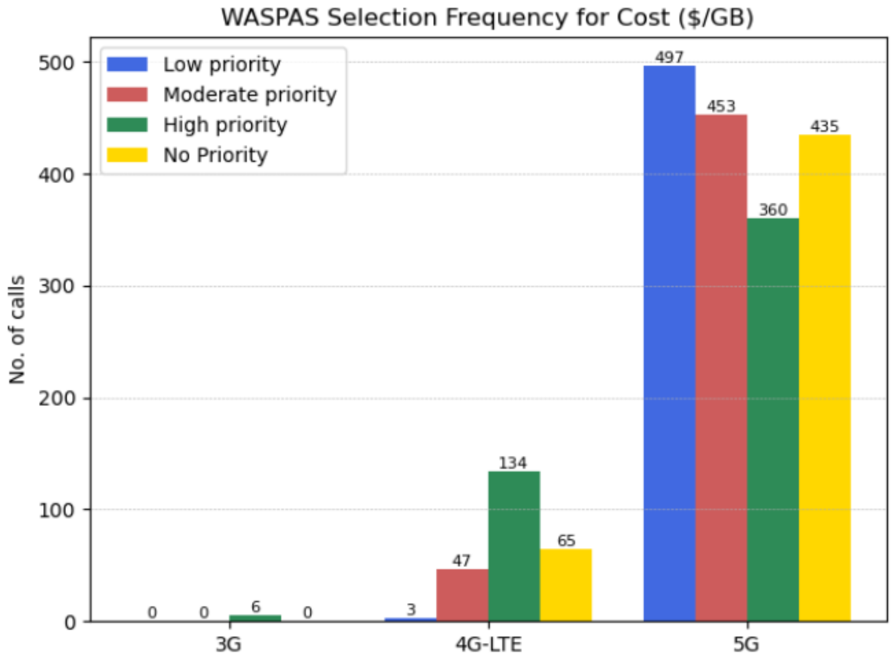


Figure 6: Effect of Cost Weight on RAT Selection

Table 7: WASPAS Selection Frequency for Different Cost Priorities

RAT	Low Priority	Moderate Priority	High Priority	Full Priority
3G	0	0	6	0
4G LTE	3	47	134	65
5G	497	453	360	435

The bar chart in Figure 6 the effect of varying the priority (weight) assigned to the third RAT-selection criterion, Cost ($/GB), on RAT-selection decisions during new or vertical handoff calls in the heterogeneous wireless network.

At low priority, the influence of Cost on the WASPAS score is minimal. Other criteria, such as Signal Strength and Data Rate, dominate the selection outcome. As a result, 5G, which offers superior performance in these criteria, is selected 497 times, while 4G-LTE receives only 3 selections. 3G is not selected at all in this scenario, as its poor performance in Data Rate and Signal Strength cannot compete even when Cost is deprioritized.

When the priority of Cost is increased to moderate, its influence on the WASPAS score begins to grow. 5G remains the dominant selection with 453 calls, but 4G-LTE starts to become more competitive, increasing to 47 selections. 3G remains unselected at this level, as its advantages in Cost alone are not sufficient to overcome its weaknesses in other criteria.

At high priority, where Cost is given strong influence in the WASPAS score, there is a noticeable shift. The selection of 4G-LTE increases substantially to 134, while 5G selections decrease to 360. Interestingly, 3G records 6 selections at this level, showing that as Cost becomes more dominant, RATs with low cost begin to gain competitiveness, even if they are weaker in other areas.

When no priority is assigned (weights fully randomized), 5G remains the dominant RAT with 435 selections. 4G-LTE receives 65 selections, and 3G is not selected. This pattern confirms that when no specific priority is enforced, the overall strength of 5G across multiple criteria makes it the most preferred option.

The reason for these shifts lies in the structure of the WASPAS method. As the weight assigned to Cost increases, RATs with lower Cost scores gain an advantage in the overall score. However, the combined additive and multiplicative nature of WASPAS ensures that RATs with strong performance across multiple criteria, such as 5G, remain competitive even when Cost is prioritized. Conversely, RATs like 3G, which excel only in Cost but are weak in other criteria, can only gain limited competitiveness.

In conclusion, increasing the priority assigned to Cost gradually shifts RAT selection decisions towards RATs with lower costs, such as 4G-LTE and, to a lesser extent, 3G. However, 5G remains dominant across all priority levels due to its strong overall performance. This reflects real-world behavior, where users may still prefer high-quality networks even if they come at a higher cost.

0.10 Task 10: Effect of the proportion of the weighted sum model and the weighted product model on RAT-selection decisions.

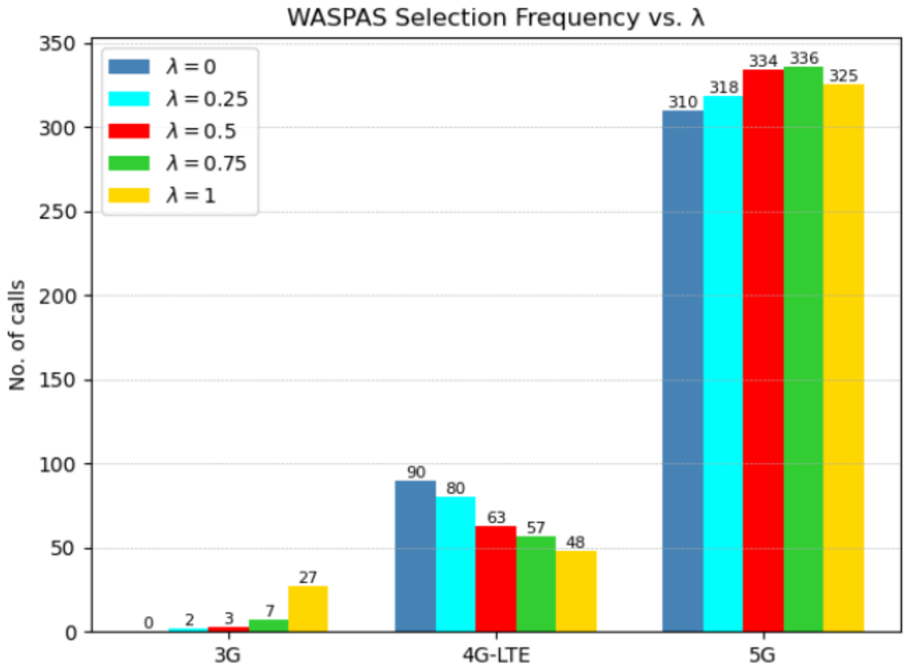


Figure 7: Effect of the proportion of the weighted sum model and the weighted product model on RAT-selection decisions

Table 8: WASPAS Selection Frequency for Different λ Values

RAT	$\lambda = 0$	$\lambda = 0.25$	$\lambda = 0.5$	$\lambda = 0.75$	$\lambda = 1$
3G	0	2	3	7	27
4G LTE	90	80	63	57	48
5G	310	318	334	336	325

Table 8 shows how the WASPAS selection frequency changes as the λ parameter varies from 0 to 1. This parameter controls the weighting between the weighted sum model (WSM) and the weighted product model (WPM).

At $\lambda = 0$, the decision is based purely on the multiplicative model. In this case, 5G is selected 310 times, 4G LTE is selected 90 times, and 3G is not selected at all. The multiplicative model tends to favor RATs that maintain balanced performance across all criteria because poor performance in any one criterion has a stronger penalty in WPM.

0.10. Task 10: Effect of the proportion of the weighted sum model and the weighted product model on RAT-selection decisions.

As λ increases to 0.25, the additive component begins to influence the overall score. The selection of 5G increases to 318 calls, while 4G LTE decreases slightly to 80, and 3G gains 2 selections. The introduction of WSM allows RATs with strong scores in dominant criteria to become more competitive, even if they have weaknesses in others.

At $\lambda = 0.5$, where the additive and multiplicative components are equally weighted, the selection of 5G increases further to 334, 4G LTE drops to 63, and 3G increases slightly to 3. This reflects the fact that WSM allows RATs with excellent performance in key criteria to dominate more strongly.

At $\lambda = 0.75$, the additive component is now more dominant. 5G selection peaks at 336, while 4G LTE declines to 57, and 3G increases to 7 selections. The trend shows that as WSM gains more influence, RATs with the best individual criterion scores, such as 5G in Signal Strength and Data Rate, are increasingly favored.

At $\lambda = 1$, where the model is purely additive, the selection pattern changes slightly. 5G selections decrease slightly to 325, while 4G LTE drops to 48, and 3G increases to 27. The increase in 3G selections under pure WSM reflects the fact that additive models can sometimes favor RATs that excel in a single criterion, such as cost, even if they are weaker in others.

The reason for these shifts lies in the mathematical properties of the WPM and WSM models. WPM penalizes poor performance more strongly, requiring RATs to maintain balanced performance across all criteria. WSM, in contrast, allows strong performance in one or two criteria to compensate for weaknesses in others. As λ increases, RATs with dominant strengths in key criteria (such as 5G) become increasingly favored. At the same time, RATs like 3G, which are weak in most areas but strong in cost, gain some competitiveness under WSM.

In conclusion, the value of λ has a significant influence on RAT selection behavior. Increasing λ shifts the model from one that rewards balanced performance to one that rewards strong individual criterion scores. This explains why 5G remains dominant at all λ levels, but 3G becomes more competitive at higher λ, and why the selection of 4G LTE gradually decreases as λ increases.

0.11 Task 11: A summary of the key findings of the project

This project explored the application of the WASPAS multi-criteria decision-making method for optimal RAT selection in heterogeneous wireless networks. The key findings from the analysis can be summarized as follows.

First, it was observed that increasing the priority assigned to Signal Strength consistently shifts RAT selection towards networks with superior signal quality. 5G remained the dominant choice as Signal Strength was prioritized, which aligns with the expectations for applications requiring strong and stable connections.

Second, when the priority was shifted to Data Rate, 5G again emerged as the most selected RAT due to its excellent throughput capabilities. As Data Rate became the dominant criterion, RATs with lower data rates, such as 3G and 4G LTE, became progressively less competitive.

Third, prioritizing Cost revealed an interesting trade-off. While 4G LTE and even 3G gained more selections under high Cost priority, 5G continued to receive a significant portion of selections across all cost priorities. This demonstrated that WASPAS balances multiple criteria, and RATs with strong performance in other areas can still dominate even when cost is heavily weighted.

Finally, the sensitivity analysis on the λ parameter showed that the choice of λ significantly influences selection outcomes. Lower values of λ (favoring WPM) encouraged more balanced RAT selection, while higher values (favoring WSM) amplified the influence of dominant criteria such as Signal Strength and Data Rate, further favoring 5G. Interestingly, 3G became slightly more competitive at higher λ due to its advantage in Cost.

Overall, the project demonstrated that the WASPAS method provides a flexible and effective approach for RAT selection in heterogeneous networks. The findings highlight the importance of carefully tuning criterion weights and the λ parameter to match the requirements of specific applications or user preferences. The results also confirm that 5G offers a strong overall advantage across multiple selection scenarios, though cost and application-specific needs can influence the optimal choice.

References

[1] S. Abdullah, I. Ullah, and F. Ghani, “Heterogeneous wireless network selection using feed forward double hierarchy linguistic neural network,” *Artificial Intelligence Review*, vol. 57, p. 191, Jul. 2024.

[2] N. Lan, “Evolution of wireless technology: From 1G to 5G,” *Asian Journal of Applied Science and Technology*, vol. 7, pp. 68–73, Jan. 2023.

[3] I. Stanic, D. Drajic, and Z. Cica, “Overview of network selection and vertical handover approaches and simulation tools in heterogeneous wireless networks,” in *Proc. 16th Int. Conf. Advanced Technologies, Systems and Services in Telecommunications (TELSIKS)*, Nis, Serbia, Oct. 2023, pp. 133–137.

[4] R. Honarvar, A. Zolghadrasli, and M. Monemi, “Context-oriented performance evaluation of network selection algorithms in 5G heterogeneous networks,” *Journal of Network and Computer Applications*, vol. 202, p. 103358, 2022.

[5] K. H. Hsu, C. H. Hsieh, and M. T. Lu, “A multi-criteria RAT selection scheme for 5G heterogeneous networks using the Weighted Sum Model,” *IEEE Access*, vol. 8, pp. 185321–185330, 2020.

[6] A. Abdelli, L. Mokdad, and Y. Hammal, “Dealing with value constraints in decision making using MCDM methods,” *Journal of Computational Science*, vol. 44, p. 101154, 2020.

[7] D. Więcek, I. Michalski, K. Rzeźniczak, and D. Wypiór, “Multi-RAT orchestration method for heterogeneous wireless networks,” *Applied Sciences*, vol. 11, no. 18, p. 8281, 2021.

[8] K. Zia, A. Chiumento, and P. J. M. Havinga, “AI-enabled reliable QoS in multi-RAT wireless IoT networks: Prospects, challenges, and future directions,” *IEEE Open Journal of the Communications Society*, vol. 3, pp. 1906–1923, Oct. 2022.

[9] F. Bendaoud, M. Abdennebi, and F. Didi, “A MADM method for network selection in heterogeneous wireless networks,” *arXiv preprint arXiv:2201.12011*, 2022. [Online]. Available: https://arxiv.org/abs/2201.12011

[10] K. Zhou, X. Bai, and Z. Wang, "A review of vertical switching algorithms for heterogeneous wireless networks," in *Proc. 8th Int. Conf. Computer and Communication Systems (ICCCS)*, Guangzhou, China, Apr. 2023, pp. 326–331.

[11] F. Bendaoud, "Network selection in a heterogeneous wireless environment based on path prediction and user mobility," in *Comprehensive Guide to Heterogeneous Networks*, K. Ahuja, A. Nayyar, and K. Sharma, Eds. London, U.K.: Academic Press, 2023, ch. 3, pp. 59–86.

[12] A. K. Yadav, K. Singh, N. I. Arshad, M. Ferrara, A. Ahmadian, and Y. I. Mesalam, "MADM-based network selection and handover management in heterogeneous network: A comprehensive comparative analysis," *Results in Engineering*, vol. 21, p. 101918, 2024.

[13] R. Honarvar, A. Zolghadrasli, and M. Monemi, "Context-oriented performance evaluation of network selection algorithms in 5G heterogeneous networks," *Journal of Network and Computer Applications*, vol. 202, p. 103358, 2022. [Online]. Available: https://doi.org/10.1016/j.jnca.2022.103358