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Network Selection Algorithm for Satisfying Multiple User Constraints Under Uncertainty in a Heterogeneous Wireless Scenario

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Abstract

The constant evolution of various wireless access technologies has led to an advancement in the communication domain where mobile clients (MCs) are equipped with multiple interfaces for simultaneous access to different types of networks. This heterogeneous wireless scenario satisfies the user’s preferences and offers the desired quality of service (QoS). Route selection satisfying multiple constraints has proven to be NP-Complete and various approximation schemes exist which consider the network state resources to be fixed and complete. Additionally, in practical scenarios, the user’s constraints are imprecise and vague and the changing network conditions force the condition of uncertainty to exist in a routing mechanism. This thesis focuses on the imprecise and dynamic nature of network parameters and maps it to uncertain user constraints. We, hence consider a heterogeneous wireless network (HWN) and propose a novel approach to identify the key network metrics that satisfies the user’s criteria. Our design of a fuzzy model maps the underlying uncertainty in the metrics to crisp values and demonstrates the stability of our proposed technique through extensive simulations and analysis. In order to satisfy the user’s imprecise demands, we consider the problem of decision making in a HWN where emphasis is on selecting the best network interface to forward the data. We propose an enhanced minimization of maximal regret (MMR) approach to rank the available network interfaces by considering pure uncertainty in a user’s constraint. MCs state their needs based on application requirements and thus, we implement a generalized MMR and include Ordered Weighted Averaging (OWA) operators to enable each MC to efficiently select the best possible alternative. The weights utilized in OWA are modeled using application characteristics. Our simulations and experiments compare the sensitivity of user demands depicted in MMR and OWA to that of existing multiple attribute decision making (MADM) algorithms. Simulation results prove that variability in a user’s preference and changes in a network scenario can impact decision making and influence the routing process.
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Chapter 1

Introduction

Wireless communication access technologies like wireless local area networks (IEEE 802.11 protocols), cellular networks (GSM/GPRS, UMTS, HSA, LTE) and broadband wireless networks (IEEE 802.16 WiMAX protocols, LTE) are evolving rapidly and have a growing demand in the network domain [1]. The advent of fourth generation (4G) wireless system has enabled many new possibilities for various wireless access networks to collaborate and form a Heterogeneous Wireless Network (HWN).

Heterogeneous wireless networks have allowed mobile clients (MCs) simultaneous access to various networks using multiple interfaces. Previous researches has extensively analyzed situations where MCs migrate between homogeneous and heterogeneous network structures through Mobile IP [2]. With many options for network access, MC’s are provided with greater flexibility and improved performance than that feasible by any single deployed wireless access technology. HWNs have also given rise to integrated applications and services, with high quality of service (QoS), enhanced capacity and improved coverage. Users having access to different technologies, enables them to make efficient use of associated attributes and characteristics of each interface. Also, they enjoy the flexibility of switching between multiple networks while keeping their session active which allows them to choose the most appropriate one at a given instance of time. And, it is not just the MC who benefits from a HWN. This kind of collaboration proves to be quite generous in offering higher profits to network service providers who take full advantage of the positive aspects of each wireless
technology in the scenario. Hence, through a HWN, information communication for the MCs is made possible by a number of routes/paths. Such a system of multiple networks coexist to offer a wide array of services to both the users and network operators and has revolutionized the era of wireless communication. Figure 1.1 clearly demonstrates a heterogeneous wireless scenario where different access technologies are connected to the internet through a backbone network or channel.

![Heterogeneous Wireless Network](image)

Figure 1.1: Heterogeneous Wireless Network

In a HWN, the MCs and the underlying networks must be able to dynamically and quickly adjust to the varying network conditions and satisfy the communication constraints. However, MCs expect a multitude of performance constraints to be satisfied in order to have a desired QoS. QoS routing based on user requirements has been studied in previous work where the routing path is established based on various constraints and specifications [3]. The problem of finding a feasible path satisfying $k$ constraints ($k \geq 2$) has coined the popular term, Multi Constrained Path Selection (MCP) in the communication arena. The idea of considering multiple metrics represents the requirements of both the user and the network.
more accurately. Figure 1.2 shows a simple representation of a network topology establishing a route between source S and destination D while satisfying multiple constraints.

![Multi-Constrained Network Topology](image)

**Figure 1.2: Multi-Constrained Network Topology**

Here, the remaining nodes are used for forwarding the data. The topology shows two sample paths from S to D satisfying multiple constraints. The % associated with each metric shows the percentage of satisfiability required from each metric which is dictated by the MC. While the path S-1-D satisfies three constraints, the alternative path S-4-3-D satisfies only two constraints, delay and throughput more efficiently at that instant of time. Hence, irrespective of whether multiple paths exist from the source to the destination, multi-constrains require all the desired metrics to be satisfied in its entirety. Hence, finding a feasible path is not a simple task like a conventional distance vector algorithm which computes a path between any two nodes in a network topology using the cost factor.

Finding a path that satisfies k independent constraints is shown to be NP-complete [3] which implies that there exists no efficient solution to solve this problem in a polynomial time. A large number of heuristic algorithms and approaches have been implemented to solve this problem. However, these solutions work under the assumption that the network state information is fixed and the user has a complete knowledge of the existing network conditions, given certain constraints [4]. An interesting variant of the multiple constraints
problem (MCP) problem is a restricted shortest path problem (RSP) which is limited to two constraints, and focuses on satisfying one constraint while optimizing the other. Not surprisingly, a large number of pseudo-polynomial time running algorithms have been proposed to tackle both MCP and RSP problems. A challenging version of MCP has been discussed in the literature which finds the shortest length amongst the set of established feasible paths. This is commonly known as the Multi-Constrained Optimal Path (MCOP) selection problem and is observed to be an even greater challenging task.

The problem of finding a feasible path satisfying multiple constraints still lacks a concrete solution that could maximize QoS for the user. Our in-depth study on HWNs and its potential advantages of offering a wide variety of network services to the user, instigated us to probe into MCP in a heterogeneous wireless scenario. However, in a traditional deployment, multiple interfaces tend to be used independently, thereby not fully exploring the capabilities of a HWN [5]. Another problem MCs face, is to decide in a dynamic and distributed fashion which interface it should forward the data to. This decision is made based on the network’s inherent capabilities to satisfy the MC’s constraints and demands.

1.1 Approaches to Decision Making

Analyzing possible alternatives and making a decision is a binding factor in almost all fields of science and engineering. Decision making strategies and evidential analysis cover a broad area from which a choice has to be made. While earlier research combined decision theory with the management theory [6], new areas have been explored and some common applications of decision making based on analytical reasoning, fuzzy systems and multiple attributes have been published.

1. Military Applications: The selection of weapon systems in military applications is very
subjective and is usually based on imprecise terms. Fuzzy based analytical hierarchical process has been implemented in tactile missile systems to select the right weapon based on multiple criteria and parameters [7]. This fact is taken into consideration during the analysis process.

2. Engineering Design: Modeling engineering systems mandates making a decision in every possible stage such as selection of materials, modeling technique, impact on the final product, etc. A real world example, demonstrating the design selection problem in cargo ship design, and retro-fitting of a sea ferry, has been discussed in detail in [8].

3. Supplier Assessment: Motorcycle evaluation which concerned supplier’s reviews in making a decision and reason out factors in the light of uncertainty has been conducted in [9].

4. Safety and Risk Assessment: Investigating the safety and risk parameters is mandatory in every engineering product. The failure cause-and-effect analysis has to be conducted and a decision has to be made to minimize the impacts. A case study was conducted on a marine system safety by considering multiple attributes and criteria [10]. Safety synthesis is a significant phase in software engineering and life-cycle. The software safety synthesis has been demonstrated in [11] with a case study.

5. Organizational self-assessment: Every organization requires a system to monitor and assess the performance of its employees and a classical decision model coupled with evidential reasoning has been carried out in [12]. This is based on multiple attributes and criteria and helps in making a decision that improves an individual’s overall performance.

6. Health care and medical applications: Decision making is extensively utilized in medical applications and is of a great importance since the final outcome is based on the analysis of the situations and attribute conditions has significant impact on the human lives. Research pertaining to decision making in the field of medicine has been
illustrated in detail [13, 14].

From the infant stages of wireless networking, decision making has been a common phenomenon where the network operator has to decide the amount of resources to be allocated to the various users taking into consideration the existing conditions, traffic, inherent network characteristics, and contention for the resources. However, the evolving trend in wireless technology, where a user possesses multi-mode terminals, has extended the decision making process to the MCs as well. With a HWN comes the added responsibility of deciding on how to efficiently route the data at a given point of time in the network.

![Decision Making Mechanisms in a Network Scenario](image)

**Figure 1.3: Classification of Decision Making Mechanism**

Decision making mechanism shown in Figure 1.3 is commonly classified into network oriented, mobile client oriented and mixed approach [15]. As the name implies, the first two approaches of network and mobile client oriented, makes a decision that is primarily
favourable to the network and user respectively. The mixed (or integrated) approach balances the requirements for the two and a final choice is made taking into consideration both the user demands and network available resources. This approach has drawn a greater interest due to its intrinsic nature of balancing the preferences and needs from both the user and the network. As participation of the MC and wireless access technology is equally encouraged in this category of decision making, some of the common techniques employed are fuzzy logic tools and techniques, as well as classic Multiple Attribute Decision Making (MADM) algorithms.

MADM approaches typically involves decision making based on a selected subset of attributes and criteria and has been extensively covered in the literature. There exist numerous techniques and the most popular being a Simple Additive Weighted method, Technique for Order Preference by Similarity to Ideal Solution, Grey Relational Analysis and Analytical Hierarchical Process [16]. These strategies rank the candidate networks by computing weighted mean for each alternative among several conflicting criteria. These methods are commonly deployed for a decision making because of their ease of implementation and being deterministic in nature.

MADM techniques use various attributes and a weighted set to address multiple criteria. They are unable to solve this problem efficiently when imprecise data is present. In addition, the weighted set is primarily determined by well defined policies established by experts in the field, that dynamically adapt depending on the application service requirements, MCs operating state, and other factors. This makes it difficult for the end user to dynamically adjust their preferences and vary their demands [17]. In spite of the shortcomings, MADM approaches have gained importance in the field of decision making because of its ability to handle multiple criteria and maintain a steady state between the user and the network.
The MADM approach to decision making seems quite relevant to our area of focus, which involves multiple metrics in a HWN. Actually, we go a step further and consider the aspect of complete uncertainty, where the decision maker has no prior knowledge about the occurrence of events, leading to the attribute conditions within a given set of attributes and alternatives. A number of schemes have been implemented considering complete uncertainty and one of the commonly used approach is the Max-Min method. Generalization of max-min algorithms have been dealt by Ronald R. Yager in [18], leading to optimal solutions. We delve upon this subject of decision making under ignorance (DMUI) because the user does not possess adequate knowledge about the network constraints under practical scenarios and his demands are stated using simple language with inherent vagueness. In addition, the network conditions are usually unpredictable and dynamic, with measured values tend to fluctuate. This is attributed to various factors like environmental conditions, congestion, packet loss, node density, etc. Hence, our work adds a new dimension to the multi-constrained path selection problem by considering a heterogeneous wireless scenario and selecting the best possible network under complete uncertainty.

The key motive for a MC to put forth multiple constraints is to achieve a desired QoS. A complex process in finding an optimal path of a network topology while satisfying multiple constraints is present due to various prevalent applications cropping up due to current evolution of the internet and the fourth generation (4G) wireless technology. A large number of solutions have been proposed to provide the expected QoS and are particularly oriented towards different applications and their associated preferences. In order to support multimedia applications [3], various algorithms have been proposed to establish a routing path satisfying multiple constraints.

There exist a number of applications and the user states his preference based on the application’s expectation and tolerance level with respect to each metric. For instance, Voice over Internet Protocol (VoIP) is very sensitive to the delay and hence a MC running VoIP
will require a minimum delay from the network and express that as its primary constraint. Applications are commonly classified based on timeliness and symmetry and different category of applications has different set of QoS requirements. Since network applications play a significant role in determining the QoS requirements, we carried out a thorough survey of the literature on various applications which will be instrumental in laying out our constraints on the HWN. A detailed classification of network applications is illustrated in Figure 1.4 based on the research results presented in [19].

![Network Applications Diagram]

Figure 1.4: Categories of Network Applications

1.2 Motivation and Organization of Thesis

Inspired by the challenges of multi-constraints path selection and the need to provide a desired QoS, our work focuses on devising an efficient network selection algorithm that satisfies multiple user constraints with uncertainty in a heterogeneous environment. While earlier works focus on multi-constrained routing or handover decision in a HWN, we con-
sider dynamically changing network conditions in a practical situation where the user is uncertain of what exactly is required under a given circumstance, indicate the preferences in vague terms and expects multiple requirements to be satisfied by the network. Exploiting varied aspects of a HWN, we balance the situation with an intelligent decision making and efficiently selecting the network to forward the data.

The remainder of the thesis is structured as follows. Chapter 2 provides details on the related work in the field of multi-constrained routing, using multiple metrics, fuzzy models and explains the process of selecting and narrowing down the key network constraints. Chapter 3 elaborates the steps involved in the fuzzy logic model and our novel fuzzy classification approach which can handle the network imprecise values. Chapter 4 explains our defuzzification mechanism to compute crisp payoff values for each interface metric. Chapter 5 gives an extensive analysis and simulation results of our fuzzy model and compares with existing MADM approach. The contributions made in Chapters 2, 3, 4 and 5 have been explained in detail in [20]. Chapter 6 introduces the concept of decision making under ignorance and blends the work of network uncertainty with imprecise user constraints. We also discuss a new network selection algorithm that aids in routing data to the best possible interface and validate our results by in-depth analysis and comparison with existing MADM techniques. In chapter 7, we extend the algorithm discussed in Chapter 6 and elaborate approaches to handle weighted user constraints modeled as per application requirements. Finally, we conclude our work in Chapter 8 and present ideas for future extensions.
Chapter 2

Identifying the Key Network Parameters

Multiple constraints have gained prominence in recent times due to the increased demand for QoS from the user’s end. Hence, establishing a mechanism that satisfies a plethora of performance constraints is our primary focus. However, literature studies such as [21] have stated that network metrics have a strong inter-dependency and correlation and hence, this chapter centres upon identifying the key constraints that will be instrumental in our interface selection process. Before we explain our work on narrowing down the metrics, we elucidate the various approaches implemented to solve the multi constrained routing problem and handling numerous constraints.

2.1 Heuristic Approaches to Multi-Constrained Routing

As stated earlier, multi-constrained routing is proven to be NP-Complete [3] and there exists no concrete or definite mathematical solution to this that can be solved in polynomial time. Hence, a study on the existing heuristic approaches provided us a direction to tackle this complex problem. An efficient depth-first search solution has been implemented
that has performance bounds almost the same as an exact solution (with exponential running time complexity) [22]. Another heuristic approach was proposed in [23] that can be used for online network operation and has the same order of complexity as Dijkstra’s algorithm. Techniques like these demand prior knowledge of accurate values in order to make a decision whereas uncertain and dynamic conditions are a common occurrence in wireless networks [24]. By applying a utility function, a single crisp value can be obtained by considering many parameters. For instance, [21, 25] discuss at length on incorporating factors like multi-channel diversity, interference and congestion to estimate the weight of link quality. Unfortunately, utility function based metrics can only be used as an indicator at best [3]. Even considering stochastic elements, as discussed in [26], does not contain sufficient information to assess whether multiple requirements can be met or not.

A compilation of routing algorithms to provide the desired quality of service has been provided by Fernando Kuipers et al. in [4]. They give a general overview on the constrained based algorithms present in the literature. The authors highlight on the exact algorithms suitable for Restricted Shortest Path (RSP) algorithms but they have a huge drawback of extreme computational complexity. One such specific solution has been put forth that explores every route between the source and the destination and determines a feasible path using brute force technique. Sadly, this method is not apt for networks that increases dramatically in size. Another exact solution presented was the Constrained Bellman-Ford (CBF) algorithm which establishes low cost paths from a sender to a receiver while simultaneously increasing their overall delays. It has been concluded that, while CFB has been proven to be successful in giving an exact solution to the RSP problem, the overall implementation time increases in the worst case scenario.

While pseudo-polynomial time running algorithms can be incorporated for NP-Complete problems, their complexity depends on the input values and their performance time gets affected by high values [27]. FallBack algorithm is a methodology which uses a single QoS
measure to determine the shortest path [4]. The computation of the path terminates if all the constraints under consideration are satisfied for a single QoS measure. In all other cases, the process continues until a feasible route is discovered. The complexity of this algorithm leans on Dijkstra’s algorithm and the most evident problem is, there is no guarantee that the search for an optimal path based on a single QoS measure will result in a feasible path. Another heuristic approach was devised by Turgay Korkmaz and Marwan Krunz who elaborate the process of Dijkstra’s algorithm in both forward and backward directions [28]. During this, they realize feasible paths during the search for shortest route to destination. Once these feasible paths are found, they go a step further to reduce them to optimal links. Again, there is no assurance for optimal paths to be discovered during the search and the time spent in execution is compromised.

Although these techniques provide significant trade-offs between obtaining the exact solution and the difficulty that lies in achieving this, the heuristic are still an approximation of the optimal solution. These algorithms work under the assumption that the network state information is static and the user has complete knowledge about the resources available and allocated to the network. Also, each technique is built with a shortcoming which could impact the performance of a network and user satisfaction. In addition, route discovery process is highly dependent on the weights assigned to the links. Consequently, our work views this problem from an entirely different perspective and enables leverage to the dynamic conditions of the network and impreciseness in the user’s preferences.

2.2 Fuzzy Approaches to Multiple Metrics

Our work overcomes the complexity issues in a MCP by looking at alternative approaches to deal with a multitude of parameters. A network interface selection metric should be intelligent enough to capture the state and quality of all the available network links and rank them so that a routing decision can be made. Hence, identifying the key parameters
which will be tolerant to vagueness and uncertainty forms a critical part of our work. With regards to this, machine learning techniques have shown favourable results, the most popular choices being the fuzzy logic and artificial neural based techniques. While numerous options are available, fuzzy logic seems to be a powerful tool to analyze systems with uncertainty and that are too complex and difficult to represent accurately using a mathematical model. Fuzzy logic permits encoding of qualitative expert language as an extremely flexible algorithm, using simple language to express classification rules. This also provides the capability of changing preferences to network operators and demands for various applications based on the environmental scenario or dynamically changing network conditions. The field of fuzzy logic is evolving and has been used in various areas [29].

2.2.1 Fuzzy Logic

Fuzzy logic is a multi-valued logic that maps vague, imprecise terms to crisp values [29]. A fuzzy model comprises of an inference rule set defined using fuzzy operators and subjective knowledge, input membership functions and crisp output value. A fuzzy process is initiated by fuzzification of the input variables, described linguistically and depicting the variable’s inherent nature to fluctuate. Following this is the inference rule set which determines the relationship of the fuzzy variables in the form on IF-THEN rules and generates the fuzzy output. The final step is defuzzification which translates the fuzzy output to crisp, accurate values. Figure 2.1 gives a clear picture of the significant steps involved in a fuzzy logic model.

The field of fuzzy logic is evolving and has applications in various areas [29]. For instance, consider a simple weather forecasting problem. This field of study involves vagueness and imprecise information and needs to provide satisfying results to the user while handle imperfect data. A prediction of 15% chance of rain showers is as good as a 10% chance of the same condition occurring from the user point of view. This sort of uncertainty is
effectively handled by using fuzzy tools and techniques which handles such data in the best possible manner. Fuzzy logic provides the leverage of using terms such as ‘above average’, and ‘very high’ rather than a simple ‘yes’ or ‘no’. These advantages are exploited in our work which deals with incomplete and uncertain inputs from the network and user end.

2.2.2 Literature Work on Fuzzy Models and Multiple Constraints

Previous work has resorted to utilizing fuzzy theory to model QoS measurement and monitoring. For instance, [30] discusses handover decision in depth using fuzzy multiple attribute decision making methods like Simple Additive Weighted methods (SAW), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and other MADM strategies. Various wireless interfaces are ranked by considering the user uncertainty, while not taking into account the networks imprecise measured data. Also, the goal is to correlate multiple criteria simultaneously without too much emphasis on the imprecise data. Zuo Jung et al. in [23] proposes a fuzzy logic model, describes a set of fuzzy inference rules and delves into the input parameters considered. But, the work does not highlight on the decision making aspects in the wireless domain, where a MC is faced with the task of routing to an appropriate interface satisfying the constraints. Although fuzzy logic model has been mapped to handle the multiple metrics, the significance lies in deriving crisp values through the

![Figure 2.1: Steps in a General Fuzzy Logic Model](image-url)
process of defuzzification which is not elaborated enough. Even the work is broad, it does not provide useful parameter ranges to implement their fuzzy controllers in a real network.

A multi-constrained dynamic source routing (DSR) protocol based on fuzzy logic was described in [31] where the QoS demands are met and a routing path considering several metrics is established that makes use of the DSR concept. But, the DSR limits the hop count to 10, and this method is not suitable for large mobile ad hoc networks. Implementation of a fuzzy routing protocol in non-deterministic networks has been researched in [32] where the aim is to find a path while reducing the overall time required for setting up the link connection. Though the use of fuzzy logic is clearly illustrated with an example, focus is only on reducing the delay and other performance constraints such as throughput, stability of the route and bandwidth have not been dealt in detail, which may be of interest to the MC. Pedro Alipio et al. also researched on mapping multiple QoS metrics into a fuzzy controller in [33]. Unfortunately they are limited to a single technology and consider only specific communication rules.

Since previous work failed to encompass the significant routing metrics and provide a feasible path by handling complete uncertainty in a heterogeneous scenario. This thesis defines a solid fuzzy classification model using a set of constraints. Before we go deep in to our fuzzy model, we elaborate the process of identifying the key network constraints which eventually aids in the network selection.

2.3 Classifying Key Components in a Routing Process

Previous work has determined the most traditional ranking metric to be hop count where the path with least number of hops is selected. This metric treats all links to be alike in the network. On the other hand, an efficient multichannel HWN metric needs to consider other features such as link stability, node density, channel diversity, interference, etc. [34].
By exploring existing published works [21, 35–38], we considered and summarized a large number of metrics. Such a thorough analysis gave us an insight into the numerous criteria and factors that influence the wireless transmission. In spite of the fact that a diverse set does exist and is crucial in the network domain, overlapping objectives forces us to select the smallest subset of attributes which is not an easy task. For instance:

- Understanding the wireless interface behaviour in the light of interference influences other performance measures such as latency and throughput due to retransmission attempts and ongoing contention for the wireless medium.

- Available bandwidth is a good indicator of the network traffic conditions and is extremely important for any real time or delay sensitive applications. While bandwidth factor helps avoid excessive nodes competing for the routing path, a high bandwidth along an unsteady link is of little use in providing the desired QoS.

- Another interesting observation is with regards to the transmission rate which directly impacts the number of packets successfully transmitted from a source to a destination and the overall time invested in routing the data. While a higher rate of transmission is desirable for a particular node, the transmission rate of the neighbouring MCs impact the quality of the communication due to contention among shared wireless medium. Clearly, this affects both the throughput and the transmission time of that interface.

Additionally, some metrics are hard to accurately measure, if not impossible. Interference, for example, can be classified into three categories: intra-flow (when the neighbouring MCs share the same channel, transmitting the same flow of data), inter-flow (when opposing flows share the same channel) and external (which is due to environmental factors, uncontrollable signals emitted in the same frequency range, and so on). Due to fluctuations in the environmental conditions, the measured value of interference may vary, even if computed...
correctly.

Because of these reasons, instead of proposing an analytical formulation that considers so many factors, we simplify the key components and represent a reduced set that encompasses the essential parameters of wireless communication. Also, a smaller set which represents all the vital factors in a wireless communication will intricate the multi-constrained path selection process without affecting the performance.

The ideal set of parameters includes the following metrics listed below:

- Node Density,
- Transmission Rate,
- Packet Loss Rate,
- Link Stability,
- Bandwidth,
- Latency; and
- Throughput.

Interference, for instance, can be reflected by most of the factors listed above. Throughput is most influenced by the packet loss rate and the rate of transmission (which is indirectly affected by link stability, overall round trip time for data forwarding and the number of nodes competing for the channel). A detailed analysis of the inter-relationship among various elements central to wireless communication helped us in arriving at the final list of constraints included in our work.

While we have a reduced subset of seven metrics which will dominate the routing process, further study proved that there is a strong interdependency amongst these elements
as well. For instance, link stability is based on the delivery ratio, which accounts for the
throughput and the effect due to link losses in both the directions of communication. Link
stability is also impacted by the number of nodes that come into existence and compete
for a path to forward the data packets. As the network area becomes congested, increased
collision occurs, thereby weakening the link stability value. It also influences hop count
because when a link fails, choosing an alternative route becomes mandatory and the num-
ber of hops traversed may change, contributing to an increase in the delay value. Also,
insufficient bandwidth can lead to greater queuing delays, causing congestion and possibly
forced retransmissions. Packet loss rate affects the overall throughput or the total number
of packets successfully sent to the destination. An increase in the above value can be due
to poor network links which in turn influences the delay factor. Combined with all these
elements is the transmission rate, which mandates to be tuned so as to attain a desired
performance level in the network which depends on the circumstances.

Figure 2.2: Interdependency Between the 7-Key Network Metrics

Hence, as we explore this discussion on the various metrics and try to isolate the com-
ponents, we realise that each metric has a substantial amount of influence on the other. As
we attempted to pair up the influential metrics with the one that could serve as the target,
we reached a point, where, instead of having a reduced subset of seven metrics, we decided to settle for three. However, we do not completely ignore the other key factors and they are still considered remain by using them as crucial inputs to the final three constraints. Figure 2.2 clearly depicts the strong correlation between the final set of constraints 1, 2 and 3 and the input variables 4, 5, 6, 7, influencing those parameters.

Our final set of constraints are latency, link stability and throughput and the factors influencing them are the node density, transmission rate, packet loss, and the bandwidth. Additionally, link stability will also be serving as an input metric because of its control over latency value. Hence, instead of stating the user preferences in terms of seven key metrics, the process is simplified by just specifying three constraints. This step leads us to defining our unique fuzzy model to handle the impreciseness in these components. We construct the model keeping in mind both the network and the user uncertainty.
Chapter 3

Fuzzy Classification Model to Handle Multiple Constraints

Fuzzy logic tools and techniques function by translating vague terms to crisp values. Hence, utilizing this powerful concept relevant to our problem, we define a fuzzy classification model (FCM) based on the final three metrics namely, latency, link stability, and throughput. This fuzzy classification model is later deployed in a HWN to compute crisp values for each interface’s metric and is used in the selection process for forwarding data. Hence, in this chapter, we begin by briefly defining the wireless network interfaces and exploit to formulate a heterogeneous wireless scenario. Then, we give a detailed explanation of our fuzzy logic model.

3.1 Fuzzy Metric Subsystems

Our environment comprises of interfaces capable of connecting to different wireless technologies such as 802.16 WiMAX, 802.11 WiFi b/g/n, UMTS, and GSM/GPRS. Based on the physical characteristics and network protocols researched in [15, 39–41], we do an exhaustive study on the six interfaces under consideration and define the bounds for various
Table 3.1: Key Component Bounds by Different Network Types

<table>
<thead>
<tr>
<th>Parameter</th>
<th>WiMax (802.16 e)</th>
<th>WiFi (802.11b)</th>
<th>WiFi (802.11g)</th>
<th>WiFi (802.11n)</th>
<th>GSM/GPRS (2.5G)</th>
<th>UMTS (3G)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node Density</td>
<td>20-70 %</td>
<td>10-60 %</td>
<td>12-60 %</td>
<td>15-70 %</td>
<td>7-30 %</td>
<td>7-30 %</td>
</tr>
<tr>
<td>Transmission Rate</td>
<td>20-75 Mbps</td>
<td>4-11 Mbps</td>
<td>12-54 Mbps</td>
<td>60-150 Mbps</td>
<td>0.02-0.09 Mbps</td>
<td>1-2.5 Mbps</td>
</tr>
<tr>
<td>Packet Loss Rate</td>
<td>2-6.5 %</td>
<td>0.5-1.5 %</td>
<td>1.5-5 %</td>
<td>3-5.5 %</td>
<td>2-3 %</td>
<td>2-4 %</td>
</tr>
<tr>
<td>Link Stability</td>
<td>5-20 %</td>
<td>30-80 %</td>
<td>20-50 %</td>
<td>30-70 %</td>
<td>20-50 %</td>
<td>20-50 %</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>5-18 MHz</td>
<td>8-20 MHz</td>
<td>8-20 MHz</td>
<td>20-40 MHz</td>
<td>0.2-1 MHz</td>
<td>1-5 MHz</td>
</tr>
<tr>
<td>Latency</td>
<td>20-40 ms</td>
<td>30-70 ms</td>
<td>10-50 ms</td>
<td>10-35 ms</td>
<td>120-500 ms</td>
<td>90-250 ms</td>
</tr>
<tr>
<td>Achievable Throughput</td>
<td>12-18 Mbps</td>
<td>4-11 Mbps</td>
<td>15-22 Mbps</td>
<td>40-100 Mbps</td>
<td>0.02-0.04 Mbps</td>
<td>0.05-1</td>
</tr>
</tbody>
</table>

metrics as depicted in Table 3.1. We model the three constraints as fuzzy subsystems with inputs derived from the set consisting of node density, transmission rate, packet loss rate and bandwidth. Each subsystem is a fuzzy based network performance constraint which is calculated from the input set influencing their final values. The flow of logic in the subsystems is clearly exhibited through the fuzzy classification model shown in Figure 3.1.

Parameters such as node density and transmission rate are fed into the link stability subsystem in an imprecise manner and the final output received is a crisp ‘link stability’ value. The course of action leading to the final outcome includes the fuzzy logic steps of defining the inference rules for fuzzy inputs, computing the membership degree and deriving the concrete output through defuzzification. These steps take place inside the fuzzy subsystem defined for each output constraint such as link stability, latency and throughput. The detailed definitions of these fuzzy tools and the process we adopted to attain desired
Transmission rate shares the dual role of determining how stable the link is as well as the overall throughput obtained from the network. Latency is strongly affected by the bandwidth and the link stability values. Hence, the stability of a link or a route shares the responsibility of being an input as well as an output constraint. As previously indicated, the close inter-dependence between various metrics is distinctly portrayed in Figure 3.1 where each subsystem is linked to another and the constraints remain tightly connected.

3.2 Fuzzy Tools and Elements

While we gave a general overview in Figure 3.1 about the fuzzy logic steps executed in each metric subsystem, we proceed to give a comprehensive explanation on each fuzzy element in this section and how we fine tune them to achieve useful results in our work.

3.2.1 Linguistic Variables

In the world of fuzzy theory, impreciseness is expressed in terms of linguistic or fuzzy variables. Linguistic terms are fundamental to fuzzy modelling and represent terminologies used in day to day life. For instance, a user, in simple language states that the delay or lag experienced in a Skype call is very low. Instead of specifying values like two milliseconds, a term such as very low is easy for the user to state and understand. Our work comprehends these linguistic variables expressed by MCs for each constraint and relates them to crisp values. Fuzzy logic makes use of a mixture of terms and a relative degree associated with it to denote the linguistic variable. A variable can be stated in many different scales. For example, on a seven point scale, the following linguistic terms could be used: very low, low, average, medium, above medium, high and very high. Similarly, it can also take a greater or lesser scale based on the needs and necessity of a particular application. Our first step in the fuzzy classification would be to define linguistic terms pertaining to our problem. We
propose on utilizing a three point scale for every metric’s fuzzy term and describe them as low, medium and high. We restrict our definition to three terms to simplify our work and achieve the desired results. This sort of flexibility and convenience is provided by fuzzy tools and it ensures that there is no compromise on the efficiency of the final output. Using a simplified number of linguistic terms achieves the desired results of projecting the uncertainty factor with minimal efforts.

3.2.2 Fuzzy Operators

The standard set theory operations in classical sets, also known as ‘crisp sets’ are **union, intersection and complement**. These elementary operations can also be applied to fuzzy sets in the same manner as they are applied to crisp sets.

**Fuzzy Union (OR) Operator** : The fuzzy OR operator is given by:

\[ \mu_{A\lor B}(x) = \min[\mu_A(x), \mu_B(x)] \].

Here A and B are the two input fuzzy sets and

\[ \mu_A(x) \text{ and } \mu_B(x), \]

are their respective degree of membership.

**Fuzzy Intersection (AND) Operator** : The fuzzy AND operator is given by:

\[ \mu_{A\land B}(x) = \max[\mu_A(x), \mu_B(x)] \].

Here A and B are the two input fuzzy sets and

\[ \mu_A(x) \text{ and } \mu_B(x), \]
are their respective degree of membership.

**Fuzzy Complement (NOT) Operator**: The fuzzy NOT operator is given by:

\[ \mu_{\text{not} A}(x) = 1 - \mu_A(x). \]

Here A is the input fuzzy set and \( \mu_A(x) \) is the respective degree of membership.

Our work implements the *Fuzzy Union* and *Intersection* operators on the input parameters. The following discussion on inference rules shows the actual use of having fuzzy operators in our work.

### 3.2.3 Fuzzy Inference Rule Matrix

We now have narrowed down the key constraints and their corresponding linguistic representation. The next step is to add more meaning to these definitions by explaining rules that would connect the input parameters and generate crisp output. This is accomplished in fuzzy theory by inference rules. Fuzzy inference rules are statements built using the conditional IF-THEN structure on the input variables. *If* section of the rule depicts the degree of the linguistic variable and is termed as antecedent and *then* section represents the corresponding action carried out based on the conditional if, and is termed as a consequent. The rule set is formed by combining the linguistic variables and fuzzy operators and the output comprising *then* portion is a value between 0 and 1. Framing the fuzzy inference rules is purely subjective and is attributed to common knowledge and experience possessed by the designer. For example, a rule in the latency subsystem is designed as follows:

| if Link Stability is low and Bandwidth is low then Latency is high |
We construct a fuzzy rule by expressing the parameters involved using linguistic terms, bind them using fuzzy operators **and** and **or**, and define a simple **if-then** based condition to output a final metric. These rules are built based on the familiarity of the metric’s behaviour in a general network topology. Hence, under a reasonable assumption that the network operator or the user defining these rules possesses adequate information about the parameter’s behaviour, we define such rules using the input set. However, if the scale of linguistic terms and the number of input variables increase, listing these rules becomes a tedious process and complex to analyze. Fuzzy logic provides a straightforward approach to solve this problem by employing a rule matrix. A fuzzy rule matrix replicates these rules in a much simpler manner and shows the exact relationship that exists between the variables in the form a square matrix. We formulate three matrices, one for each subsystem which covers all the different combination of rules developed as can be seen in Table 3.2.

**Table 3.2: Fuzzy Rule Matrix for Three Subsystems**

These matrices represent a simplified version of the inference rules and determine the manner in which the output value is calculated from the fuzzy inputs.
In case of link stability subsystem, the table entries can shown as:

<table>
<thead>
<tr>
<th>Condition</th>
<th>Stability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node Density is low and Transmission Rate is low</td>
<td>high</td>
</tr>
<tr>
<td>Node Density is low and Transmission Rate is medium</td>
<td>high</td>
</tr>
<tr>
<td>Node Density is low and Transmission Rate is high</td>
<td>medium</td>
</tr>
</tbody>
</table>

Hence, these rules show that if the node density and the transmission rates stay within the acceptable range of ‘low’ and ‘medium’, then the link stability is ‘high’. However, when the transmission rate reaches a ‘high’ scale, the stability of a link falls to ‘medium’, irrespective of the node density being low. But, when the node density is really ‘high’, then no matter how low the transmission rate is, the stability of a link drops. This is due to the fact that, congestion and the number of nodes competing for the path gains prominence over transmission rate irrespective of the link stability. Based on a subjective knowledge on various routing metrics and prevailing network conditions, we framed these inference rules and translated them into a matrix form.

In case of the latency, a ‘high’ value represents an unfavourable condition and is obtained when both the inputs fail to perform well. Hence, in the latency subsystem, the rule matrix clearly demonstrates how the value obtained is ‘high’ when either of the inputs of link stability and bandwidth lie in the ‘low’ range. On the other hand, when one of the inputs fall within the ‘high’ range, latency is ‘low’ and is acceptable. In all other cases, it takes a medium range. The matrix for throughput is also structured in a similar fashion by using the transmission rate and the packet loss rate. All the rules for the three subsystems are constructed using the fuzzy AND operator. This is evident from the manner in which the two inputs are combined to produce the final metric.
3.3 Fuzzy Membership Function

Assigning values to the linguistic terms and measuring each input accurately is achieved by using membership functions which is utilized to compute the value of each input variable in fuzzy logic and translate them to crisp terms. It clearly depicts the magnitude of participation of each fuzzy input variable and the degree to which they influence the fuzzy sets. The linguistic variables described in the above section are graphically represented using membership functions and the degree of participation of each input variable is measured. This function takes each point on the input space and maps it to their respective degree of membership which lies in the range $[0,1]$. This technique of mapping the degree to a value between 0 and 1 is analogous to probability distribution, where the probability of an event lies in the range $[0,1]$. However, fuzzy membership functions offers greater flexibility in using linguistic terms and effectively tackles uncertain conditions.

3.3.1 Categories of Membership Functions

Numerous membership functions have been defined in fuzzy logic literature and the selection and implementation of each function influences the fuzzy logic model. However, the usage of a particular type is purely subjective and is quite similar to the process of defining fuzzy rule matrices. Depending on the user’s common knowledge and past experience, a specific category of membership function is chosen to be executed. And this value forms the final outcome of the consequent built in the fuzzy inference rule. This clearly shows the strong inter-dependency between various fuzzy elements which helps in resolving imprecision with minimal effort. Some common shapes coined for the membership functions [29] are as follows:

(a) **Triangular**: The triangular membership is a function of vector, $x$ and considers three input parameters $a$, $b$, and $c$. These parameters are defined for each linguistic classification of the input, for instance, **low**. In this ‘low’ domain, ‘$a$’ and ‘$c$’ represent
the lower and upper bound of the feet of the triangle and ‘b’ denotes the median or peak value. The function is represented as:

\[ \mu_{\text{triangular}}(x, a, b, c) = \begin{cases} 
0 & \text{if } x \leq a \\
(x - a)/(b - a) & \text{if } a < x \leq b \\
(c - x)/(c - b) & \text{if } b < x \leq c \\
0 & \text{if } x > c. 
\end{cases} \]

This function returns the degree of membership lying in the range [0,1]. Figure 3.2 shows a simple visualization of the triangular membership function where the ‘low’, ‘medium’ and ‘high’ regions are clearly distinguished and there exists a small overlap between the consecutive ranges. For instance, the overlapping region lying between input values 3 and 4 belong to ‘low’ as well as ‘medium’ ranges.

![Figure 3.2: Triangular Membership Function](image)

(b) **Trapezoidal**: The trapezoidal similar to the triangular membership function considers a vector \( x \) and takes inputs. However, due to its characteristic shape, an additional
parameter ‘d’ is also considered in this case. Here, ‘a’ and ‘d’ denote the lower and upper bounds of the feet of the trapezoid while ‘b’ and ‘c’ are for the shoulder or peak values. Trapezoidal function is shown as:

\[
\mu_{\text{trapezoidal}}(x, a, b, c, d) = \begin{cases} 
0 & \text{if } x \leq a \\
(x - a)/(b - a) & \text{if } a < x \leq b \\
1 & \text{if } b < x \leq c \\
(d - x)/(d - c) & \text{if } c < x \leq d \\
0 & \text{if } d \leq x. 
\end{cases}
\]

Figure 3.3: Trapezoidal Membership Function

As mentioned before, the number of linguistic terms is left to the user’s choice as can be seen in Figure 3.3 where there exists only two types of linguistic variables, namely ‘low’ and ‘high’. Inspite of this, the method used in calculating the degree of membership and the fuzzy logic steps remain unaffected.

(c) Gaussian: The Gaussian representation considers two parameters \( \sigma \) and ‘c’ where \( c \)
denotes the mean and $\sigma$ denotes the standard deviation. The function takes the form:

$$
\mu_{gaussian}(x, \sigma, c) = \begin{cases} 
    e^{-(x-c)^2/(2\sigma^2)} & \text{if } x \leq c \\
    e^{-2(x-c)^2/(2\sigma^2)} & \text{if } x > c
\end{cases}.
$$

Figure 3.4: Gaussian Membership Function

An interesting variation of using five linguistic terms is graphically represented in Figure 3.4 where the mean and the standard deviation are assumed as per the user’s degree of preference and the impreciseness is expressed in more detail levels by using terms such as ‘very low’, and ‘very high’.

Additionally, a number of shapes have been coined for fuzzy membership functions such as bell, sigmoidal, s-shaped and z-shaped functions. The use of each membership function has been tuned according to the design requirements and the fuzzy model. For instance, depending on the application requirements, two shapes such as triangular and trapezoidal can be combined and a degree of membership value can still be derived in the same man-
Previous work using fuzzy logic has focussed on the usage of triangular membership function due its simplicity and proficient use in engineering applications [32]. For the same reason and in order to gain maximum efficiency, we use the triangular membership function for every input parameter.

### 3.3.2 A Practical Example for Triangular Membership Function

Consider the triangular membership function for WiMAX’s bandwidth as shown in Figure 3.5. A snapshot of the bound values for WiMAX derived from Table 3.1 is shown below.

The bound values for WiMAX bandwidth, as seen in Table 3.3, is 5 - 18 MHz. Keeping these values as the base reference, we define the ‘low’, ‘medium’ and ‘high’ range of values for the bandwidth metric. This demarcation for each linguistic term is clearly depicted in Figure 3.5. From these range of values, we consider the lower, middle and upper bound weights to fit into the triangular membership function. The fuzzy membership function...
Table 3.3: Bound Values for WiMAX Bandwidth

<table>
<thead>
<tr>
<th>WiMAX (802.16e)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Node Density</td>
<td>20 - 70 %</td>
</tr>
<tr>
<td>Transmission Rate</td>
<td>20 - 75 Mbps</td>
</tr>
<tr>
<td>Packet Loss Rate</td>
<td>2 - 6.5 %</td>
</tr>
<tr>
<td>Link Stability</td>
<td>5 - 20 %</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>5 - 18 MHz</td>
</tr>
<tr>
<td>Latency</td>
<td>20 - 40 ms</td>
</tr>
<tr>
<td>Achievable Throughput</td>
<td>12 - 18 Mbps</td>
</tr>
</tbody>
</table>

values for WiMAX bandwidth are as follows:

\[
\text{Bandwidth low} = [0 \ 3 \ 6]
\]

\[
\text{Bandwidth medium} = [4 \ 9 \ 14]
\]

\[
\text{Bandwidth high} = [10 \ 13.5 \ 17]
\]

The manner in which we assume these ranges for WiMAX bandwidth is purely based on the bounds shown in Table 3.3. Since WiMAX provides a reasonable bandwidth range of 5 - 18 MHz, anything lower than this is considered to be a ‘low’ bandwidth and anything above 18 MHz, is considered to be an ideal or efficient bandwidth range which comes under the category of ‘high’. But in reality, the maximum value quoted by WiMAX 802.16 might not be attainable frequently. Hence, providing a comfortable and realistic range for the constraint values, we consider 10 - 17 MHz to fall in the high range. Anything in between this low and high bounds would be the ‘medium’ or ‘normal’ category which lies in close proximity to the upper bound of ‘low’ range and lower bound of the ‘high’ range. In other words, we experience an overlap between the above mentioned bounds. This illustrates the core of fuzzy logic and makes it a preferred method for uncertain values in comparison with boolean logic which doesn’t give this luxury.

The three values in the bandwidth low are the lower bound, peak value and upper bound of a triangular membership function. Now, if the measured bandwidth for WiMAX interface is 8MHz, then the triangular membership function would output the following degree of membership as shown in Figure 3.6:
Given: \( a = 4 \) [lower bound]; \( b = 9 \) [peak value]; \( x = 8 \) [measured input],

\[
\mu_{\text{triangular}}(x, a, b, c) = \frac{(x - a)}{(b - a)} \quad \text{if} \quad a < x \leq b \quad (3.1)
\]

\[
= \frac{(8 - 4)}{(9 - 4)} \quad (3.2)
\]

\[
= 0.8. \quad (3.3)
\]

Figure 3.6: Degree of Membership when Input lies in Exclusive Medium Range

This way of computing the degree of membership gives values in the range \([0,1]\). This implies how the input range is mapped over the range of fuzzy input values and linguistically describe the fluctuation in the variable’s value. For instance, in the above scenario, the measured bandwidth of 8MHz clearly lies in the ‘medium’ range. However, if value is 12MHz, then it would have membership in both the ‘medium’ as well as ‘high’ fuzzy sets. The graphical representation of considering an input in the overlapped region of ‘medium’ and ‘high’ is demonstrated in Figures 3.7 and 3.8. The triangular function in this case would work as follows:

Given: \( b = 9 \) [peak value]; \( c = 14 \) [upper bound]; \( x = 12 \) [measured input],

\[
\mu_{\text{triangular-medium}}(x, a, b, c) = \frac{(c - x)}{(c - b)} \quad \text{if} \quad b < x \leq c \quad (3.4)
\]
This gives a computed value of 0.4 is where the bandwidth lies in the medium range.

\[
\frac{(14 - 12)}{(14 - 9)} \quad \text{(3.5)}
\]

\[
= 0.4. \quad \text{(3.6)}
\]

As seen in the previous calculations, a final membership of 0.571 is calculated for the same bandwidth input value of 12 MHz. This is due to the fact that 12 MHz lies in the overlapped region of medium and high and their degree is computed accordingly. Hence, Equation 3.4 uses peak value 9 and upper bound 14 of the medium range along with an input of 12 MHz. While, Equation 3.7 implements lower bound 10 and peak value 13.5 of the high range to get the final degree for the same measured bandwidth of 12 MHz. This flexibility and ease of fuzzy logic concepts deals with the dynamic network conditions in an
0.1

Figure 3.8: Degree of Membership when Input lies in Overlapped High Range

effective manner.

Uncertainty or vagueness of the measured value is a significant problem where a true representation of the outcome might be incorrect or vary due to dynamic and changing environmental conditions. For example, the delay computed in transmitting data might suddenly vary due to network conditions such as node failure, link stability or even new nodes joining the network, thereby causing congestion. Hence, there is no guarantee that the measured value will remain static. Due to this reason, our proposed FCM considers all possible combinations of input metric values inside the range and applies the AND operator to come up with a range of possible output metric values. This way of computing the output translates the linguistic terms to accurate values keeping in mind the dynamic network conditions. Hence, in the ‘low’ region of bandwidth, [0 3 6], we consider all possible measures from 0 to 6 while computing the crisp metric for the delay.

For example, if the measured metric value for delay is 1 ms at any instance in time, and at the next instance, the value increases to 1.2 ms, then the delay still lies in the ‘low’ range as per fuzzy logic membership function values. But, our FCM considers both 1 ms
and 1.2 ms while computing the final concrete value. This produces a final weight value to each linguistic term of the network metrics, and we utilize fuzzy logic tools to solve the inherent uncertainty. This technique of combining the wide range of values to derive one single pay-off value, while giving importance to changing network conditions and factors influencing the constraints, has never been ventured upon and our novelty and uniqueness lies in this aspect.
Chapter 4

Payoff Matrix for Wireless Network Interface Using Defuzzification

Chapter 3 elaborated our proposed procedure of defining a fuzzy model, forming inference rules, and classifying them using a triangular membership function. We accomplish this process of implementing the triangular membership function for every input metric by initially defining the three point bound values. As explained for WiMAX (802.16 e), the bound values are defined for every interface’s metric by making use of the values obtained in published works and summarized in Table 3.1. These ranges play a crucial role in our work, and considerable amount of effort has gone into defining these ranges using a three point scale for every linguistic term, namely: low, medium and high. A complete list of values used in fuzzy triangular membership function for every interface’s metric is illustrated in Table 4.1. This table plays a central role in characterizing every metric’s degree of membership which is incorporated in the final step of fuzzy logic, namely defuzzification. In addition, Table 3.1 summarized the bounds for every interface, which gives us the liberty to apply our subjective knowledge and define these ranges.
Utilizing these range of values, the inference rule set is defined and using the fuzzy operators, we execute the final phase of fuzzy logic modeling where we translate the imprecise metric values to crisp scores. This process of transforming the qualitative information to concrete values is achieved through fuzzy defuzzification. This chapter emphasizes on the process of defuzzification and our unique way of computing crisp values by considering user’s perception.

Table 4.1: Fuzzy Triangular Membership Functions Values

<table>
<thead>
<tr>
<th>Metrics</th>
<th>WiMax (802.16e)</th>
<th>Wi-Fi (802.11n)</th>
<th>Wi-Fi(802.11g)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Transmission Rate (Mbps)</td>
<td>0.10</td>
<td>0.20</td>
<td>0.30</td>
</tr>
<tr>
<td>Node Density (%)</td>
<td>0.75</td>
<td>1.00</td>
<td>1.50</td>
</tr>
<tr>
<td>Bandwidth (MHz)</td>
<td>0.80</td>
<td>1.00</td>
<td>1.50</td>
</tr>
<tr>
<td>Link Stability (%)</td>
<td>0.05</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Packet Loss Rate (%)</td>
<td>0.10</td>
<td>1.00</td>
<td>2.00</td>
</tr>
</tbody>
</table>

4.1 Deriving Crisp Values

Defuzzification is the process of translating linguistic terms to crisp values and forms the crux of fuzzy logic modelling. This final step in fuzzy logic transforms the impreciseness to concrete weights. Numerous methods relating to defuzzification are discussed in the literature [42] and a few popular techniques commonly used are weighted mean, mean of maxima (MOM), center of gravity (COG), etc. All these approaches compute the final crisp output based on the degree of membership value. For example, in case of weighted mean method, the output from the defuzzifier is as follows:

$$ WM(x) = \frac{\sum \mu_c(\bar{x}) \times \bar{x}}{\sum \mu_c(\bar{x})}.$$
Here, $\bar{x}$ is the centroid of the membership function, $\mu_c(\bar{x})$ denotes the degree of membership of input $x$ and $WM(x)$ is the weighted mean value obtained from the defuzzification.

Using the concept of defuzzification, we compute a matrix which will exhibit the final crisp values for each network’s metric subsystem. This is the final step in our fuzzy logic modeling which paves the way for the interface selection process and decision making from the user end. Since this matrix provides the utility value for every network, and influences their chances of being picked for routing the data, the term payoff matrix is utilized to show these crisp values. The following sections explains the series of steps executed to defuzzify the membership values into a payoff matrix.

### 4.2 Attitudes of Decision Makers

Prior to constructing the payoff matrix, we focus on the attitudes of the decision makers which plays a crucial role in the decision making and influences the network selection process. Hence, we begin by first categorizing the constraints as beneficial and non-beneficial [30]. As the name implies, the beneficial constraints are those where a higher value represents a better and enhanced performance. On the other hand, non-beneficial constraints are impacted by the cost factor and attain maximal efficiency with lower values. In some cases, they are also referred to as benefit and cost criteria pertaining to their utilization value [43]. In our work, link stability and throughput are classified as beneficial constraints and latency comes under the category of non-beneficial as a lower value of latency or delay represents a better performance.

We proceed further by considering the decision maker’s attitude while selecting the network interface to forward data. Richmond in [44] proposed some common attitudes posed by a decision maker which aids in the selection of an optimal alternative. They are:
• **Pessimistic Attitude** - The decision maker possessing this attitude chooses the worst possible outcome for each choice of alternatives and then selects the best among the worst alternatives. Also known as the *maximum* strategy, this reflects the pessimistic attitude of the user.

• **Optimistic Attitude** - As the name implies, the user having this characteristic selects the best possible result for each choice of alternatives and then opts for the best among the best options. This *maximax* technique portrays the optimism or positive thinking of the decision maker.

• **Hurwicz Attitude** - This technique allows a decision maker to choose a value $\alpha$ between 0 and 1. This value is analogous to the probability of a value being optimistic or pessimistic. A weighted average of optimistic and pessimistic value is computed as follows:

$$H = \alpha \cdot Opt + (1 - \alpha) \cdot Pess.$$  

The highest $H$ value is chosen as the best possible alternative.

• **Normative Attitude** - The decision maker using this method, aggregates the net outcome of all possible alternatives and selects the one which has the maximum value.

Considering complete uncertainty, where the user possesses no knowledge about the attributes and alternatives, the attitude of the decision maker needs to be taken into account while making a selection. In our scenario, user impreciseness motivates us to focus on a MC’s attitude to implement defuzzification and compute crisp values.

We base our payoff matrix computations on the pessimistic attitude of the MC. Our choice of a pessimistic attitude for the MC is justified by stating that, if the dynamic network conditions can satisfy the user’s pessimistic needs efficiently, then anything better than the worst case scenario will only result in an enhanced performance. Hence, our assumption of the worst case strategy gives more space for an enhanced performance and an optimal
network selection under ideal conditions.

4.3 Construction of Payoff Matrix

Considering our proposed fuzzy classification model (FCM), we take the combination of inputs and compute their degree of membership function for each value lying in their respective linguistic range, for instance ‘low’. We then employ the fuzzy inference rules to the combination of inputs and compute the min of their membership degrees using AND operator. For example, we consider the ‘low’ range for node density and transmission rate for WiMax(802.16e) wireless interface. The bound values derived from Table 4.1 are as follows:

\[ \text{Node density low} = [0 \ 7 \ 14], \]
\[ \text{Transmission rate low} = [0 \ 10 \ 20]. \]

For each value in this range, we compute the degree of membership \( \mu_{\text{node density}}(x) \) and \( \mu_{\text{transmission rate}}(x) \). Here, \( x \) denotes each value in the ‘low’ range as specified above. Then, we apply the AND operator and compute the \( \min \) of their respective membership degrees.

\[ \mu_{\text{link stability high}}(x) = \min[\mu_{\text{node density low}}(x), \mu_{\text{transmission rate low}}(x)]. \quad (4.1) \]

A high link stability value is obtained from a low node density and a low transmission rate and this is based on the inference rule matrix we coined in Table 3.2 for the link stability subsystem. The \( \min \) operator is applied since the rule is framed with an AND as:

\[
\text{If node density is low AND transmission rate is low THEN link stability is HIGH.}
\]

Taking into account all possible values in the low range of node density and transmission rate, we derive a range of output value for high range of link stability by implementing the Equation 4.1. We then implement the pessimistic attitude of the decision maker and pick
the worst possible outcome amongst the high link stability values derived using a single inference rule.

This method of deploying all possible combination of values in a particular linguistic range guarantees that we lay emphasis on the dynamic network conditions where the state and characteristics of a particular wireless interface can fluctuate at any instant of time. Hence, while considering a high link stability, instead of confining to a single value of input parameters (such as node density and transmission rate in this case), we encompass all possible combination of inputs to derive a particular outcome in it’s linguistic range.

\[
\text{High Link Stability} = \min[\text{range of high link stability values}].
\] (4.2)

Equation 4.2 depicts that we select the worst possible outcome by applying the \( \min \) operator for a single inference rule. In case of beneficial constraints like link stability and throughput, the same approach is followed. However, in case of non-beneficial constraints like latency, a high value represents the worst case scenario. Hence, we implement the \( \max \) operator for non-beneficial or cost constraints. We repeat the above process for all possible inference rules defined for each metric subsystem. This generates three sets of ‘low’, ‘medium’ and ‘high’ for each metric. For example, in link stability subsystem, the three fuzzy inference rules leading to a high link stability are:

- If node density is low AND transmission rate is low THEN link stability is HIGH.
- If node density is low AND transmission rate is medium THEN link stability is HIGH.
- If node density is medium AND transmission rate is low THEN link stability is HIGH.

Similarly, by referring to Table 4.1, it is evident that three sets of each linguistic term is derived for each output metric. We translate them to one single value for each set by applying the \( \max \) operator (beneficial constraints) and \( \min \) operator (non-beneficial constraints).
Final High value = 
\[ \max \text{ (or min) } [\text{high1, high2, high3}] \]

\[ \text{centroid of output membership function.} \] (4.3)

In the above Equation, high1, high2 and high3 symbolize the final weight value obtained for a high link stability derived using Equation 4.2 for each inference rule shown in Table 3.2. Correspondingly, the final ‘low’, ‘medium’ and ‘high’ values are derived for each of the proposed subsystems. Utilizing the key bounds of each performance metric for each network, we rely on our FCM and repeat the above mentioned steps for each wireless interface. In this manner, we ensure that all the performance constraints of a network which plays a crucial role in user’s satisfaction are considered and a payoff or utility value is assigned to each network interface, which determines the handover decision in a heterogeneous scenario.

Table 4.2: Payoff Matrix for WiMAX (802.16 e)

<table>
<thead>
<tr>
<th>Metrics</th>
<th>WiMAX (802.16 e)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link Stability (%)</td>
<td>0.1644</td>
<td>0.7</td>
<td>1.75</td>
<td></td>
</tr>
<tr>
<td>Latency (ms)</td>
<td>1.7143</td>
<td>8.3333</td>
<td>13.75</td>
<td></td>
</tr>
<tr>
<td>Throughput (Mbps)</td>
<td>0.119</td>
<td>0.4</td>
<td>1.2</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.3: Payoff Matrix for WiFi (802.11 n)

<table>
<thead>
<tr>
<th>Metrics</th>
<th>WiFi (802.11 n)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link Stability (%)</td>
<td>0.5</td>
<td>1.2143</td>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>Latency (ms)</td>
<td>0.2</td>
<td>1.2667</td>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>Throughput (Mbps)</td>
<td>0.667</td>
<td>1.1429</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

The payoff values calculated for each network are shown in a matrix form. Tables 4.2, 4.3, 4.4, 4.5, 4.6 and 4.7 clearly illustrates the values for each metric’s ‘low’, ‘medium’ and ‘high’ ranges for each network. For instance, utilizing the values in WiFi 802.11g column, if the latency of-
Table 4.4: Payoff Matrix for WiFi (802.11 g)

<table>
<thead>
<tr>
<th>Metrics</th>
<th>WiFi (802.11 g)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link Stability (%)</td>
<td>0.3</td>
<td>1.1364</td>
<td>7.083</td>
<td></td>
</tr>
<tr>
<td>Latency (ms)</td>
<td>1.25</td>
<td>3.6111</td>
<td>6.666</td>
<td></td>
</tr>
<tr>
<td>Throughput (Mbps)</td>
<td>0.1385</td>
<td>0.5455</td>
<td>3.333</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.5: Payoff Matrix for WiFi (802.11 b)

<table>
<thead>
<tr>
<th>Metrics</th>
<th>WiFi (802.11 b)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link Stability (%)</td>
<td>0.2857</td>
<td>1</td>
<td>3.429</td>
<td></td>
</tr>
<tr>
<td>Latency (ms)</td>
<td>0.5333</td>
<td>3.2</td>
<td>5.25</td>
<td></td>
</tr>
<tr>
<td>Throughput (Mbps)</td>
<td>0.0914</td>
<td>0.1833</td>
<td>0.543</td>
<td></td>
</tr>
</tbody>
</table>

fered by this network is low, then a weight or payoff value of 1.25 is assigned to that metric
for the specific interface. The subsystems deriving these matrices originally comprised of
values that may have been inaccurate or vague. However, our FCM coupled with defuzzifi-
cation generated a single numeric value for subsequent ordering and ranking of the networks.

Table 4.6: Payoff Matrix for UMTS (3G)

<table>
<thead>
<tr>
<th>Metrics</th>
<th>UMTS (3G)</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link Stability (%)</td>
<td>0.2</td>
<td>2</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>Latency (ms)</td>
<td>1.6667</td>
<td>6.1583</td>
<td>23.333</td>
<td></td>
</tr>
<tr>
<td>Throughput (Mbps)</td>
<td>0.002</td>
<td>0.0055</td>
<td>0.1035</td>
<td></td>
</tr>
</tbody>
</table>

Also, the proposed FCM, coupled with any MADM method, can effectively identify the
appropriate network through which any user or MC can forward data, even when faced with
the risk of uncertain network conditions. This implies that a user can specify imprecise needs
and preferences and using any existing MADM method, can rank the available networks
in an effective manner. Additionally, the range of values assumed in our computations
handles dynamic and varying network conditions, with greater ease and offers flexibility to
user satisfaction.
Table 4.7: Payoff Matrix for GSM/GPRS

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link Stability (%)</td>
<td>0.2</td>
<td>2.4044</td>
<td>5.769</td>
</tr>
<tr>
<td>Latency (ms)</td>
<td>8</td>
<td>30</td>
<td>60</td>
</tr>
<tr>
<td>Throughput (Mbps)</td>
<td>0.0007</td>
<td>0.0037</td>
<td>0.0086</td>
</tr>
</tbody>
</table>
Chapter 5

A Practical Comparison of MADM approaches with FCM

The usefulness of our FCM in practical scenarios is best illustrated by practical experiments and analysis. This chapter accomplishes that by doing a thorough comparison with the existing MADM algorithms. We utilize the HWN consisting of the six interfaces, namely WiMAX, 802.11n, 802.11g, 802.11b, UMTS and GSM/GPRS and the payoff matrix values shown in Table 5.1 for this purpose. The simulations are initiated by modelling the user constraints based on QoS requirements of the network applications.

Earlier techniques adopted conventional MADM strategies to rank the alternatives and consequently determine a choice of action. Methods such as Simple Additive Weighted method (SAW) and Technique for Order preference by Similarity to Ideal solution (TOPSIS) have been executed in a heterogeneous wireless scenario to rank the candidate networks [30]. Another popular MADM algorithm, ELECTRE has been adopted in [45] to carry out the network selection process in a heterogeneous scenario. ELECTRE is popular and deterministic as it performs a pair-wise assessment of the attributes and arrives at a choice that is best suited under the given subjective conditions. Although ELECTRE is apt for decision making under multiple criteria, similar to other MADM techniques, it lacks the
ability to process indefinite data with efficiency. Hence, a comparison of MADM with FCM will throw more light on the effectiveness of our model in handling complete uncertainty.

5.1 Multiple Attribute Decision Making

As discussed earlier, MADM techniques have been widely used in the decision making process and selecting an alternative has remained as a challenging job. MADM deals with the task of ranking and evaluating the possible list of choices and actions and selecting the most suitable one. These methods work by assigning preference weights to alternatives and their motive is to handle multiple criteria rather than tackle the problem of uncertainty and impreciseness [30]. A comparison of our modified MMR with these MADM techniques will throw more light on the advantages of implementing our FCM in practical scenarios of decision making.

MADM techniques researched by Hwang and Yoon in [16] haven’t clearly specified which MADM technique is to be adopted for a given scenario. Some of the popular MADM approaches commonly used in decision making are Simple Additive Weighting Method (SAW), Analytical Hierarchical Process (AHP), Grey Relational Analysis (GRA), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). These techniques, quite similar to MMR, initiate the process for the decision matrix construction.

We concentrate on the SAW and TOPSIS for our analysis, and compare results to that of our enhanced FCM. SAW is a simple method and relatively easy to understand and implement. It employs all the attribute values of each alternative in the decision making process and exercises the usual arithmetic operations of addition. Like any scoring method, SAW necessitates a comparable scale of all the attribute values and this is achieved by normalizing the decision matrix. TOPSIS is another conventional MADM technique which is quite simple to execute and has a strong decision making capability. This procedure,
as the name indicates, strives to find the ideal or positive solution. The importance of an alternative reduces monotonically when it deviates from an ideal or most desirable solution. Hence, TOPSIS defines an index or value that has the shortest distance from the best solution and longest distance from the worst solution. In other words, the final value computed lies in a close proximity to the ideal solution and is away from the negative ideal solution. Like SAW, TOPSIS also requires normalization of the decision matrix to justify the comparison of values having different units of measurement.

To demonstrate the working of SAW and TOPSIS, we begin by considering a sample decision matrix as shown below.

\[
\begin{bmatrix}
X_1 & X_2 & X_3 \\
A_1 & x_{11} & x_{12} & x_{13} \\
A_2 & x_{21} & x_{22} & x_{23} \\
A_3 & x_{31} & x_{32} & x_{33} \\
A_4 & x_{41} & x_{42} & x_{43}
\end{bmatrix}
\]

Here, \( A_1 \) to \( A_4 \) denotes the set of alternatives available to the decision maker whose states space comprises of attributes \( X_1, X_2 \) and \( X_3 \). \( x_{ij} \) \( (i = 1...4 \text{ and } j = 1..3) \) are the values of each attribute corresponding to each alternative. The overall preference weight assigned to each attribute are represented as a weight matrix.

\[
W_j = [w_1 \ w_2 \ w_3].
\]

5.2 Working of SAW

SAW normalizes the decision matrix by considering the beneficial and non-beneficial criteria separately and utilizing the following equations,

\[
\text{norm}(x)_{ij} = x_{ij}/x_{j\text{max}}; \quad i = 1..4, \quad j = 1..3.
\]
\[ \text{norm}(x)_{ij} = x_{j_{min}} / x_{ij}; \quad i = 1..4, \quad j = 1..3. \] (5.2)

Equation 5.1 is applied to benefit factors and 5.2 to cost factors. Once the values are normalized to a comparable scale, the matrix becomes:

\[
\begin{pmatrix}
X_1 & X_2 & X_3 \\
A_1 & \text{norm}(x)_{11} & \text{norm}(x)_{12} & \text{norm}(x)_{13} \\
A_2 & \text{norm}(x)_{21} & \text{norm}(x)_{22} & \text{norm}(x)_{23} \\
A_3 & \text{norm}(x)_{31} & \text{norm}(x)_{32} & \text{norm}(x)_{33} \\
A_4 & \text{norm}(x)_{41} & \text{norm}(x)_{42} & \text{norm}(x)_{43}
\end{pmatrix}
\]

Now, applying the weights (preference matrix) to the normalized decision matrix:

\[ R_i = \sum_{j=1}^{3} w_j \ast \text{norm}(x)_{ij}; \quad i = 1..4. \]

The weighted values computed above determine the rank assigned to each alternative with the maximum being the most favoured choice.

### 5.3 Working of TOPSIS

We annotate the steps involved in TOPSIS by considering the same decision matrix and weight matrix used by SAW. TOPSIS normalizes values by executing the following equation:

\[ \text{norm}(x)_{ij} = x_{ij} / \sqrt{\left( \sum_{i=1}^{4} x_{ij} \right)} ; i = 1..4, \quad j = 1..3. \] (5.3)

The resulting normalized matrix entries are multiplied with the weight vector to attain the weighted normalized matrix as depicted below:
\[
\begin{pmatrix}
X_1 & X_2 & X_3 \\
A_1 & W_{\text{norm}}(x)_{11} & W_{\text{norm}}(x)_{12} & W_{\text{norm}}(x)_{13} \\
A_2 & W_{\text{norm}}(x)_{21} & W_{\text{norm}}(x)_{22} & W_{\text{norm}}(x)_{23} \\
A_3 & W_{\text{norm}}(x)_{31} & W_{\text{norm}}(x)_{32} & W_{\text{norm}}(x)_{33} \\
A_4 & W_{\text{norm}}(x)_{41} & W_{\text{norm}}(x)_{42} & W_{\text{norm}}(x)_{43}
\end{pmatrix}
\]

As per the definition of TOPSIS, the idea is to compute the most perfect and imperfect solution and maximize the distance of our result to the perfect one.

\[
A^+_{\text{ben}} = \max_i [W_{\text{norm}}(x)_{ij}],
\]

\( (5.4) \)

\[
A^+_{\text{non-ben}} = \min_i [W_{\text{norm}}(x)_{ij}],
\]

\( (5.5) \)

\[
A^+ = [a_1^+ \ a_2^+ \ a_3^+],
\]

\( (5.6) \)

\[
A^-_{\text{non-ben}} = \max_i [W_{\text{norm}}(x)_{ij}],
\]

\( (5.7) \)

\[
A^-_{\text{ben}} = \min_i [W_{\text{norm}}(x)_{ij}],
\]

\( (5.8) \)

\[
A^- = [a_1^- \ a_2^- \ a_3^-].
\]

\( (5.9) \)

Hence, the positive and negative solutions are given by the equations 5.4 and 5.7. The distance of each alternative from the ideal and non-ideal solutions are computed as follows:

\[
D_{i+} = \sqrt{\sum_{j=1}^{3} (W_{\text{norm}}(x)_{ij} - a_j^+)^2 } \quad i = 1..4 \quad , j = 1..3.
\]

\( (5.10) \)

\[
D_{i-} = \sqrt{\sum_{j=1}^{3} (W_{\text{norm}}(x)_{ij} - a_j^-)^2 } \quad i = 1..4 \quad , j = 1..3.
\]

\( (5.11) \)

Once the distance from the positive and negative solutions are obtained, the final step in TOPSIS involves showing the close proximity to the positive or ideal solution for each alternative and ranking them based on this closeness value. The one’s with a higher value
are closer to the ideal solution and tends to be the most satisfying choice. Hence, the ranking scores are generated by:

\[ R_i = \frac{D_i^+}{D_i^+ + D_i^-}; \quad i = 1..4. \] (5.12)

### 5.4 Simulation and Analysis

We analyze the performance of our FCM by modeling the user constraints based on the application requirements and comparing the results with existing MADM approaches which mandates a weight to be assigned to it. User preferences are completely based on the application needs and in our experiments and computations, we consider the two significant and commonly used user applications, namely Web Browsing and VoIP. Each has an entirely different set of constraints with regards to the network performance. Web Browsing requires a high throughput and error free transmission while giving considerable tolerance to increase in the delay value. However, VoIP’s primary concern is to experience minimum delay while forwarding data packets and gives less emphasis on the throughput. Considering such contrasting application demands helps us to model user constraints accordingly and see the difference in performance by various network interfaces.

The QoS requirements for these applications have been discussed in depth [19] and based on this study, we define the user constraints by using linguistic terms implemented in our work, namely ‘low’, ‘medium’ and ‘high’. The constraints are specified in the order of [link stability, latency and throughput].

*User Constraints for VoIP* = [MED LOW MED].

*User Constraints for Web Browsing* = [HIGH MED HIGH].

The user states the preferences based on the application being executed and the network is ranked accordingly. Weights are assigned to the linguistic terms for each constraint
based on the application requirements and fuzzy tools and techniques. The weights for these application based user constraints are computed using fuzzy tools and triangular membership function as illustrated in [46]. This work discusses in depth on assigning weight values to linguistic terms by using simple fuzzy tools and techniques. Since, our calculations for user constraints are not dependent on any prior condition or changes, we execute this technique to compute our final weight values for linguistic user preferences. Consider the user constraint for web browsing defined as:

\[
\text{User Constraints for Web Browsing} = \{\text{HIGH MED HIGH}\} \quad (5.13)
\]

Based on the values discussed in [19] for each metric corresponding to each application, we define range of values for a ‘high’ link stability, ‘medium’ latency and ‘high’ throughput. The membership function corresponding to these ranges are clearly depicted in Figures 5.1, 5.2 and 5.3. Utilizing these range of values in the triangular membership function, we derive a set of equations for each metric’s linguistic term as follows:

\[
\mu_{\text{high}}(\text{link stability}) = \begin{cases} 
(x - 0.6)/(0.2) & \text{if } 0 < x \leq 0.8 \\
(1.0 - x)/(0.2) & \text{if } 0.8 < x \leq 1.0
\end{cases}
\]

Figure 5.1: Fuzzy Values for VoIP Link Stability
A crisp score for fuzzy variables is obtained using the set of equations as defined in [46].
and shown below:

\[
\mu_{\text{max}}(x) = \begin{cases} 
  x & \text{if } 0 \leq x \leq 1 \\ 
  0 & \text{otherwise}
\end{cases}
\]

\[
\mu_{\text{min}}(x) = \begin{cases} 
  1 - x & \text{if } 0 \leq x \leq 1 \\ 
  0 & \text{otherwise}
\end{cases}
\]

Equating the left side of our triangular membership function with the \(\mu_{\text{min}}(x)\), we obtain the degree of membership represented as \(\mu_{\text{Left}}(x)\). Similarly, we obtain the value for \(\mu_{\text{Right}}(x)\). Once, we compute these values for each metric in our web application, the total value is computed as follows:

\[
\mu_{\text{Total}}(x) = \frac{\mu_{\text{Right}}(x) + 1 - \mu_{\text{Left}}(x)}{2}
\]

The total degree of membership computed for each metric’s linguistic term is assigned as preference weight to our application constraint and are illustrated below for VoIP and Web applications.

\[
\text{VoIP} = \begin{bmatrix} 0.4 & 0.2 & 0.4 \end{bmatrix}
\]

\[
\text{Web} = \begin{bmatrix} 0.35 & 0.3 & 0.35 \end{bmatrix}
\]

Using these weights and the payoff matrices derived for each interface in Chapter 4, we execute TOPSIS, SAW and our FCM to obtain the ranking scores for various networks. The individual payoff matrices whose values are utilized in the simulation analysis are condensed and depicted in Table 5.1. Since our work focuses on decision making by adapting to

<table>
<thead>
<tr>
<th>Matrix</th>
<th>WMAX (802.11a)</th>
<th>WMAX (802.11g)</th>
<th>WMAX (802.13)</th>
<th>LM (11g)</th>
<th>LM (2.4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.8849</td>
<td>0.7073</td>
<td>0.5149</td>
<td>1.1549</td>
<td>0.7549</td>
</tr>
<tr>
<td>Medium</td>
<td>0.7073</td>
<td>0.5149</td>
<td>1.1549</td>
<td>0.8849</td>
<td>0.7073</td>
</tr>
<tr>
<td>High</td>
<td>0.5149</td>
<td>1.1549</td>
<td>0.8849</td>
<td>0.7073</td>
<td>0.5149</td>
</tr>
<tr>
<td>Latency (ms)</td>
<td>1.7169</td>
<td>8.9999</td>
<td>13.79</td>
<td>0.2</td>
<td>1.2807</td>
</tr>
<tr>
<td>Throughput (Mbps)</td>
<td>0.139</td>
<td>0.4</td>
<td>1.2</td>
<td>0.867</td>
<td>1.3429</td>
</tr>
</tbody>
</table>
uncertainty and dynamic conditions, we introduce variability to the measured constraints and metrics to see how performance varies based on this fluctuation. Figure 5.4 shows the variation in link stability from little/no uncertainty, to higher levels of impreciseness.

Figure 5.4: VoIP network ranking under link stability variation with TOPSIS

In this scenario, only the link stability metric is varied while the others are kept constant. However, variability is bounded by the interface’s range as specified in Table 3.1 and within the user constraints for that particular application (in this case, VoIP). Hence, a ‘medium’ link stability required by the user for VoIP application introduces variation that is bound by values and is suitable for any MADM algorithm. This change in the value for a particular metric is introduced to demonstrate that even with low variability (which has little impact on a metric’s usefulness given the user’s preference), the MADM technique introduces drastic changes in the decision ranking order for various network interfaces. Figure 5.5 and 5.6 clearly depicts the instability in the ranking order with variability in the corresponding metric.

For instance, as the uncertainty in measured throughput has impreciseness of the magnitude 1% to 8% at any given instance of time, then the user is provided with a ranking score that opts for WiMAX to 802.11 b. However, if the fluctuation increases to 15%, then the user is provided with an entirely new set of interface choices that could fail to satisfy
the user demands and cause re-routing of data packets. Hence, using MADM approach such as TOPSIS carries out the selection process under the assumption that the network state information is static and any change in the metric value causes a disturbance in the ranking order. While MADM approach is suitable for handling multiple criteria, changing conditions affect the algorithm’s overall performance.

On the other hand, our FCM with multiple interfaces and complete uncertainty tactfully handles this variation in the measured metric since we consider all possible range values
Figure 5.7: VoIP network ranking under uncertainty with FCM

and encompass them into one single payoff value for the network. Hence, any magnitude of changes in the network conditions under practical scenario does not impact the user’s decision in selecting a network interface and the multiple constraints are guaranteed to be satisfied. Our FCM generates a stable ranking order in spite of the changes made to the prevailing network conditions as can be seen in Figure 5.7. For instance, if VOIP requires medium link stability, then through our FCM, we provide a certain ‘immunity’ to the network by specifying a range for the medium link stability that deals with variations in the measured value within that range, such that it will not impact the ranking order of the wireless interfaces. Hence, the network selection remains stable and eliminates the need to know the exact value of the network condition at every instance.

We implemented TOPSIS with web browsing under the same set of conditions and Figure 5.8 clearly portrays the order of interface selection under these set of constraints. One interesting observation in this scenario of web traffic is with respect to the ranking values of the latency. Variability in the latency shows little change in the ranking order of GSM/GPRS. This is due to the fact that the latency values for this particular interface is very high as compared to the others as seen in Table 3.1. Hence, the ‘low’ range for latency has little impact and the variability we introduce produces negligible changes in the overall
Figure 5.8: Web browsing network ranking under uncertainty with TOPSIS

ranking. As the user latency requirements for web browsing is ‘medium’, GSM/GPRS has a very low ranking value. Our FCM implemented with web browsing affirms the fact that our model remains stable to changes in the network conditions and this is evident from Figure 5.8.

To further validate our work and explanations based out of TOPSIS, we repeated the similar simulation scenarios using SAW, another popular MADM technique. Using the same set of constraints running the two application, VoIP and Web browsing, we demonstrate that ranking order fluctuates at different points for the various interfaces when implemented with SAW. Another interesting fact is that, ranking values with TOPSIS vary gradually while SAW depicts a sharp change in the ranking scores. Using SAW, variations in the ranking
score for VoIP are vividly seen in Figures 5.9, 5.10, 5.11 and 5.12 and the overlapping values show that ranking orders changed during different levels of input. We observe that the classical SAW is significantly more sensitive to variations while our approach ensures stability in the network selection process and guarantees user satisfaction.

These simulations also demonstrate how each attribute influences the network ranking values and aids in the decision process. As compared to the link stability and throughput, latency shows relatively small changes in the ranking order. This is due to the fact that latency is influenced by the link stability (according to our classification model), and therefore the impact of varying latency alone is much smaller than varying latency alongside with
the link stability. Results obtained by implementing web browsing with SAW are shown in Figures 5.13, 5.14 and 5.15. The output as seen in 5.16 demonstrates our enhanced FCM producing steady ranking scores with respect to Web browsing when implemented with SAW.

These results also demonstrate how SAW and TOPSIS rank networks differently, given the same constraints and weights. Hence, even under the same set of conditions and input parameters, different ranking approaches give different outcomes and the choice of the ranking scheme is left to the decision maker’s discretion and desirability. Our proposed approach can easily be adapted to any classic decision making problem efficiently, and
Figure 5.13: Web browsing network ranking under link stability variation with SAW

Figure 5.14: Web browsing network ranking under latency variation with SAW

the simulation results of TOPSIS and SAW justify this argument. With our proposed FCM, decision making can now be accomplished with imprecise data, and the problem of uncertainty in MADM can be easily avoided.
Figure 5.15: Web browsing network ranking under throughput variation with FCM

Figure 5.16: Web browsing network ranking under uncertainty with FCM
Chapter 6

Decision Making Under Complete Ignorance

The earlier chapters handled network uncertainty by blending our FCM with payoff matrix and assigned crisp weights to various parameters while this chapter deals with the user demands and unique methods of collaborating user ignorance with our FCM that could assist in the decision making process. Since we look at uncertain conditions from both the user and the network perspective, decision making under complete ignorance (DMUCI) proposed in this work is an extension to the existing DMUI introduced by Ronald R. Yager [47]. By studying the experiments and results conducted in Chapter 5, we concluded the stability in the ranking order obtained using our enhanced FCM as compared to existing algorithms on multiple attribute decision making. This motivated our research on an entirely different class of decision making algorithms that involves user impreciseness as well. We combine the advantages of the FCM and derived the payoff matrix with a concrete and definite decision making strategy and introduce a ranking order for DMUCI.

As shown in the previous chapters, decision making is a broad area of study and has varied flavours associated with it. Decision making under ignorance or complete uncertainty deals with the problem of selecting the most favourable choice in the light of complete un-
awareness of the environment [18]. The decision maker is unaware of the occurrence of events leading to the current state. The evaluation of each alternative and the ranking mechanism often conflicting in nature, is carried out by multiple attributes and criteria. They may have different preference values and weights assigned during the selection process. In a wireless networking scenario, uncertainty tends to exist both at the network and the user’s end. In a similar manner, MC demanding a certain threshold of performance from the network may state their needs in a linguistic manner that can be easily comprehended by a common user.

An important class of decision making approach became widespread with the advent of Minimization of Maximal Regret (MMR). Yager [47] generalized the MMR algorithm to work with Ordered Weighted Average (OWA) and Demspter Shefer (D-S) belief structure, which are known for decision making under uncertainties. These approaches gave a new dimension to making a selection by stressing upon the decision makers attitudes under various circumstances. Yager basically combined numerous parameters and a total uncertainty of the prevailing attributes and alternatives and implemented a decision making algorithm by extending the conventional MMR approach.

6.1 Decision Making Using Minimization of Maximal Regret

Minimization of Maximal Regret (MMR) has been one of the earliest decision making approaches under complete ignorance coined by Savage in [48]. This technique works by depicting the user’s regret for choosing an alternative, and strives to select the one with minimal value. MMR considers imprecise information, thereby eliminating the need to translate them to concrete values. The choice of alternatives can be widely subjective and will be assumed based on user’s personal preferences.

The MMR algorithm works by first constructing a decision matrix comprising of attributes and alternatives. Consider the following decision matrix:
where $A_1...A_m$ are the possible set of alternatives available to the decision maker and $C_1...C_n$ are the attributes associated with some value. $w_{ij}$ represent the cost incurred by every user if alternative $A_i$ is chosen, and the respective attribute value is $C_j$. The aim of MMR is to find the maximal regret or cost value associated with every alternative and pick the one which has the minimal regret to the user. The MMR procedure builds a regret matrix from the decision matrix, whose elements show the decision maker’s regret in selecting an alternative $A_i$ for a given attribute $C_j$ with the associated payoff $w_{ij}$. For each alternative, we compute the maximal regret and the ranking score is obtained by selecting the minimal of the maximal regret. The formal steps in the basic MMR algorithm devised by Savage [48] are illustrated below:

1. Compute $W_j = Max[w_{ij}]$ for each $C_j$, and all $A_i$.

2. Compute $r_{ij} = W_j - w_{ij}$ for each combination $A_i$ and $C_j$.

3. Compute $R_i = Max[r_{ij}]$ for each $A_i$, and all $C_j$.

4. Select $A_i^*$ such that $R_i^* = Min[R_i]$.

In the above mentioned steps, $r_{ij}$ represents the regret matrix, $R_i$ is the maximal regret obtained for each alternative and $R_i^*$ is the minimal of the maximal regret derived for each alternative. We modify MMR, by using different $W_j$ equations for each $C_j$:

$$W_j = Max[w_{ij}] .$$  \hspace{1cm} (6.1)
\[ W_j = \text{Min}[w_{ij}], \quad (6.2) \]

Equation 6.1 is applied to beneficial constraints where we filter out the maximal payoff and Equation 6.2 is used for non-beneficial constraints where minimum value is desired. Consequently,

\[ r_{ij} = |W_j - w_{ij}|. \quad (6.3) \]

Additionally, the regret matrix is normalized in the range \([0,1]\). Since the network metrics have different units of measurements, normalization is done to facilitate a fair comparison between them. Normalization is carried out as follows:

\[ N(r_{ij}) = r_{ij} / (W_{j\text{max}}' - W_{j\text{min}}'). \quad (6.4) \]

Finally, the maximal regret is then computed by

\[ R_i = \text{Max}_i[r_{ij}]. \quad (6.5) \]

### 6.2 Modified MMR for Network Selection Satisfying Multiple Constraints

The significance of MMR lies in handling complete uncertainty and we employ this approach at every MC to rank available network interfaces, thereby enabling the user to forward data to a network that efficiently satisfies multiple constraints. We introduce all possible combination of user constraints in our implementation. The novelty lies in coupling the network and user uncertainty while simultaneously giving adequate importance to multiple constraints. To the best of our knowledge, MMR has never been implemented as a network selection algorithm and our research introduces this, while adding a new dimension to wireless access technologies with realistic scenarios.
Table 6.1: Key Component Bounds by Different Network Type

<table>
<thead>
<tr>
<th>Parameter</th>
<th>WiMax (802.16 e)</th>
<th>WiFi (802.11b)</th>
<th>WiFi (802.11g)</th>
<th>WiFi (802.11n)</th>
<th>GSM/GPRS (2.5G)</th>
<th>UMTS (3G)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node Density</td>
<td>20-70 %</td>
<td>10-60 %</td>
<td>12-60 %</td>
<td>15-70 %</td>
<td>7-30 %</td>
<td>7-30 %</td>
</tr>
<tr>
<td>Transmission Rate</td>
<td>20-75 Mbps</td>
<td>4-11 Mbps</td>
<td>12-54 Mbps</td>
<td>60-150 Mbps</td>
<td>0.02-0.09 Mbps</td>
<td>1-2.5 Mbps</td>
</tr>
<tr>
<td>Packet Loss Rate</td>
<td>2-6.5 %</td>
<td>0.5-15 %</td>
<td>1.5-5 %</td>
<td>3-5.5 %</td>
<td>2-3 %</td>
<td>2-4 %</td>
</tr>
<tr>
<td>Link Stability</td>
<td>5-20 %</td>
<td>30-80 %</td>
<td>20-50 %</td>
<td>30-70 %</td>
<td>20-50 %</td>
<td>20-50 %</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>5-18 MHz</td>
<td>8-20 MHz</td>
<td>8-20 MHz</td>
<td>20-40 MHz</td>
<td>0.2-1 MHz</td>
<td>1-5 MHz</td>
</tr>
<tr>
<td>Latency</td>
<td>20-40 ms</td>
<td>30-70 ms</td>
<td>10-50 ms</td>
<td>10-35 ms</td>
<td>120-500 ms</td>
<td>90-250 ms</td>
</tr>
<tr>
<td>Achievable Throughput</td>
<td>12-18 Mbps</td>
<td>4-11 Mbps</td>
<td>15-22 Mbps</td>
<td>40-100 Mbps</td>
<td>0.02-0.04 Mbps</td>
<td>0.05-1 Mbps</td>
</tr>
</tbody>
</table>

Wireless networks equipped with interfaces to GSM/GPRS, UMTS, 802.11 WiFi b/g/n and 802.16 WiMAX would possess performance characteristics as depicted in Table 3.1. We focus on these networks and forward data to the best possible network satisfying the user’s imprecise constraints. Utilizing values of Table 3.1 as shown in Table 6.1, a crisp payoff value is derived for each network’s performance constraint and is shown clearly in Table 6.2. The payoff matrix obtained by resolving the network uncertainty is now employed in our modified version of MMR. For example, if the user specifies the preference set as medium link stability, medium delay and high throughput, a decision matrix is constructed by choosing the corresponding values computed for each network’s metric. In this case, the decision matrix becomes:

Table 6.2: Payoff Matrix

<table>
<thead>
<tr>
<th>Metrics</th>
<th>WiMax (802.16e)</th>
<th>WiFi (802.11b)</th>
<th>WiFi (802.11g)</th>
<th>WiFi (802.11n)</th>
<th>GSM/GPRS (2.5G)</th>
<th>UMTS (3G)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Link Stability (%)</td>
<td>0.5448</td>
<td>0.2</td>
<td>0.7</td>
<td>1.2154</td>
<td>3.5</td>
<td>0.3</td>
</tr>
<tr>
<td>Latency (ms)</td>
<td>1.7148</td>
<td>8.8352</td>
<td>18.79</td>
<td>1.2607</td>
<td>2.3</td>
<td>1.25</td>
</tr>
<tr>
<td>Throughput (Mbps)</td>
<td>2.115</td>
<td>1.2</td>
<td>1.2</td>
<td>1.9428</td>
<td>2</td>
<td>0.185</td>
</tr>
</tbody>
</table>
Hence, the decision matrix reduces to:

\[
W_j \begin{pmatrix}
\text{Link Stability} & \text{Latency} & \text{Throughput} \\
\text{WiMAX} & 0.7000 & 8.3333 & 1.2000 \\
\text{802.11n} & 1.2143 & 1.2667 & 2.0000 \\
\text{802.11g} & 1.1364 & 3.6111 & 3.3333 \\
\text{802.11b} & 1.0000 & 3.2000 & 0.5430 \\
\text{UMTS} & 2.0000 & 6.1583 & 0.1035 \\
\text{GSM/GPRS} & 2.4044 & 30.000 & 0.006
\end{pmatrix}
\]

The regret matrix \( r_{ij} \) for each pair of network is calculated from the constraints as:

\[
W_j \begin{pmatrix}
\text{Link Stability} & \text{Latency} & \text{Throughput} \\
\text{WiMAX} & 1.7044 & 7.0666 & 2.1333 \\
\text{802.11n} & 1.1901 & 0.0000 & 1.3333 \\
\text{802.11g} & 1.2680 & 2.3444 & 0.0000 \\
\text{802.11b} & 1.4044 & 1.9333 & 2.7903 \\
\text{UMTS} & 0.4044 & 4.8916 & 3.2295 \\
\text{GSM/GPRS} & 0.0000 & 28.733 & 3.3273
\end{pmatrix}
\]

The normalized regret matrix is calculated as:
Finally, the maximal regret for the normalized regret matrix is found as:

$$
\begin{bmatrix}
\text{WiMAX} & 1.0000 & 0.2459 & 0.6411 \\
802.11n & 0.6982 & 0.0000 & 0.4006 \\
802.11g & 0.7439 & 0.0815 & 0.0000 \\
802.11b & 0.8239 & 0.0672 & 0.8386 \\
UMTS & 0.2372 & 0.1702 & 0.9706 \\
GSM/GPRS & 0.0000 & 1.0000 & 1.0000 
\end{bmatrix}
$$

The minimal of the maximal regret is the preferred choice of network alternative satisfying these three constraints. Therefore, \text{WiFi n} has the minimal regret value. Hence, this network is the desired alternative to the MC. In our modified MMR approach, it can be clearly seen that the need to translate the user’s linguistic variables to crisp weight values is eliminated and efficient ranking is still achieved that helps in decision making and achieving our goal.

### 6.3 Simulation and Comparison of Results

This section explains the simulation steps that demonstrates the significance of MMR as compared to classic MADM strategies. Extensive experiments are carried out in a HWN scenario, comprising of the following networks: \text{802.16 WiMAX}, \text{802.11 WiFi b/g/n}, \text{UMTS} and \text{GSM/GPRS}. All possible combinations of user constraints are considered using the three simplistic terms: ‘low’, ‘medium’ and ‘high’ and the three metrics namely, link stability, latency and throughput. The novelty of our approach in comparing with existing MADM methods is evident in eliminating the need to translate the user constraints to weight values so as to obtain the ranking score. As done in our previous experiment, we
use existing SAW and TOSPSIS approaches in comparing our results.

Simulation results show the sensitivity and influence of the user constraints on the ranking order of the networks. The results also reflect how the constraints behave differently based on the network and inherent characteristics. The ranking order also varies based on the strategy implemented. From Figures 6.1 and 6.2, the weight of the link stability is varied while the other two metrics, latency and throughput are kept constant. Using these conditions and all possible combinations of user preferences, we observe that the ranking
score for various networks increases for certain values of link stability, while drop down in other cases. Such a difference is observed as we increase the link stability’s weight, there are scenarios where the user could demand a low throughput and a low latency. In this case, the ranking score fluctuates and the value drops.

As compared to SAW, TOPSIS shows a steady behaviour in the ranking values. Under the same conditions used for SAW, TOPSIS shows an increase in the ranking values for certain networks like UMTS and GSM/GPRS while the score decreases in other scenarios like 802.11 WiFi n and 802.16 WiMAX. Results also show that variation in the link stability has a very little impact on 802.11 WiFi g whose ranking value remains consistent. Variation in the link stability can be computed with MMR and Figure 6.3 depicts that 802.11 WiFi n is influenced most when the ranking value drops to as low as zero under certain constraint conditions. 802.16 WiMAX shows a steady increase in the ranking values as the weight assigned to link stability is increased.

Similarly, the experiments are repeated by varying the latency and keeping the other two constraints unchanged, under the same set of conditions. Figures 6.4, 6.5 and 6.6 demonstrate our results, and with SAW, the trend is quite similar to the results seen with respect to the link stability variation. However, with regards to the latency variation, 802.11 WiFi
Figure 6.4: Variation in the Latency with Constant Link Stability and Throughput

Figure 6.5: Variation in the Latency with Constant Link Stability and Throughput

\( n \) shows a noticeable increase in the ranking score as compared to the link stability. The results also show a difference in the ranking order for both the scenarios. This explains how various networks behave differently when the performance metrics are varied. The capability of each network is considered, which explains these differences using the SAW method. Experiments with MMR shown in Figure 6.6 illustrates that 802.11 WiFi \( n \) again drops to zero value as the weight assigned to the latency is increased. Hence, when the latency is at a peak, 802.11 WiFi \( n \) provides no performance enhancement, which portrays the sensitivity of this network with respect to given metrics.
Figure 6.6: Variation in the Latency with Constant Link Stability and Throughput

Variations in the throughput values while maintaining the other two metrics constant is depicted in Figures 6.7, 6.8 and 6.9. While SAW exhibits similar behaviour, TOPSIS shows a steady and consistent change in the ranking values for all the networks. However, MMR shows that we obtain a different ranking value for each network as the throughput constraint increases.

Figure 6.7: Variation in the Throughput with constant Link Stability and Latency

In this case, 802.11 WiFi n score shows a consistent increase with an increase in demand for throughput. This shows that 802.11 WiFi n tends to be more favourable towards the
throughput performance as compared to other metrics. 802.16 WiMAX and GSM/GPRS also exhibit an increasing value while 802.11 WiFi b’s value drops. This indicates that this network’s performance depends on other metrics as well.

Simulations use MMR and directly applied the user constraints without converting them to crisp values and a network selection is efficiently carried out in a manner similar to SAW and TOPSIS. Hence, multiple attributes are handled and decision making under complete ignorance is executed effectively using MMR approach. This avoids the additional overhead.
of converting the user’s imprecise preferences to weights unlike other MADM techniques. While MMR shows varying behaviour for various networks under different scenarios, it also indicates that this approach is not solely determined by only one metric, which is true in practical and dynamic situations.
Chapter 7

Generalized Approach of MMR for Network Selection

In the previous chapter, we discussed in depth the implementation of a modified version of MMR as a network selection algorithm and rank the alternatives based on imprecise user constraints. Comparison of this algorithm with two other MADM approaches showed that unlike the conventional methods, MMR eliminated the need for translating the linguistic terms to crisp values. This was made possible through our payoff matrix which efficiently handles the network uncertainty. Yager has generalized the MMR algorithm to carry out decision making which is discussed in detail in [47]. We utilize this extension of MMR to carry out the network selection process using ignorance and involving multiple criteria.

There are several reasons behind our choice of using Ordered Weighting Average (OWA) [18] in this research. Firstly, OWA deals with multiple criteria and attributes which is parallel to our line of work. Given a set of alternatives and attributes, OWA’s priority is to pick a suitable alternative and can be applied to our problem of satisfying multiple constraints in a HWN by selecting the best interface to forward the data. However, the most important factor which distinguishes OWA from MMR is the weight vector employed which helps us model the imprecise user constraints as crisp weights. Though MADM also assigns weights,
OWA is proven to be an optimal technique under ignorance [18] and adds a different dimension to decision making process by exploiting the decision maker’s attitude. Hence, extending MMR with OWA operator helps us perform a reasonable comparison with existing MADM approaches and motivates us to venture upon an innovative approach in the history of decision making algorithms for a HWN.

### 7.1 Application of Ordered Weighted Averaging to MMR

A generalized technique to carry out optimal alternative selection has been elaborated in [18] where Ordered Weighting Averaging (OWA) operators are applied to the basic MMR algorithm to come up with a favourable alternative selection method. An OWA operator of measurement $n$ is a function represented as:

$$F : R^n \rightarrow R. \quad (7.1)$$

Additionally, OWA operator comprises of a weight vector $W$ denoted as:

$$W = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} \quad (7.2)$$

such that the following two conditions are satisfied:

1. $w_i \in [0, 1]. \quad (7.3)$
2. $\sum_i w_i = 1. \quad (7.4)$
As the name implies, OWA computation takes place by applying the function and basic aggregation operator for any set of inputs $a_1, a_2, ..., a_n$.

$$F(a_1, a_2, ..., a_n) = \sum_i (w_i \cdot c_i).$$  \hspace{1cm} (7.5)

In the Equation 7.5, $c_i$ represents the largest component in the set of inputs $(a_1, a_2, ..., a_n)$ passed to the function.

### 7.2 OWA as a Network Selection Operator

To better demonstrate the working of an OWA operator and the usage of it’s components, we consider our heterogeneous scenario comprising of the six interfaces and proceed to explain the procedure by initiating the steps involved in the MMR algorithm. Considering the following set of user constraints:

<table>
<thead>
<tr>
<th>Link Stability</th>
<th>Latency</th>
<th>Throughput</th>
</tr>
</thead>
<tbody>
<tr>
<td>User Constraint</td>
<td>High</td>
<td>Medium</td>
</tr>
</tbody>
</table>

For these set of constraints, MMR begins by first constructing the decision matrix utilizing the payoff values obtained for each in network in Table 5.1. The given set of preferences generates the following decision matrix:

$$\begin{pmatrix}
\text{Link Stability} & \text{Latency} & \text{Throughput} \\
\text{WiMAX} & 1.7500 & 8.3333 & 0.1190 \\
802.11n & 2.5000 & 1.2667 & 0.6670 \\
802.11g & 7.083 & 3.6111 & 0.1385 \\
802.11b & 3.429 & 3.2000 & 0.0914 \\
UMTS & 6.0000 & 6.1583 & 0.0002 \\
GSM/GPRS & 5.769 & 30.000 & 0.0007 \\
\end{pmatrix}.$$
The next step is to construct the matrix of maximum utility value for every constraint listed in the decision matrix as shown in Equations 6.1 and 6.2. $W_j$ is computed as:

$$W_j \left( \begin{array}{ccc} \text{Link Stability} & \text{Latency} & \text{Throughput} \\ 7.0830 & 1.2667 & 0.6670 \end{array} \right).$$

The regret matrix $r_{ij}$ for every pair of interface and metric is calculated using Equation 6.3 and is:

$$\begin{array}{ccc}
\text{Link Stability} & \text{Latency} & \text{Throughput} \\
\text{WiMAX} & 5.333 & 7.0666 & 0.548 \\
802.11n & 4.583 & 0.0000 & 0 \\
802.11g & 0 & 2.3444 & 0.5285 \\
802.11b & 3.654 & 1.9333 & 0.5756 \\
UMTS & 1.083 & 4.8916 & 0.6668 \\
GSM/GPRS & 1.314 & 28.733 & 0.6663 \\
\end{array}$$

To attain a comparable scale, the regret matrix is normalized using Equation 6.4 and calculated as:

$$\begin{array}{ccc}
\text{Link Stability} & \text{Latency} & \text{Throughput} \\
\text{WiMAX} & 1.0000 & 0.2459 & 0.8218 \\
802.11n & 0.8593 & 0.0000 & 0.0000 \\
802.11g & 0.0000 & 0.0815 & 0.7926 \\
802.11b & 0.6851 & 0.0672 & 0.8632 \\
UMTS & 0.2031 & 0.1702 & 1.0000 \\
GSM/GPRS & 0.2464 & 1.0000 & 0.9990 \\
\end{array}$$

Now, basic MMR computes the maximal regret matrix using Equation 6.5. However, we apply the OWA operator at this stage and compute the maximal regret matrix. To achieve
this, we first define a weight vector for the ordered set of arguments. Now, we assign the following weights to the set of user constraints defined in Figure 7.2. The weight vector is defined as follows:

\[
W = \begin{bmatrix}
0.5 \\
0.3 \\
0.2
\end{bmatrix}
\]  

(7.6)

Equation 7.6 shows that the conditions defined for a weight vector are satisfied where the values lie in the range \([0,1]\) and the sum of values equals 1. The function \(F\) is defined for every row in the regret matrix as seen Figure 7.2 and the weights are associated with every element of the function \(F\). The following are the set of functions described for each interface:

\[
\begin{align*}
WiMAX &= F_1(1.0000 \ 0.2459 \ 0.8218). \\
802.11n &= F_2(0.8593 \ 0.0000 \ 0.0000). \\
802.11g &= F_3(0.0000 \ 0.0815 \ 0.7926). \\
802.11b &= F_4(0.6851 \ 0.0672 \ 0.8632). \\
UMTS &= F_5(0.2031 \ 0.1702 \ 1.0000). \\
GSM/GPRS &= F_6(0.2464 \ 1.0000 \ 0.9990).
\end{align*}
\]

(7.7-7.12)

For the set of values defined for each function, we associate them with the weight vector shown in Equation 7.6 as follows:

\[
\begin{bmatrix}
\text{Link Stability} \\
\text{Latency} \\
\text{Throughput}
\end{bmatrix}
\begin{bmatrix}
\text{High} \\
\text{Medium} \\
\text{Low}
\end{bmatrix}
\]

Then, we apply Equation 7.5 to obtain the maximal regret matrix. As per the definition of OWA, we associate each weight \(w_i\) where \(i = 1...n\) with the largest element in the set of values belonging to each function. Hence, considering the function for \(WiMAX\), the OWA
computes as follows:

\[ F_1(1.0000 \ 0.2459 \ 0.8218) = (0.5 \times 1.000) + (0.3 \times 0.8218) + (0.2 \times 0.2459). \]  
\[ = 0.5 + 0.2465 + 0.04918. \]  
\[ = 0.7956. \]

The value 0.7956 is the maximal regret value computed for the WiMAX interface. In a similar manner, the computations are carried out for every interface’s function and the maximal regret matrix obtained is as follows:

\[
\begin{pmatrix}
\text{WiMAX} & \text{802.11n} & \text{802.11g} & \text{802.11b} & \text{UMTS} & \text{GSM/GPRS} \\
0.7965 & 0.4296 & 0.4207 & 0.6505 & 0.5949 & 0.8489
\end{pmatrix}
\]

The most favourable alternative depends on the minimal of the maximal regret value and this choice satisfies the three constraints. Hence, based on the values in Figure 7.2, 802.11g has the minimal regret value and is the preferred choice of an alternative for the MC.

### 7.3 Comparison of OWA with MADM approaches

This section elaborates the simulation analysis carried out to compare the sensitivity of user’s demands and weights assigned to various metrics to show their influence on the network selection. Although, multiple constraints specified by the user are considered for selecting a route, there is always some factor amongst those user preferences that will have a greater impact on a particular interface being selected. Our work progresses by considering this variation in the weights being assigned to the user preferences and their corresponding network ranking score. Although OWA and MADM approaches focus on the same goal of selecting the best possible network, we do a thorough study of the user sensitivity on the network ranking and compare them by utilizing these approaches. The implementation is carried out by considering one constraint and varying the weight assigned to it while keeping
the other two constraints constant. In this manner, we observe the network behaviour with regards to this particular constraint whose user weight is varied. We repeat this for all the metrics under consideration namely, link stability, latency and throughput. This ensures that all possible combinations of user constraints are satisfied which are specified using the linguistic terms ‘low’, ‘medium’ and ‘high’.

![Figure 7.1: Variation of the Link Stability with TOPSIS](image1)

![Figure 7.2: Variation of the Link Stability with SAW](image2)

Figures 7.1, 7.2 and 7.3 depict the impact of varying the link stability metric on ranking of the interfaces in a HWN. The other two metrics, namely latency and throughput are kept
constant and the results are observed which show SAW to be more sensitive to variation in link stability in comparison with TOPSIS and OWA. While TOPSIS shows gradual rise in the ranking values, SAW depicts a sharp increase in the ranking scores for UMTS and GSM/GPRS networks. It is also distinctly seen that cellular networks such as UMTS and GSM/GPRS demonstrate a higher ranking value as the weight assigned to link stability increases. WiFi 802.11g reaches the maximum ranking value of 1 when the user’s preference to link stability is 1. This implies that the weight assigned to other two metrics are 0 (in order to have the sum of weights equal to 1) and hence, providing maximum priority to link stability ranks WiFi 802.11g as the most efficient network. This pattern is observed with TOPSIS as well as SAW. On the other hand, when a weight value of 1 is assigned to the link stability, WiMAX’s rank drops to zero when implemented with TOPSIS. Hence, WiMAX shows a better level of user satisfiability when the link stability is coupled with other network factors. Variation in the link stability when implemented with OWA provides stable results in comparison to TOPSIS and SAW.

Experiments are repeated in a similar manner by varying the user preference for latency while maintaining the link stability and throughput as constant. The output obtained is given in Figures 7.4, 7.5 and 7.6.
As compared to the results obtained earlier with link stability, latency portrays an entirely different scenario where the performance score of Wifi 802.11n appears to be extremely favourable to the user as compared to other interfaces. With TOPSIS, the ranking value for Wifi 802.11n reaches the maximum value of 1 and SAW seems to provide a relatively high ranking value too. The capability of this interface doesn’t show any difference during the execution of OWA where the ranking value reaches zero. Since the ranking value for OWA actually represents the regret value, the minimum value of 0 indicates Wifi 802.11n provides no regret and has the maximum ranking efficiency. Similarly, the perfor-
formance of GSM/GPRS shows unfavourable ranking scores when implemented with all the three algorithms.

In case of OWA, a higher value shows the maximum regret and hence GSM/GPRS is the least opted for in the above considered scenario when only latency is varied. Each interface is equipped with the ability to satisfy some constraints maximally than the others when the constraints are varied. Hence, in a multi-constraint scenario, implementing a HWN provides the user with a wide variety of QoS offered by various interfaces involved in the scenario.

Variation in throughput weight and their corresponding influence on the network’s performance is illustrated in Figures 7.7, 7.8 and 7.9. While a steady ranking order is observed by WiMAX in all the approaches, WiFi 802.11n and 802.11g seems to be more preferred for forwarding data while the cellular networks comprising of the UMTS and GSM/GPRS seem to be the least opted choice with their low ranking values. However, one interesting thing noted is the behaviour of WiFi 802.11b in the three cases. While SAW and TOPSIS implementation shows a lower ranking value for the above mentioned interface, OWA shows a minimum regret (maximum rank value) for WiFi 802.11b as the weight assigned by the user to throughput increases. This clearly explains the difference involved with various
ranking approaches and how OWA shows a steady increase or decrease in values based on the varied conditions executed for each user preference.

Conventional MADM focusses on decision making involving multiple attributes and alternatives. But, in a real life scenario, conditions and factors influencing any application or entity is not static and fixed. With changes evolving at every instance of time, the concept of uncertainty is a significant but a dormant factor. While it is always easier to consider known conditions to approach a problem, we resorted to a more difficult and challenging approach
where complete uncertainty prevails in the user’s domain and in the network conditions. Handling this incomplete and qualitative information in wireless communication is our key motivation and decision making techniques such as MMR and OWA provided an innovative blend in addressing this problem.

Figure 7.9: Variation of the Throughput with OWA
Chapter 8

Conclusion and Future Work

8.1 Conclusion

While earlier published works addressed the multi-constrained path selection by defining heuristic models and approximation algorithms, our work solves this problem considering dynamic and practical impreciseness. We integrated multiple metrics in a heterogeneous scenario where MCs are equipped with multiple network interfaces and are capable of simultaneously connecting to GSM/GPRS, UMTS, 802.11 WiFi b/g/n, and 802.16 WiMAX.

We aim at selecting the best possible network that is capable of routing the data while satisfying the user constraints upto the specified preference level. The crucial factor in our work lies in exploring various performance metrics and emphasize on uncertainty and vague conditions from both the network and the user point of view.

We developed a fuzzy based mechanism that allows for multiple attribute decision making (MADM) algorithms and efficiently deals with uncertainty. Our fuzzy classification model identifies a number of metrics that play a key role in governing the network performance. Based on the fuzzy model, we proceed to define the fuzzy inference rules and operators that relate and bind the key constraints. Our final step of defuzzification and calculation of payoff matrix for each interface shapes our proposed fuzzy model and makes
it fully functional. These crisp values aid in the decision making process and we define a modified Minimization by Regret (MMR) by utilizing values derived from the payoff matrix. Simulation results obtained from experiments involving the fuzzy model under practical scenarios indicate that our approach does not affect the user’s way of selecting the networks due to negligible changes in network conditions while still satisfying multiple constraints. The ranking order obtained by our method remains stable irrespective of changes made to the network conditions within the particular range specified by the application requirements.

While MMR deals with complete user uncertainty, we generalize MMR and apply Ordered Weighted Averaging (OWA) operators to model the user constraints with weight values. This implementation leads us to interesting analysis and simulation results where we vary each metric’s weight value while keeping the others constant. In this process, we observe that the relative ordering of the wireless interfaces is highly influenced by various metrics involved at each instance of time. These simulations are carried out using conventional MADM techniques and our proposed MMR and generalized MMR with OWA. Hence, this research carefully blends the network and user uncertainty and proposes efficient mechanisms for decision making in a communication industry.

8.2 Future Work

An interesting extension to this work would be to integrate the network ranking and repeat these experiments at each point to establish an optimal path to the destination. This work also provides scope for implementing another popular decision making under ignorance techniques, namely, the Demspter Shefer (D-S) belief structure. D-S belief structure is a popular field in the area of decision making and considers multiple criteria and alternatives. Extending MMR with D-S by utilizing our proposed fuzzy model can lead to interesting observations and results.
Bibliography


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