OPTIMIZING THE SERVICE POLICY OF A MOBILE SERVICE PROVIDER THROUGH COMPETITIVE ONLINE SOLUTIONS TO THE 0/1 KNAPSACK PROBLEM WITH DYNAMIC CAPACITY

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ABSTRACT

OPTIMIZING THE SERVICE POLICY OF A MOBILE SERVICE PROVIDER THROUGH COMPETITIVE ONLINE SOLUTIONS TO THE 0/1 KNAPSACK PROBLEM WITH DYNAMIC CAPACITY

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Demand for sustainable and environmentally friendly communication systems with energy efficient transmission schemes has increased eminently in the last decades. Resource allocation problems for energy harvesting networks have been studied and many offline solutions have been proposed. An online problem is examined throughout this thesis. Recent industry efforts to provide Internet service to areas deprived of telecommunications infrastructure have been the main inspiration for the studies conducted here. A mobile Internet service provider, a flying platform in the lower stratosphere empowered by the renewable energy (solar, wind, etc.), is envisioned to provide Internet access to the users as it moves over an area. Throughout its path, the station aims to achieve maximum throughput by responding to the demands of the users while prudently managing its available energy. Given the related background, first, the problem is modelled as a 0/1 knapsack problem. Then, several online heuristics are proposed using threshold policies obtained through various methods applied to the decision problem, including rule-based heuristics. Performances of these policies are compared via competitive ratio analysis with the optimal offline solution, which yield a computationally efficient outcome.

Keywords: Energy Harvesting, Service Provider on the Move, Competitive Ratio Analysis, Deterministic Resource Allocation, Online Heuristics, Efficient Threshold Determination Techniques, Genetic Algorithm, Rule Based Optimization, Decision Problem, 0/1 Knapsack Problem, Knapsack with Dynamic Capacity

ÖZ

DİNAMİK KAPASİTELİ 0/1 KNAPSACK PROBLEMİNE REKABETÇİ ÇEVRİMİÇİ ÇÖZÜMLER GETİREREK HAREKETLİ SERVİS SAĞLAYICILARIN SERVİS VERME POLİTİKALARINI ENİYİLEME

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Son yıllarda enerji verimli gönderim şemalarına sahip, kendi-kendine yetebilen ve çevre dostu haberleşme sistemlerine duyulan ihtiyaç önemli ölçüde artmıştır. Şu ana kadar yapılan çalışmalarda enerji hasatı yapan ağların kaynak paylaşım problemlerinde kullanılabilecek çevrimdışı çözümler üzerine çalışılmış ve birçok yöntem önerilmiştir. Bu tez kapsamında çevrimiçi bir problem incelenmiştir. Son yıllarda endüstriyel girişimlerle geliştirilmesi ve yaygınlaştırılması düşünülen yeterli alt yapıya sahip olmayan bölgelere internet sevisi sağlama fikri bu çalışmanın temel esin kaynağı olmuştur. Güneş, rüzgar gibi yenilenebilir enerji kaynaklarını kullanarak kendi-kendine yetebilen, stratosferde uçan bir platform üzerine yerleştirilmiş mobil servis sağlayıcılar, üzerinden geçtikleri alanlardaki kullanıcılara internet erişimi sağlayarak bu fikri hayata geçirme imkanı sunmaktadır. İzlediği yol boyunca gelen kullanıcı taleplerini en yüksek oranda karşılama eğiliminde servis sağlama amacı taşıyan bu istasyonların, servis devamlılığını garanti edebilmeleri için mevcut enerji kaynaklarını ölçülü bir şekilde kullanmaları gerekmektedir. Konu ile ilgili yapılan çalışmalar incelenerek gerekli alt yapı verildikten sonra problem, 0/1 knapsack problemi olarak modellenmiştir. Daha sonra, kural tabanlı vb. çeşitli yöntemler karar verme problemine uygulanmış ve eşik bulma yöntemi izlenerek çeşitli çevrimiçi çözümlere ulaşılmıştır. Önerilen çevrimiçi çözüm yöntemlerinin performansları çevrimdışı en iyi çözüm ile rekabetçi oran analizi yoluyla karşılaştırılmış ve testler sonucunda bu yöntemlerin performans verimliliği gösterilmiştir.

Anahtar Kelimeler: Enerji Hasatı, Hareketli Servis Sağlayıcılar, Rekabetçi Oran Analizi, Deterministik Kaynak Paylaşımı, Çevrimiçi Çözümler, Etkili Eşik Belirleme Teknikleri, Genetik Algoritma, Kural Tabanlı Eniyileme, Karar Verme Problemi, 0/1 Knapsack Problemi, Dinamik Kapasiteli Knapsack

To my beloved grandma and my dearest family

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TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

AP	Access Point
APOM	Access Point on the Move
DP	Dynamic Programming
GA	Genetic Algorithm
KP	Knapsack Problem
MEMS	Microelectromechanical Systems
MF	Membership Function
WSN	Wireless Sensor Network

CHAPTER 1

INTRODUCTION

The worldwide increase in the demand for energy efficient transmission schemes has prominently enhanced the priority of the self-sustainable communication networks. Wireless communication technologies have introduced mobility as a major advancement, but these suffer from energy constraints due to dependence on batteries. An outstanding implementation area in communications where the energy efficient transmission is important is wireless sensor networks (WSN). The constructed sensor architecture may be spread over a wide area where accessibility of the sensors is limited and changing the batteries is not an option in case of energy depletion. There are several solutions to deal with that challenge. One is to reduce the power consumption to prolong the sensors' lifetime whereas another proposes the use of an energy harvesting system [52].

Energy harvesting communication systems consist of transmitters empowered by environmental renewable resources such as solar, vibration, and thermal etc. The ability to scavenge energy from renewable energy sources is profoundly applicable to distributed networks such as WSNs. For the transmission of information the system may not be able to guarantee the same amount of rate at all times when depending on a variable energy source instead of a constant power supply. The well known resource allocation problem comes into the picture where a decision has to be made considering the forthcoming events in addition to the present demands to achieve effective transmission.

Recently, upgrading the available energy harvesting WSN technology to an inventive level, major industry players have been pushing for ubiquitous Internet access for areas around the world lacking telecommunication infrastructure. For this purpose, mobile Internet service providers (ISP) have been deployed in the Earth's atmosphere (e.g. [19, 36]) and this Layer type wind patterns in the stratosphere allowed changing the locations of these units which is proving to be a promising technology to bring Internet access to such areas. These mobile self-sustainable ISPs provide internet access at 3G speeds to the users at fixed locations such as homes or offices.

Inspired by such a novel initiative, in this thesis, we examine the resource allocation problem of a mobile station, called an Access Point on the Move (APOM). It harvests its own energy particularly using solar cells and tries to maximize the throughput it provides to as many users as possible as it flies over a geographic area. In addition, there may be multiple APOMs covering a certain area. While moving, considering its energy limitation, each APOM should decide which users to be served or left for the next APOM. To the best of our knowledge, there are no known competitive online algorithms in the literature about this version of the problem where the resource capacity is dynamic, which is the case when energy arrivals replenish the available capacity of the access point.

This thesis consists of 8 chapters. The next chapter provides a literature review on related resource allocation problems while stating the conceptual differences with the solutions we plan to propose for our problem. Then, in Chapter 3 a detailed review on a very well known combinatorial optimization problem, 'Knapsack Problem' is provided within the scope of efficient solutions and performance metrics for the deterministic offline and online versions of this problem. In Chapter 4, the system model is introduced thoroughly where the optimal decision problem of resource allocation on user demands is defined and set up as a generalized version of the classical knapsack problem. The optimal offline and online solutions for a non-harvesting stationary service provider is analysed at the first two sections of Chapter 5. Following that the optimality of the online algorithm for the dynamic capacity case assuming some initial constraints is exhibited, and a threshold based heuristic solution to this problem is proposed. Then, the extended optimal model is adapted to energy harvesting mobile access point scenario by proposing two alternative deterministic threshold policies in Section 5.3. Several online heuristics to solve the APOM scenario problems are also presented in Chapter 6, the constructed structure and the compatibility of these methods with APOM problem are further examined. Detailed numerical and simulation results are provided in Chapter 7 where the performance comparison between the heuristics are presented. Finally, the results are interpreted and future directions are outlined in Chapter 8.

CHAPTER 2

LITERATURE REVIEW ON ENERGY HARVESTING NETWORKS

Energy harvesting devices converting ambient energy into electrical energy have attracted much interest in many sectors such as telecommunications, military, MEMS etc. Energy scavenging technology can be used to empower cellphones, mobile computers, radio communication equipment, etc. Solar and piezoelectric energy harvesting are the most common techniques due to their high power densities. Different harvesting schemes requires different means to be efficient and have distinct energy profiles. For example, some systems convert motion, such as that of ocean waves, into electricity to be used by oceanographic monitoring sensors for autonomous operation whereas solar cells take the advantage of sun in a daily period. As stated in [26], energy sources can be categorized as follows: *Uncontrollable and Unpredictable*, *Uncontrolled but Predictable*, *Fully Controllable* and *Fully Predictable*.

In most theoretical works, energy storage device in an energy harvesting system is considered as an energy buffer [5]. The simplest model of energy dynamics for a time-slotted energy harvesting system is as follows:

$$e_{i+1} = (e_i - w_i) + b_i, w_i < e_i \tag{2.1}$$

Here e_i represents the available energy at the i^{th} slot and b_i denotes the harvested energy at that slot whereas w_i stands for the energy consumption. Equation 2.1 presents the available energy amount in the $(i + 1)^{th}$ slot considering the energy expenditures and replenishments in the previous time slot i.

In [49], efficient energy management policies for an energy harvesting sensor network are proposed, first by deriving throughput optimal polices for a single node, then extending the results to multiple sensor structure. Sharma et al. assumed a stochastic model in which data transmission and energy replenishment rate are presumed to be i.i.d. and it is shown that these assumptions are general enough to cover most of the stochastic models developed for traffic and energy harvesting at sensor networks [49]. The optimal power policy can be substantially altered by taking into account the inefficiencies of energy storage in an energy harvesting network. In [55, 56], an average rate maximizing policy is proposed for an energy harvesting transmitter with inefficient energy storage where the transmitter is to transmit with the harvest rate. That may change the total rate throughout the transmission, implying that the optimization problem is an instance of a utility maximization framework.

In [28], a single source node with energy harvesting capability making the decision whether to transmit or not at each slot is examined in detail. In such a structure, the optimal policy is proved to be a threshold type one considering the stochastic channel states and available energies at each instant. The throughput performance on a Gilbert-Elliot Channel based on a threshold type policy is used for the performance results. Tassiulas et al. showed that it is possible to find an optimum maximum throughput policy via equalizing the node pressures (weights) at each server while examining the stability properties of queueing systems and scheduling policies [53]. This fundamental idea is utilized throughout this work as well.

In [41] it is stated that if the net consumption rate is lower than the possible harvesting rate, then it is possible to establish a self-sustaining system via enough mobile nodes. In addition to energy scavenging sensor nodes, recent studies have revealed that employing energy harvesting via alternative energy sources such as solar irradiation [11], vibrations [37] and wind [61] to power transmitters of network devices such as Internet service providers has gained tremendous interest [31, 34] as well.

Meanwhile, the most recent studies conducted by METU Communications Network Research Group should be mentioned separately in this section as well. In [6, 10] identification and localization on a wireless magnetic sensor network is examined in detail, which brings the discussion of whether magnetic sensors to be used in WSNs or not. Considering the sensing limitations of magnetic sensors, target detection, identification and sequential localization were accomplished using *Minimum Euclidean Distance* method. In [7], Baghaee et al. proposed *Orthogonal Matching Pursuit* algorithm for target localization and identification in multiple sensors multiple target case. These studies proved that an energy efficient, intelligent magnetic sensor network could be designed. In [8, 9], the implementation of a WSN demonstration testbed powered up by vibration energy as a part of *E-CROPS* project has been illustrated in addition to demonstration of *Energy-Neutral Operation* for the same setup. In [35], the implementation of a very well-known decision theory problem, *Restless Multi Armed Bandit Problem*, over a single hop network is studied where two scheduling scenarios are proposed mainly. The first transmission scheme under energy harvest constraints tries to find a low complexity scheduling policy whereby the fusion center can collect the maximum amount of throughput in this data backlogged system as also mentioned in [22]. The extended form of this problem is examined in finite and infinite time horizon schemes in [20]. Secondly, the infinite data backlog assumption is lifted. Gul et al. proposed a low-complexity policy called *UROP (Uniformizing Random Ordered Policy)* in [21] and showed its near optimality under *uniform, non-uniform, independent, Markovian* energy harvest processes, the results of which reveal that UROP uses the arriving energy with almost perfect efficiency.

In [1], duty cycle optimization in energy harvesting sensor networks is studied, in which duty cycles of sensor nodes are determined according to energy harvest patterns. In addition, Akgun implemented the proposed algorithms using *Bluetooth Low Energy* technology under indoor and outdoor experimental setups, which revealed that the maximum throughput is achieved. WSN applications with low energy harvesting rates such as piezoelectric or indoor solar cell implementations, it is important to manage the energy harvest and transmission scheme. The ideal transmitter assumption requires the full knowledge on the channel state and power allocation schemes, however in reality this information is provided via feedback channels to the transmitter. Considering this problem, in [47, 48] Shakiba-Herfeh et al. studied the optimization of feedback in *multiple input single output (miso)* downlink multiuser systems with energy harvesting capability where the nodes are designated to distribute their feedback transmissions judiciously across time in order to achieve a certain throughput. In [18, 57], Uctu et al. analysed and made the real life implementation of various scheduling algorithms for energy harvesting systems on a software defined radio setup. Optimal power and rate allocation schemes introduced in [3, 5] are studied for data packets arriving at arbitrary but known instances considering channel state, energy and data buffers' states over an energy harvesting fading channel. Also, the implementation of a very recent study, a near optimal transmission scheme, has been conducted using *Expected Threshold Lazy Scheduling Policy* introduced by Bacinoglu et al. in [4] over a finite horizon fading channel. Energy efficient transmission schemes and throughput maximization transmission scheduling policies are studied in energy harvesting WSN problem setups as previously mentioned above but the mobility concept has not been examined in that sense so far.

The transition from immobile to mobile problem structures first proposed to increase the network longevity. The mobile sensors in communication networks are examined in detail in [16, 39, 50], but the use of renewable energy in mobile sinks is not. The most common offline scheme used in these works involves integer linear programming where the previous knowledge on the sensor nodes and energy schemes are available. Comparing the mobile service providers with fixed ones, the studies in [50, 60] revealed the main benefits of using the mobile service providers. Since path planning turns out to be a critical concept regarding mobility, some of the these studies mainly dealt with determining optimal paths to prolong network lifetime as in [23, 29]. A rule based path planning strategy is adopted by Alkesh et al. in [2] to decide on cluster heads of a network to maximize the lifetime of wireless sensor networks with limited batteries. In this rule based scheme, neither the data collection nor the energy consumption rate are not examined considering the rules developed, only the optimum movement strategy to retrieve a longer lifetime for sensor nodes is proposed.

The recent studies show that most of the resource allocation problems of mobile energy harvesting stations presume a constant service capacity and aim to find an optimal path to meet the maximum service rate as in [43]. Xie et al. address the problem of collocating the mobile service provider on the wireless charging machine in [59] with the objective of minimizing energy consumption an approximate distributed online algorithm applying optimal offline solution method to smaller problem instances to reach online solution. In studies [44, 45], a distributed time allocation method to maximize data collection under constant path planning is proposed in a WSN, with sensors having their own renewable resources. In these studies, the resource allocation problem is formulated as a knapsack problem where the mobility of the sink is randomized but related channel assumptions made on the sensor nodes are rather known in advance.

The studies introduced throughout this thesis stems from the previous study, in which Erkilic et al. denoted that there exists no non-trivial solution to the dynamic capacity resource allocation problem for an energy harvesting mobile service provider and they implemented various optimization tools to evaluate the total achieved throughput performances considering the optimal offline solution via dynamic programming [14].

Most of the related studies used a stochastic model as observed which turns out to be more advantageous to fit in the real life conditions. In [13, 54] a Kalman filter based solar prediction algorithm is examined in detail for fixed transmitters and real energy harvesting statistics are utilized to model the solar irradiation pattern of solar panels. Then, extending this study to mobile energy harvesting transmitters in [13], Ceran investigated the transmission scheme of a mobile service provider assuming a fully stochastic model, which defines the randomness of user appearances, characteristics and energy harvesting pattern thoroughly and proposed several online heuristics. However, the statistics on available data, user characteristics, channel states or energy replenishment patterns are necessary for such methods to be implementable. Considering this deficiency, there has been no similar study related to online resource allocation problem of mobile Access Points with energy harvesting capability using a deterministic decision making strategy.

The previous studies rather propose an efficient scheme whether on reduction of energy consumption rate or maximization of data collection, but none of them proposes an instantaneous threshold based scheme for the resource allocation problem at an energy harvesting downlink. The study conducted throughout this thesis differs from the previous literature background as mentioned in this section since the main purpose is to reach an optimum service policy through competitive online solutions. It is tried to develop efficient online decision making strategies here considering the throughput maximization scheme of an energy harvesting mobile service provider while trying to maximize the service provided to the users appearing in a sequential manner under energy constraints.

CHAPTER 3

A REVIEW OF THE KNAPSACK PROBLEM

The APOM resource allocation problem will be mapped to the very well known combinatorial optimization problem known as the Knapsack Problem (KP). This chapter not only provides related terminology on the knapsack problem but also presents the main ideas behind applying the solution techniques to similar resource allocation problems.

The knapsack problem arises often in economic resource allocation problems and also studied in fields such as combinatorics, computer science, complexity theory, cryptography, applied mathematics and operation research where the real life decision making processes are considered.

The most common form of KP is the 0/1 knapsack problem which can be presented with the help of a story in [40] as follows: Suppose a robber finds N items while robbing a store ($i = [1, 2, ...N]$). Each item has a distinct value, i.e. v_i is the value of the i^{th} item, and weighs w_i pounds where x_i is the action to be taken whether to take that item or not, assuming all integer (v_i, w_i) values for each item. The thief can carry at most W pounds in his sack and tries to collect the most valuable items respecting this sack capacity constraint. To solve this problem, the 0/1 knapsack problem formulation is proposed. For each item, the robber has to either take that item or pass it up; he cannot take a partial or fractional amount of any item [46].

The standard 0/1 knapsack problem can be formulated as follows:

Problem 1. *Offline 0/1 Knapsack Problem with Static Capacity*

$$\text{Maximize: } \sum_{i=1}^{N} v_i x_i$$

$$\text{subject to: } \sum_{i=1}^{N} w_i x_i \leq W$$

$$x_i \in \{0, 1\}$$

For various reasons, the knapsack problem is an interesting topic from the perspective of computer science. The decision problem form of the offline knapsack problem is denoted as *whether a value V can be achieved or not under capacity constraint of W*. There is no possible algorithm both correct and fast polynomial-time at all problem instances since the decision problem is an NP-complete one. As stated in [32], there are two existing techniques to solve NP-complete problems: *Exact Algorithms* such as dynamic programming and *Heuristic Algorithms*. The optimum proposed solution to the classical KP is dynamic programming, however *the curse of dimensionality* of this method decreases the computational efficiency most of the time. In addition to NP-completeness of the decision problem, optimization problem is NP-hard which is also as difficult as the decision problem. That implies there exists no known polynomial algorithm to verify whether a solution is optimal or not.

3.1 Variations of the Offline Knapsack Problem

In the classical sense, the problem is an offline one where the knowledge on the items is available and an optimum decision plan can be derived and implemented.

Different from the standard 0/1 knapsack formulation which restricts the chosen number of each kind of item to zero or one, there are extended forms of this problem. In addition to capacity constraints over the decision process of 0/1 KP various individual limitations can be defined according to the required application using *multi-objective knapsack problem*. Another one is the *fractional knapsack problem* where the items can be subdivided [38] and complete load of an item is not necessary. Furthermore, it is possible to use more than one sack which composes a multiple knapsack structure (which may be used in multiple base station architecture for example), called *bin* *packing problem*. Different from considering all available capacity at one sack, this problem requires an optimization not only for the available energy of one sack but also an optimum decision has to be made within the various sacks, which is widely used in operation research scheduling problems. There is also *subset-sum problem* related to knapsack terminology, which is a special form of KP assuming each item has the same value and weight $v_i = w_i$.

Regardless of the special instances of the problem mentioned above, an item i to be evaluated in a knapsack problem is mainly characterized by its value and weight pair (v_i, w_i).

The classical offline knapsack problem approach is often unsuitable for real time applications where the decisions are need to be made over an incomplete set of information on the items. Many realistic and interesting applications require the online solution to the knapsack problem.

3.2 Online Knapsack Problem

The knapsack problem was first examined in [51] without even relating it to KP terminology since they compared the performances of different algorithms for *list access problem*. In this work, an upper bound was shown while comparing the cost performance of the algorithm with the optimal cost at all problem instances. Then, pursuing these studies, Karlin et al. [27] proposed a competitive analysis method as follows.

Let an online instance of a problem be σ_i and through the end of horizon a set of instances occur as $\sigma = [\sigma_1\sigma_2...\sigma_N]$. $A(\sigma)$ is defined as the total value achieved by algorithm A over a problem instance σ, whereas $OPT(\sigma)$ is defined as the value achieved by the optimal offline algorithm with complete knowledge on the future instances. An online algorithm is said to be α*-competitive* if it is guaranteed to satisfy the following inequality over all problem instances:

$$OPT(\sigma) \leq \alpha A(\sigma) + b \tag{3.1}$$

Most problem formulations presume $b = 0$, but it may be useful to keep this in the equations for a rescaled problem instance [38].

It is intuitively assumed that the performance of an online algorithm is precisely revealed by its competitive ratio, and the less knowledge on the future instances results in more degradation in performance [38].

In Chapter 5 considering this related performance criteria, the competitive ratio analysis conducted for online knapsack problem in [62] is extended to the APOM problem setup.

CHAPTER 4

SYSTEM MODEL

4.1 Movement of the Mobile Station

Energy harvesting Internet service provider, APOM, is assumed to follow a predefined linear path. Its velocity is constant, v_c, for the time being to assure a predictable user appearance rate before generalizing the problem to randomized user arrival case. APOM relies on renewable energy resources (solar, wind etc.) and its linear movement contributes to the predictability of its energy replenishment pattern.

As to be stated in the following sections and illustrated in Figure 4.1, the user demands are evaluated along the path of APOM and the harvests of amount B_j where $j \in \{1, 2, ..., k\}$ are expected at N_j^{th} slots where the expected harvest intervals may change at each slot. For the sake of simplicity and as a necessity for the deterministic model let us discard the time concept by presuming an event-based structure. As the APOM travels on its route, the decisions are made on an event-based schedule where each user request represents the start of the corresponding slot, which implies N slots for a system of N users. Since every energy replenishment will change the service capacity of APOM, the problem may be examined in k subintervals regarding k harvest instances.

4.2 User Characteristics and Demands

A finite sequence of users $\gamma = [1, ..., N]$ appears on the APOM's route demanding Internet service. In this model, one user is observed per time slot as stated above,

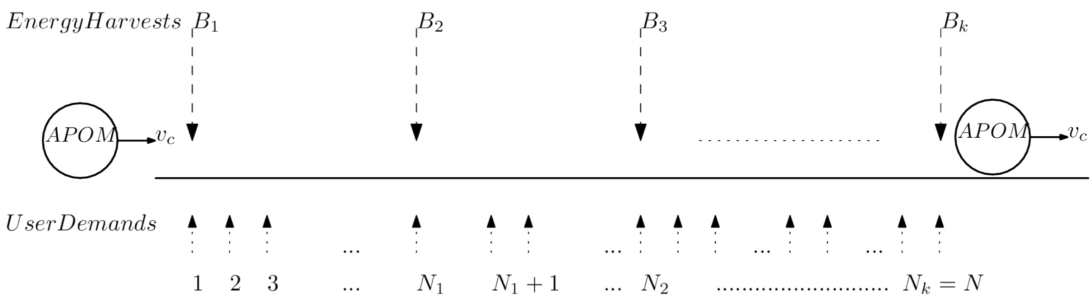

Figure 4.1: System Model of User Demands and Energy Replenishment Pattern

which corresponds to a problem horizon of N slots. Then, the user metrics are evaluated at each slot which are the utility achieved by serving that user (i.e. amount of transmitted data), and the energy consumption it requires.

For each user i, APOM chooses whether to transmit to it or not based on that user's individual characteristics. Once a decision is made on a user, there is no re-evaluation of the same user. The main purpose in this work is to develop an efficient scheme to provide maximum utility for user demands throughout the path of a mobile service provider . Each user is classified by a *value* and *weight* pair: (v_i, w_i) for the i^{th} user, where the *value* corresponds to the utility gained by serving this user and *weight* stands for the power consumption required to serve it. Also, let us denote an *efficiency metric* of a user i as the v_i/w_i ratio.

In the model considered throughout this work, users appear to the APOM one by one during its route. The value and weight metrics for each appearing user presents a reward and a cost to the APOM. The reward could be the utility of providing service to that user, which may be total rate or quality of service assured on the corresponding path etc. The cost may be defined as the burden of that user to the system, which is mainly the total energy expenditure giving service to this user. For example, if the user has a poor link with the APOM due to bad weather conditions or throughput maximization is tried on a fading channel or there exists an interference over the transmitting channel, the cost of serving that user will be high. As expected the efficiency ratio of each user will be critical on the decision problem since maximizing total throughput by serving many users with lower costs will be more advantageous. Still, energy scavenging will be a relief factor to increase the total service capacity eventually.

4.3 Energy Model

The Access Point on the Move is modelled to rely on the renewable energy resources (solar, wind etc.), moving on a predefined linear path. Following a widely adopted assumption about energy replenishment, the amounts of harvested energy in certain time periods are non-deterministic but predictable as stated in [24, 30, 42, 54], so energy harvesting instants and amounts are assumed to be predicted.

The sequence of user appearance events between consecutive energy harvests are taken as energy harvest intervals. The initial energy amount is assumed to be B_1 and incoming energy with the next j^{th} harvest is denoted as B_{j+1}. In the same manner, $(j+1)^{th}$ harvest occurs after N_j^{th} user appearance, i.e. energy is replenished right after N_1^{th} slot, N_2^{th} slot, and so on, up to some $N_k = N^{th}$. There are a total of k energy harvest intervals.

APOM should develop an efficient deterministic strategy to achieve maximum utilization whereas the total energy consumption should remain below the available energy plus the harvests that come along till the end of each energy harvest interval. At first energy replenishment model of the APOM is accepted as deterministic and of known amounts using the arguments in [54]. However, eventually the model is extended to a randomized scenario and its performance is tested under different input streams to reach practical results for real life implementations.

4.4 The Problem Setup

Combining movement pattern, user characteristics and energy model of the the APOM, as a main function it makes a binary decision whether to serve a user or not. If there was no energy constraint for the access point, it would respond to all user demands affirmatively to achieve maximum utility. However, due to the fact that the energy scavenging rate is slower than the power consumption rate, giving service to all users is not feasible. Thus, there will be a decision process which will result in rejection of a number of user demands. Hence, the problem turns out to be an *online decision and optimization problem* with the aim of picking the optimum set of users to maximize the total utility under energy limitations of APOM considering the causality constraints as well. There will be no point in developing a method with the previous knowledge on energy replenishments and possible future user demands since variations of this offline model have already been addressed in the literature.

Within the problem setup, users appear in a sequential manner and APOM must decide whether or not to provide service to each user demand. The main goal of APOM is to maximize a total value such as the total data rate provided to the encountered users. Following knapsack terminology, the main constraint on sack filling problem is the *capacity* as it is the case for the AP. The service capability of APOM is mainly determined by the amount of available energy it has stored in its battery plus the energy replenishments as they occur, which will be referred as its service capacity. The problem is to collect the maximum value over a user set γ of N users while ensuring that the total weight does not exceed the service capacity. Stated this way, the problem is a dynamic capacity 0/1 online knapsack problem where capacity replenishment takes place in accordance with energy harvesting capability.

Let the access point start its route with a certain amount B_1 of energy stored in its battery. Energy is replenished right after N_1^{th} slot, N_2^{th} slot, and so on, up to some $N_k = N^{th}$ slot. Using this setup, the problem can be stated in terms of x_i's, which indicate the decision to either serve user i or pass it up:

Problem 2. *Offline 0/1 Knapsack Problem with Dynamic Capacity*

$$\textit{Maximize: } \sum_{i=1}^{N} v_i x_i$$

$$\textit{subject to: } \sum_{i=1}^{N_1} w_i x_i \leq B_1,$$

$$\sum_{i=1}^{N_2} w_i x_i \leq B_1 + B_2,\ \ldots,\ \sum_{i=1}^{N_k} w_i x_i \leq \sum_{j=1}^{k} B_j$$

$$N_k = N \ \ and \ \ x_i \in \{0, 1\}$$

The problem formulation given in Problem (2) is a generalization of standard 0/1 knapsack problem with multiple constraints. In each energy harvest interval, the available energy is the newly harvested energy plus the energy left over from previous intervals. Energy expenditure in an interval cannot exceed this amount. The overall structure may be modelled as a knapsack problem with increasing capacity due to energy harvests prevailing at N_j instants where $j \in \{1, 2, ..., k\}$. At the first subinterval when there exists no energy harvest in the picture, the energy constraint is over B_1 amount, the initial stored energy in APOM batteries. As the slots pass and energy replenishments occur, the available service capacity of the APOM expands. However, it is prominent to restate that the decisions made in the passing slots are not to be reconsidered in the forthcoming ones. Since there will be no concrete information on the possible future harvests, the system cannot take a necessary action before a replenishment even occurs, which guarantees the causality of the model that the system is non-anticipative.

As explained in Chapter 3, including its dynamic capacity version presented in Problem 2, the classical knapsack problem is an offline combinatorial optimization problem, the standard proposed solution of which is dynamic programming. For the online instances of this problem, there are a number heuristics with eligible performance. On the other hand, the online knapsack problem with dynamic incremental capacity, which is of interest to us, is still quite open.

CHAPTER 5

OPTIMAL SOLUTIONS TO THE APOM RESOURCE ALLOCATION PROBLEM

5.1 Optimal Offline Solution for Static Capacity

Dynamic Programming (DP) is a standard technique in the literature for solving dynamic decision problems. This technique, firstly proposed by a famous U.S. mathematician Richard Bellman in 1950s, is constructed upon a divide and conquer idea and solves the sub problems that the original problem breaks into. It does not propose a pure programming approach but rather provides an *optimum planning* [32].

The classical knapsack problem is a well studied combinatorial optimization problem in Computer Science and Operations Research literature, which is NP-hard with no efficient polynomial time solution [17]. The standard solution for the offline classical knapsack problem involves dynamic programming approach as expected. Each sub problem instance consists of two branches. For an item j and available capacity B, let $V(B)$ denote the maximum achievable value using that amount of that energy and $v_j x_j$ imply the individual reward contribution of the j^{th} item. As mentioned before, $x_j \in \{0, 1\}$ shows the decision on the corresponding item whether to take it or not. The DP recurrence equation for APOM stated in Problem 2 is as follows:

$$V(B) = \max_{j}[v_j x_j + V(B - w_j x_j)] \tag{5.1}$$

This recurrence equation first evaluates the value to be gained by taking j^{th} item (v_j) where $x_j = 1$ plus the profit to be collected using the iteration of equations on the next items appearing after j with the remaining capacity $V(B - w_j)$. Then, the evaluation of the total reward reached with the next items by discarding the current one j is conducted where $x_j = 0$. After making this iteration at each j, using all possible x_j values over the whole problem instance space, we reach a matrix of available paths to achieve the maximum utility involving all possible selections on the items (i.e. users, for APOM). Based upon this analysis, optimum set of decisions is attained for the solution of offline knapsack problem.

As stated above, DP proposes an offline solution to Problem 2, in which apriori knowledge on the energy harvests and user characteristics are assumed to be available to the access point. Since no competitive solution has appeared in the literature to the online knapsack problem with incremental capacity, the offline results of DP with complete knowledge on the problem instances will be used as a performance criteria which shall never be reached by any online algorithm but may be approximated by a certain competitive ratio.

5.2 An Online Solution for Static Capacity that Achieves an Optimal Competitive Ratio

Responding to instantaneous requests of encountered users, APOM has to adopt an efficient and fast decision making strategy as a new user demand appears. In such problems, if a well defined threshold could be stated, using a threshold based approach as a decision mechanism gives a satisfactory result in terms of overall performance and computational complexity. Hence, we shall mainly look for threshold based schemes which provably exhibit experimentally strong performance.

Following the approach of [62] this section restricts attention to threshold based decision rules, where the values and weights of the encountered users are compared with a time-varying threshold. In addition to time, the threshold may also be a function of the fraction of remaining capacity in the battery as mentioned in [51]. To consider the deterministic online knapsack problem in a threshold based scheme using the initial setup proposed by [62], upper and lower bounds on the user rate, energy requirement and energy harvesting will be assumed, which are not unrealistic considering practical correspondents to these limitations exist. In practice, APs admit only users in a certain area of coverage, which automatically limits the power consumption. Rewards from a user (rate, pricing, etc.) are inherently bounded as well. Finally, solar irradiation is quite predictable on an hourly basis and almost constant in an hour as stated in [54]. Therefore , upper and lower bounds on energy replenishment rate can be predicted.

Each new user can be taken into account only if the residual energy of APOM is greater than the weight of that user. If the available energy exceeds the weight of the user, a decision to offer or deny service to this user is made based on its weight (energy consumption) as well as its value (utility). A threshold based user admission mechanism was proposed in [62] for a related problem with a static and presumably large available capacity. Here, the efficiency of the users (v/w), will be the critical parameter for each user. The instantaneous threshold is defined as a monotonic increasing function of the used fraction of the energy capacity denoted as z where $z_i = \frac{\sum_{m=1}^{i} x_m w_m}{B}$, the filled up capacity till i^{th} instant. There exists upper and lower bounds on the efficiency ratios of the user sequence as $U, L > 0$ such that $L \leq \frac{v}{w} \leq U$. The online threshold function proposed in [62] is defined as:

$$\Psi(z) = (\frac{Ue}{L})^z \frac{L}{e} \quad where \;\; L \leq \frac{v}{w} \leq U \tag{5.2}$$

where e denotes the natural logarithm and z represents the used fraction at any corresponding slot. At the beginning, APOM welcomes most of the users when there is plenty of energy ($z << B \;\; and \;\; \psi \backsimeq L/e$). As the energy is used up ($z \backsimeq 1$), threshold increases along with the filled up fraction since it reaches its upper limit as $\psi(z = 1) \backsimeq U$. At the end, the system only admits users with very high efficiency, which means the scheme adopts a greedy attitude at beginning of the horizon while it becomes more and more conservative towards the end.

As mentioned in Chapter 3, the usual success metric for an online algorithm is its *competitive ratio*, the worst-case ratio of the algorithm's performance to the optimal offline solution under the same input [12]. Therefore, having complete uncertainty in the input, the heuristic proposed should build solutions with a competitive ratio better than the worst-case ratio by α. For different sets of users, the achieved value is compared to the one obtained by any computationally all-powerful optimal algorithm which has complete knowledge about the set of items. If an online algorithm A, for a user sequence γ is α-competitive:

$$\frac{OPT(\gamma)}{A(\gamma)} \leq \alpha, \quad where \;\; \alpha \geq 1 \tag{5.3}$$

should be satisfied where $OPT(\gamma)$ and $A(\gamma)$ are the values obtained from optimal offline algorithm and the proposed online heuristic A respectively.

In the following parts, different threshold-based admission mechanisms are investigated and compared on their performance regarding the total utility (rate) they provide. Competitive ratio analysis is used to test the performance of the online algorithms.

5.3 Extended Online Solution with Deterministic Threshold Method for Dynamic Capacity

In Chapter 4, it was argued that Problem 2 is a generalization of 0/1 knapsack problem. In [33], authors reveal that no non-trivial competitive algorithm existed for the general case of the online knapsack problem. Hence, following the work of Chakrabarty et al. [62] and in the direction of the statement in [33]; several assumptions are made and a threshold based online algorithm is proposed. The first assumption is that all of the users have a weight much smaller than the sack capacity (i.e., $\frac{w_i}{B} \leq \varepsilon, \forall i \in A \;\; where \;\; \varepsilon << 1$). The second one is that the efficiency (v/w) of the users are neither too high nor too small. That is, there exists upper and lower bounds on the user efficiencies as $U, L > 0$ such that $L \leq \frac{v_i}{w_i} \leq U, \forall i \in A$.

As introduced in [62], the idea of the algorithm is straightforward. Early on, any item which arrives should be picked. As the knapsack is filled, the algorithm becomes more and more selective, that is, we pick items if the corresponding v/w ratio exceeds the corresponding value of the following threshold function at that instant.

Let the threshold function be $\Psi(z) = (\frac{Ue}{L})^z \frac{L}{e}$ following the work of [62] where U and L are the upper and lower bounds for the v/w ratios of the incoming users. Let $z_i = \frac{\sum_{m=1}^{i} x_m w_m}{B}$ denote the fraction of the energy capacity (i.e. sack) filled up to that instant. When an item i arrives, let z_i be the fraction of energy capacity filled in case of selecting i^{th} item. The APOM picks user i if i does not overfill the knapsack capacity at that time and the efficiency ratio stays above the corresponding value of the threshold function, $\frac{v_i}{w_i} \geq \Psi(z_i)$ [62].

The user sequences demanding service appear to the access point as it routes over an area. As mentioned in Section 4.3, k energy harvests are expected with amounts $B = [B_1, B_2, ..., B_k]$ with an incoming prediction on the corresponding problem instances $N = [N_1, N_2, ..., N_k]$.

We propose two adaptive threshold-based algorithms for the online version of the dynamic capacity knapsack problem for APOM with energy harvests, based on the function introduced in [62]. In the first one, while the fraction $z_i = \frac{\sum_{m=1}^{i} x_m w_m}{B}$ is computed, B is taken as the total energy available $B = B_1 + B_2 + ... + B_k$. It is based upon a well stated assumption on possible future harvest capacity of APOM where the energy replenishment rate are presumed to be predictable in a deterministic problem setup as mentioned in Section 4.3. In this case the threshold function $\Psi(z)$ becomes a nondecreasing monotone function of z.

Definition 1. *Monotone Threshold is an adaptive threshold function such that, for users $i = [1, ..., N]$, it accepts user i if $v_i/w_i \geq \Psi(z_i)$, and $\sum_{m=1}^{i} x_m w_m \leq B$. Here z_i is computed as $z_i = \frac{\sum_{m=1}^{i} x_m w_m}{B}$, where B is the total amount of energy $B = B_1 + B_2 + ... + B_k$ after all the harvests occur.*

Monotone Threshold function uses the total service capacity in decision metric z, but proposed threshold function does not provide service to users unless the capacity constraints are satisfied as stated in the definition. Thus, verifying the system's causality constraints regarding energy, this method does propose a looser bound at the beginning and becomes fiercely conservative to the end of the user sequence. The following theorem presents the competitive ratio analysis for monotone threshold function introduced for dynamic knapsack problem with incremental capacity assuming one energy replenishment occurs.

Theorem 1. *Under the condition $\sum_{m=1}^{N_1} x_m w_m \leq B_1$, Monotone Threshold guarantees a competitive ratio no more than $\ln(U/L) + 1$ assuming two energy harvest intervals, i.e. $k = 2$.*

For the sake of completeness, the derivation of the competitive ratio analysis of Theorem 1 under APOM Monotone Threshold assumptions considering the causality constraints for energy harvests is provided in Appendix A .Extending the proof in [62] to the dynamic capacity case, the derivation given in Appendix A reveals that this proof can be further extended to the cases for $k > 2$.

As an alternative way to the Monotone Threshold approach, the second function utilizes the the amount of energy harvested up to that time instant at denominator of the fraction discarding the strict nondecreasing assumption in the threshold function.

Definition 2. *Jumping Threshold is an adaptive threshold function which implements the Monotone Threshold function at each energy harvest interval such that, for* $i = [1, ..., N]$*, it chooses to serve user* i *if* $v_i/w_i \geq \Psi(z_i)$ *and* $\sum_{m=1}^{N_k} w_m \leq B_k$ *where the available energy is equal to* B_k *at that instance. In other words, Jumping Threshold function is a piecewise monotone function of the current fraction in each energy harvest interval. When a new energy arrival occurs, the fraction* z *jumps to a lower level.*

Detailed simulation results and numerical competitive ratio analysis of Monotone and Jumping Threshold functions are illustrated in Chapter 7.

CHAPTER 6

ONLINE HEURISTICS FOR RESOURCE ALLOCATION PROBLEM FOR A MOBILE SERVICE PROVIDER

6.1 Genetic Algorithm: A Stochastic Approach to a Deterministic Problem

As the first online heuristic, Genetic Algorithm (GA) is proposed. In the computational science, engineering, bioinformatics, economics, manufacturing, mathematics, physics and many other fields, genetic algorithm (GA) is a widely used search heuristic, also called a metaheuristic, that uses the process of natural selection as a model. This heuristic is utilized for optimization purposes to various problems using techniques inspired by natural evolution such as inheritance, mutation, selection, and crossover.

In the literature, we encounter the implementation of GA to knapsack problems in various applications since it is a widely used technique for optimization and search problems, mostly NP-hard ones. The main idea as stated in [32] is that the candidate solutions represented by GA are stochastically selected, recombined, mutated, either eliminated or retained based on the relative fitness; even the original problem is based upon a deterministic model. This stochastic approach to a deterministic problem drew our attention and we propose the implementation of it to an even more novel concept where the capacity of the knapsack may also change as the solutions are evolved toward better ones. Thus, both the generation adaptation and the capacity change effect due to energy harvests should be taken into consideration using this method.

In the implementation genetic algorithm to find an optimal threshold function, a population of candidate solutions for threshold values, each having a set of properties, which can be mutated and altered, is evolved toward better solutions. Most of the time, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible [58]. An efficient utilization of GA requires the use of genetic operators such as crossover, mutation and selection, which are essential to improve the candidate solutions where strings are chosen, combined or altered in a stochastic process [32].

In the following sections employing GA, we try to reach an optimal threshold function from two different perspectives such as a user based evolution and an approach taking into account every possible value of the fraction of available capacity.

6.1.1 User Based Genetic Algorithm

The first attempt to construct a feasible threshold for APOM via genetic algorithm is realized by making a fitness evaluation over incoming user demands. The fitness evaluation conducted through each generation performs on the user sets to maximize the total service provided to users while checking the total weight constraint each time. A user set which achieves the best competitive ratio is chosen as a solution, then next generations are formed using the best candidates from previous generation. This procedure continues until the total achieved reward converges to a certain level at the end. First, upper and lower bounds on the efficiency ratios of randomly assigned user sets are determined. Then, using random user sequences satisfying $L < \frac{v_i}{w_i} < U$, the parent chromosome stream is constructed. Before taking into account the energy harvests, a Mutation Function is defined to force the threshold function evolve in a nondecreasing manner. So, after setting the Crossover Rate to 0.8 and stating capacity constraints under fitness evaluation function to be verified at each step, the algorithm is started for a 100 generations with a parent generation of 1000 users. The solution has converged to an optimal point via the examination of the random selection on users with distinct efficiency ratio over 100 generations. Then, for this setup the optimum stepwise increments to be added up to the threshold function at each step is proposed to reach the maximum utility.

To illustrate the performance of this heuristic compared with the online solution

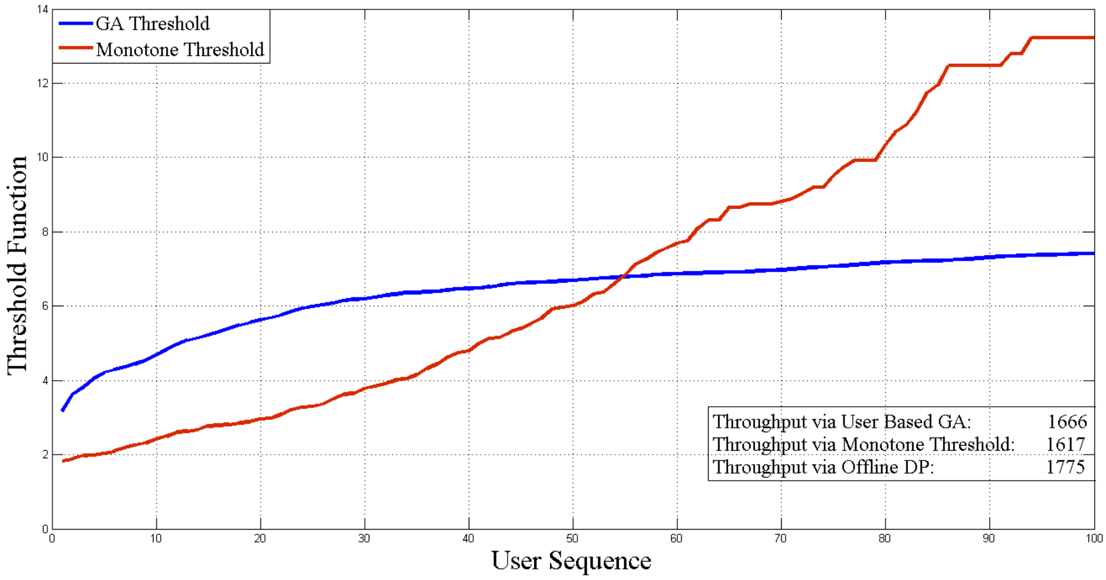

Figure 6.1: User Based Threshold Function by GA vs Monotone Threshold Function Computed over a Randomly Generated User Sequence of 100 Users with Efficiency Ratios varying between $U = 10$ and $L = 5$

method proposed in [62], results in Figure 6.1 shows the attained utility using both methods in addition to the threshold trends they adopt. Since online threshold function proposed in the previous chapter $\psi(z_i)$ is an explicit function of fraction but not directly the user appearances (or item numbers), the GA, formed upon user demands, follows a smoother trend through the end. The results are taken for the user sequence γ composed of 100 randomly generated users with $U = 10$ and $L = 5$ as upper and lower bounds. The achieved utility is as expected since genetic algorithm constructed upon user demands in a static capacity KP proposed a more greedy threshold while the Monotone Threshold used in [62] tends to be strictly conservative through the end of horizon due to its available fraction dependent construction. Thus, without considering the harvest instants, the analysis conducted in 6.1 revealed that Monotone threshold achieved a competitive ratio of 1.098 whereas user based GA has a ratio of 1.065 compared with the optimum strategy. It is beneficial to restate that the performance of an online algorithm increases as its competitive ratio approaches to 1, i.e. the performance gets more and more closer to the optimum algorithm.

Next, user based GA approach is implemented for the energy replenishment model. After constructing the parent chromosome, the same mutation function is forced over generations to get a monotonic threshold trend at the end. However, the harvest model required an update on the available energy of APOM and did not satisfy a reasonable competitive ratio for this scenario. Thus, adopting a fraction based approach eludes from these observations proposing a new perspective where the utilization of the available energy and the effect of energy harvests on the fraction of the service capacity should be taken into account at each step as explained in Section 6.1.2.

6.1.2 Fraction Based Genetic Algorithm

To apply GA on a fraction based scheme, a chromosome is chosen as a vector that defines a threshold for each region of fraction. For this purpose, the values that remaining fraction of capacity (z) can take are quantized in the following manner: The range of fraction ($[0, 1]$) is divided into equal regions as $[t_1 t_2 ... t_{1000}]$, where t_i corresponds to the threshold for region i, i.e. $\psi(z) = t_i$, and note that $z \in [\frac{i-1}{1000}, \frac{i}{1000}]$. A quantization over 1000 intervals are assumed to be sufficient providing an opportunity to sweep over a wide range. A number of chromosomes as stated in the previous section are randomly formed, and their corresponding competitive ratios are found through the fitness function evaluation. The fitness function checks the energy constraint on the available capacity at each step as well. In addition, capacity is updated at each energy replenishment, so is the fraction z. Following the standard mutation and crossover procedures, the chromosomes evolve into an optimal threshold vector. The observations on the fraction based method on the natural selection of the best users over generations give a certain competitive ratio in the best and the worst cases for randomly generated parent sequences, which is provided and discussed in Chapter 7.

To briefly illustrate the general tendency of the fraction based threshold function generated by GA, the comparison of the outcome with the Monotone Threshold function is given in Figure 6.2. As seen, both are nondecreasing linear functions of fraction z. The simulations are run over a sequence of 1000 users with randomly assigned v/w ratios varying between $U = 10$ and $L = 5$. Considering the total throughputs at the output, the Monotone Threshold has an performance metric 1.048 whereas the fraction based threshold achieves a competitive ratio of 1.062.

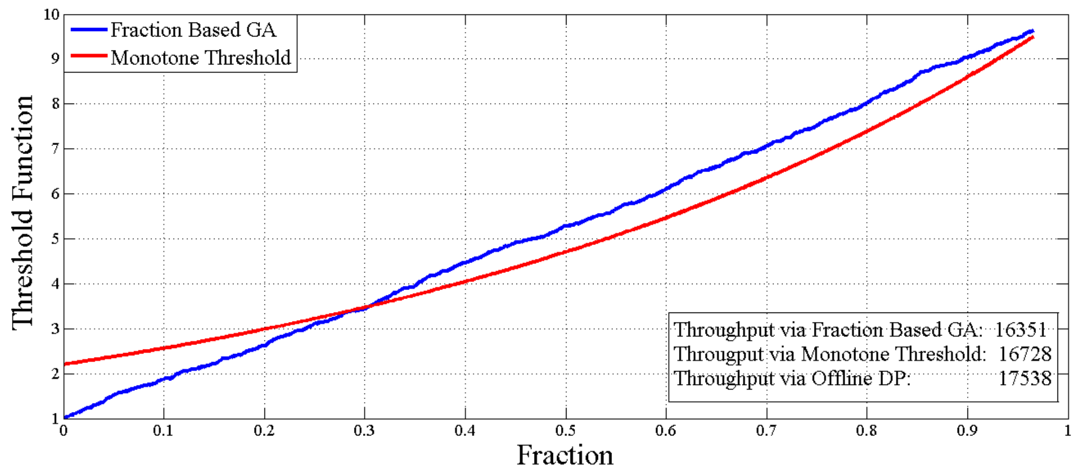

Figure 6.2: Performance of Fraction Based Threshold Function by GA vs Monotone Threshold Function Computed over Fraction on a Randomly Generated User Sequence of 1000 Users with Efficiency Ratios varying between $U = 10$ and $L = 5$

Then, the energy replenishments are simulated using these methods. The performance graphs of the GA Threshold function and Jumping Threshold functions are illustrated in Figure 6.3 for one energy harvest model. As observed from the figure, fraction based genetic algorithm manages to trace the extended optimum online solution described in Section 5.3 very closely since it reaches the best set of solutions over generations. The achieved competitive ratio for GA threshold is 1.086 for this case, with only a minimal decrease in performance compared with previous no-harvest user based GA example.

As a result of genetic algorithm studies regarding the proposed heuristics, the computational complexity of GA method turns out to be high and the time efficiency is very low; however, it presents a reasonable performance for resource allocation and throughput maximization problem of energy harvesting APOM.

6.2 Rule Based Method

Handling uncertain knowledge is a tricky problem when decisions based on such knowledge appear to be critical. In such cases, a system that employs a broad set of rules may efficiently deal with uncertainty in the data [15]. A connected set of well defined rules, consisting of related variables in both the propositions and consequences,

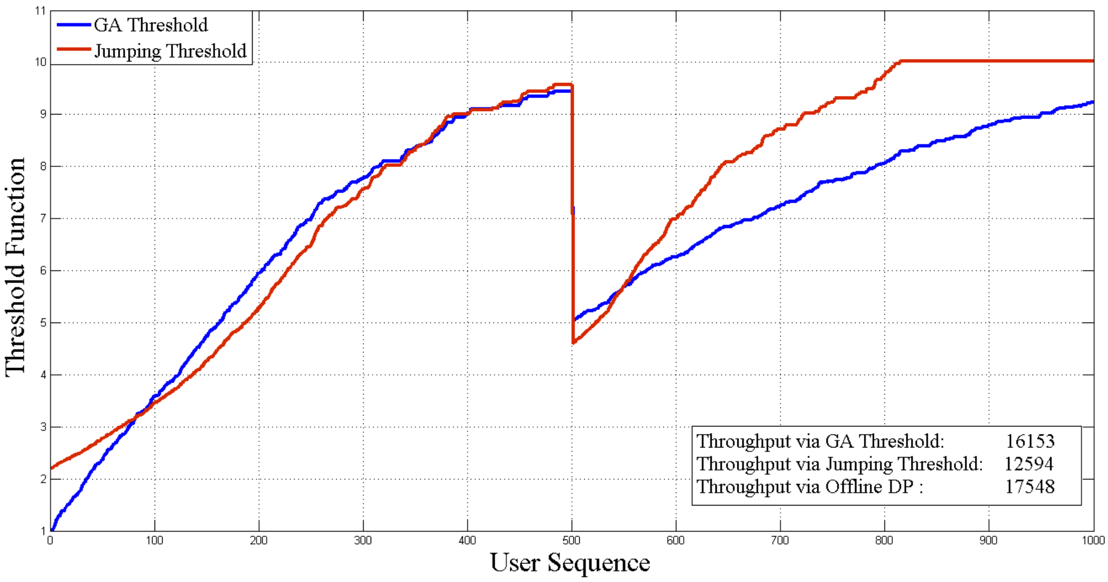

Figure 6.3: Performance of Fraction Based Threshold Function by GA vs Jumping Threshold Function on Energy Harvesting Model over a Randomly Generated User Sequence of 1000 Users with Efficiency Ratios varying between $U = 10$ and $L = 5$

are competitive to manage the uncertain cases. An efficient rule based system must depend on accurate decision criteria which adopts ‘if-then’ rules while constructing the decision structures. These rules can be attained by summarizing the reduced data set from the attribute reduction process, which is discussed in [25] considering rule extraction using soft computing techniques.

The main problem in rough set technique is to discretize the real values associated with the membership degrees to form the rules. The method here is to transform the corresponding real values into a tuple that represent the membership degrees in all of the attribute subsets [25].

Although the rule based approach has been implemented in a few resource allocation problems in the literature [2], there has been no previous study on the threshold determination via this method so far. Hence, within the scope of this work rule based method is proposed as the second heuristic which turned out to be a useful technique to determine a threshold function for the resource allocation decision problem of APOM. Once, the rules are stated wisely considering the critical decision making metrics in the problem setup, the results lead us to an efficient threshold function at the end. The attained function works fast and even better than the optimal online

Table 6.1: Membership Rules of 5 Degrees for Threshold Determination Belonging to the Membership Functions given in Figures 6.4,6.5, 6.6

Energy Harvest Closeness	Capacity Fullness	Threshold
Very-Near	Very-High	Med
Very-Near	High	Low
Very-Near	Med	Low
Very-Near	Low	Very-Low
Very-Near	Very-Low	Very-Low
Near	Very-High	High
Near	High	Med
Near	Med	Low
Near	Low	Very-Low
Near	Very-Low	Very-Low
Med	Very-High	High
Med	High	Med
Med	Med	Med
Med	Low	Low
Med	Very-Low	Very-Low
Far	Very-High	Very-High
Far	High	High
Far	Med	High
Far	Low	Low
Far	Very-Low	Low
Very-Far	Very-High	Very-High
Very-Far	High	Very-High
Very-Far	Med	High
Very-Far	Low	Med
Very-Far	Very-Low	Low

heuristic of Chakrabarty et al. [62] in most cases since the overall threshold is a well trained one under random sets of users and calibrated via distinct characteristic randomized user sets as well.

Details of the rule based system constructed for the Access Point on the Move are presented in Table 6.1. There are two input memberships functions (MF) assigned to define the decision strategy in each possible case to be encountered by APOM. Both of the input MFs are defined as trapezoidals of 5 degrees as can be traced in Figures 6.4 and 6.5. The output MF is assigned as the desired change in the threshold as shown in Figure 6.6, the ultimate trend of which will be used to determine which users to serve eventually.

One of the input membership functions is chosen as the closeness to energy harvest instants in terms of the number of user arrivals. This parameter is prominent in real life scenarios since expecting an energy harvest sooner or at a far instant may completely alter the possible decision at the corresponding slot. Once, the harvest instant gets closer and closer, the service provider should adopt a greedy attitude since it would serve as long as its service capacity allows it to do. This metric is chosen to vary between $[0, 1]$ where the values closer to 1 denotes that an energy arrival is presumed to happen soon. As illustrated in Figure 6.4, *Very-Near* covers the input MF values near by 1, i.e. the current user appears at a slot close to the harvest instant N_i, whereas *Very-Far* stands for the user arrivals at the beginning of an energy harvest interval where the input MF is set to be in the vicinity of 0. The other degrees as *Near*, *Med* (for Medium) and *Far* represent the degrees in between *Very-Near* and *Very-Far* in the descending order through the harvest instant.

In addition to the energy replenishment rate, the fraction of the utilized energy of available capacity is a critical measure as well. Thus, the second MF is assigned as the depletion of available energy of APOM. The values vary between $[0, 1]$ interval same as the first MF function, ranging from *Very-Low* to *Very-High* in 5 levels. The instances where the capacity fullness metric is closer to 1 indicate that most of the available energy is utilized where the threshold trend to accept new users shall diminish in that direction. On the other hand, the values closer to 0 implies there is available capacity of APOM to serve more users. So, considering the energy harvest closeness the threshold should remain at relatively low values to increase total throughput.

Using the input MFs and following the well defined calibrated rules from Table 6.1, the behaviour of the threshold function is attained in Figure 6.7. To interpret these results, consider a problem instance where access point gets closer to an energy scavenging point. If the available energy is high (implies that the capacity fullness closer to 0), the algorithm shall respond any user demand affirmatively. As the capacity fills and the energy harvests are awaited in the long term (which represents the energy harvest closeness value in the vicinity of 1), the service quality decreases and only the user with highest rates get service.

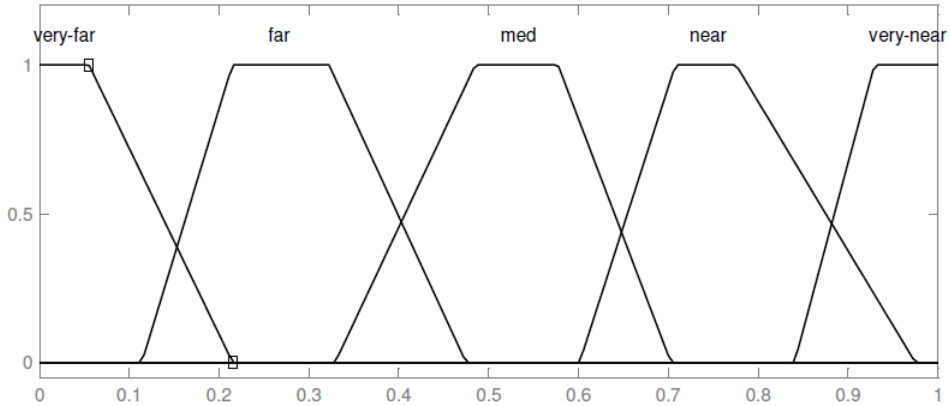

Figure 6.4: Input Membership Function of Energy Harvest Closeness

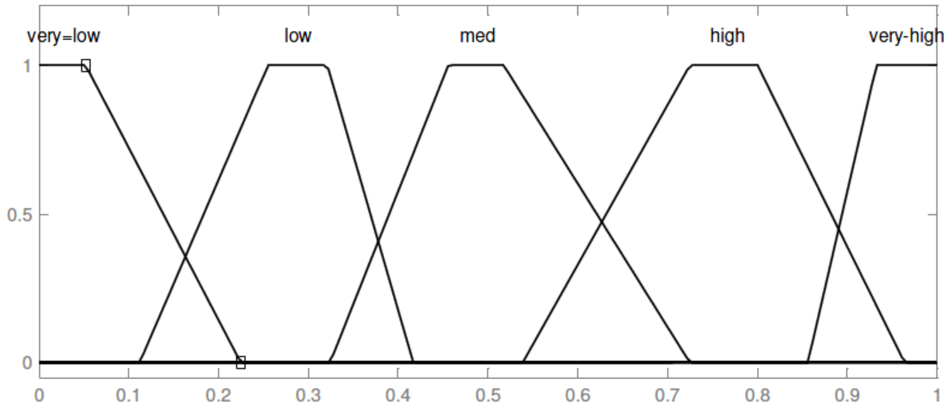

Figure 6.5: Input Membership Function of Fraction of Capacity Fullness

It should also be noted that the increased performance of this heuristic is tremendously related with the enlarged problem dimension. The complexity is increased as the problem instances are defined in one more dimension but the accuracy on decisions leads to an improved utility maximization performance via proposing a 3D solution to a 2D problem. After attaining the threshold function over a rule based structure, this function is used as the decision metric for the new randomly assigned users to get overall performance results provided in Chapter 7.

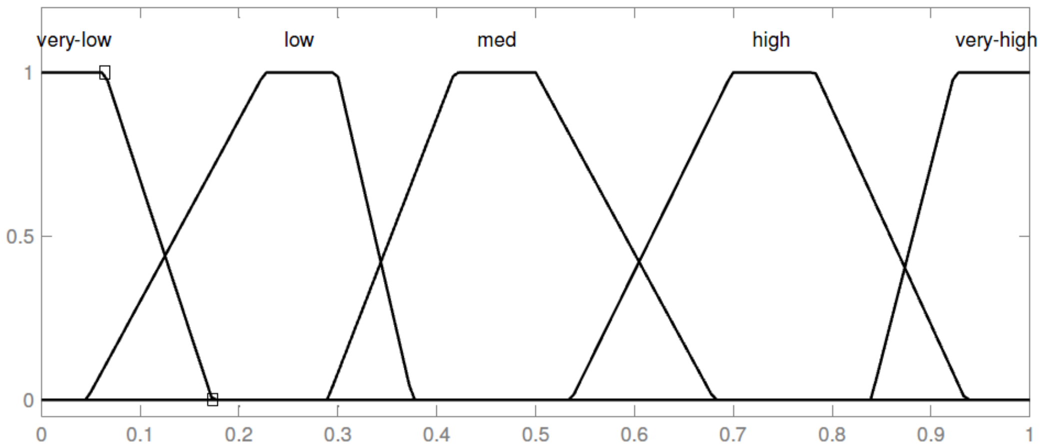

Figure 6.6: Output Membership Function of Threshold

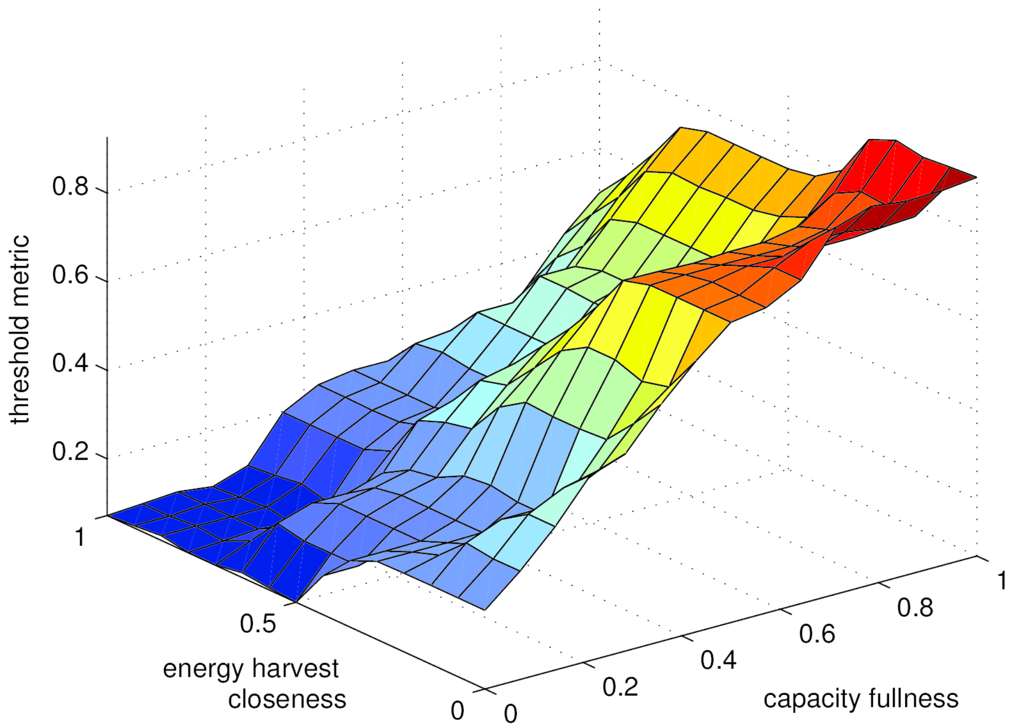

Figure 6.7: Surface Graph of Threshold Function Attained via Rule Based Algorithm Described in Section 6.2 Indicating the Behaviour of Output Threshold Function with respect to Input Membership Functions

CHAPTER 7

NUMERICAL AND SIMULATION RESULTS

Access Point on the Move is envisioned as a moving station providing Internet access at 3G speeds or more to users demanding service. For a service advertised as 3G essentially needs to meet MT-2000 standards which implies peak data rates of at least 200 kbps. Up to this point different methods are analysed in Chapters 5 and 6 and their performances are compared with the optimal offline solution in terms of competitive ratio analysis and possible throughput results. The previous chapters include some illustrative examples on the general behaviour of the threshold functions and explained the critical decision metrics they use to construct an efficient allocation model for APOM while achieving throughput maximization. In this chapter, more generalized results are attained testing the performances of the proposed heuristics systematically. Worst-case and average case analysis are performed under Monte Carlo Simulations.

Transmission power decisions may be chosen as (5; 10; 23; 26; 74; 100; 159; 256 mW) are based on relative data rates provided in Table 7.1 retrieved from 802.11n standard. Considering the user types and the dimension of user sequences a transmission rate is presumed and the performances are different heuristics are evaluated.

For the sake of simplicity, the first evaluation is conducted under the predicted energy replenishment rate under perfect channel assumption. The results of which are illustrated in Tables 7.2 and 7.3. User efficiency (v/w) ratios are bounded with $U = 10$ and $L = 6$ where $L \leq \frac{v}{w} \leq U$. User efficiency ratios take uniformly distributed randomly real-time assigned values within this interval. APOM total transmission rate capacity is taken as $2000mW$. 1000 Monte Carlo trials are conducted, generating

Table 7.1: Single Stream Data Rates in 802.11n Standard for 40MHz Channel

Modulation Type	Coding Rate	Data Rate (Mbps)
BPSK	1/2	15
QPSK	1/2	30
QPSK	3/4	45
16-QAM	1/2	60
16-QAM	3/4	90
64-QAM	2/3	120
64-QAM	5/6	150

Table 7.2: Competitive Ratio Comparison of Different Threshold Heuristics with Optimal Offline Solution for a User Sequence of 1000 Users and Capacity=2000

Threshold method	Average comp. ratio	Worst comp. ratio	Best comp. ratio
Monotone threshold	1.1084	1.3100	1.064
Jumping threshold	1.3700	1.7200	1.3500
GA based threshold	1.1422	1.5102	1.1087
Rule based threshold	1.0362	1.2066	1.0229

1000 user arrivals at each session.

The total achieved throughput and related competitive ratio results given Tables 7.2 and 7.3respectively show that even the worst-case competitive ratio of the offered heuristics never exceeds 1.75. Moreover, the results for the monotone threshold function following [62] are consistent with the worst possible competitive ratio derived in Appendix A, which is 1.51 since the worst case competitive ratio cannot be worse than that limit $ln(U/L) + 1$ as . Rule based threshold achieves the lowest worst competitive ratio, among the tested algorithms. As mentioned before, due to the increase in problem model complexity by defining another decision parameter, the rule based threshold starts to provide the best performance over all.

Then, a time varying channel extension is examined and a channel fading parameter is introduced in the following simulation. For indoor applications we may observe constant channel states and gains for long durations, but for outdoor problems including mobile transceivers or users the channel state may change even at each slot [3]. A fading factor γ_k may be modelled as a Markov process with well defined states but

Table 7.3: Total Throughput Comparison of Different Threshold Heuristics with Optimal Offline Solution for a User Sequence of 1000 Users and Capacity=2000

Method	Average total value	Worst total value	Best total value
Offline optimal solution	17599	17167	18050
Monotone threshold	15880	13374	16647
Jumping threshold	12778	10221	13103
GA based threshold	15416	11581	16042
Rule based threshold	17003	14524	17163

in this deterministic model, perfect channel assumption is used with no other outdoor interference, only a constant decrease the throughput is to be expected in some slots. Following this setup the energy harvest patterns are also considered in a more realistic scenario where the overall resource allocation problem is examined over N_k energy harvests where $k = 10$, assumed to occur in a 24-hour cycle. The amounts of the harvests are presumed to be different as well as their occurring slots. This assignments allow us to examine a relatively arbitrary model which prevails upon the potential weather condition changes and fading channel conditions for randomly located users demanding service.

The competitive ratio analysis for all of the threshold function methods proposed in Chapters 5 and 6 yield the results shown in the performance graphs 7.1 and 7.2. The worst-case results illustrated in Figure 7.1 reveal that the Monotone Threshold function and Rule Based Threshold function present closer performances as the user characteristics differ more and more by loosing U and L bounds on the user efficiency ratios (changing the required service rates on a larger scale) whereas their performances differ more as similar characteristic user sequences are encountered, which implies an increased quality of service demanding a stable transmission rate. The rule based threshold provides the best competitive ratio for a less distinct user set as the decrease in user efficiency diversity rate approaches to 0.9 in the worst-case analysis in Figure 7.1. As the difference in diversity of user efficiency rates increase, the performances of Jumping Threshold and Monotone Threshold Functions get closer as expected since they end up in the same decisions for relatively similar user sequences. The Genetic Algorithm does not propose a competing performance in terms of competitive ratio analysis, but proves to be sufficiently efficient in most cases.

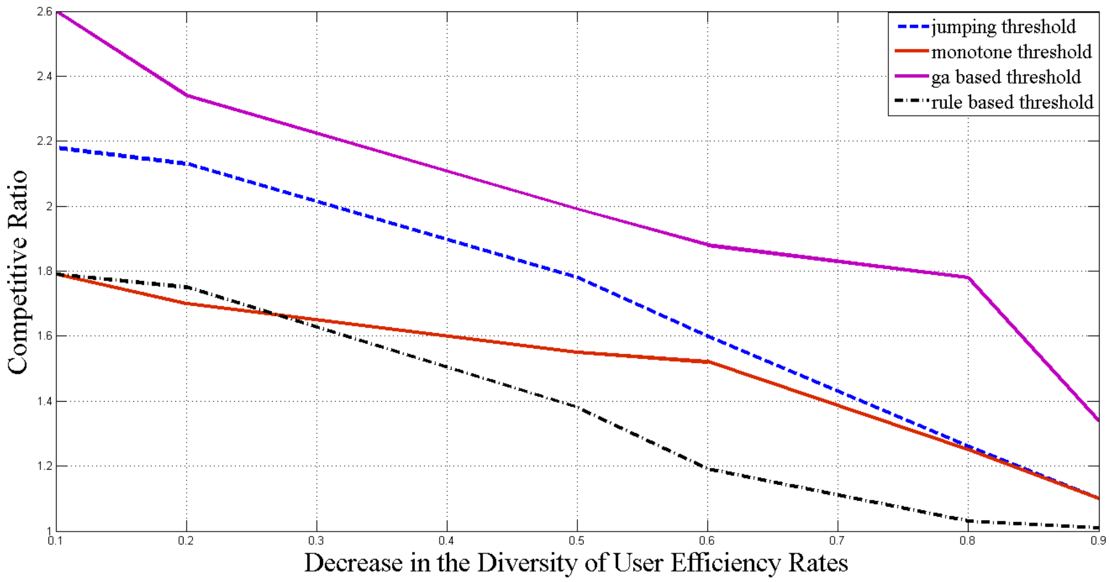

Figure 7.1: Performance Evaluation of Different Online Threshold Heuristics vs. Diversity in Users Characteristics: 'Worst Case Competitive Ratio Analysis', Monte Carlo Simulation of 1000 runs over a Randomly Generated User Sequence of $N = 1000$ Users under $k = 10$ Energy Harvests of Different Amounts between $[0, 250mJ]$ Modelled on a 24-Hour Daily Period with APOM Capacity Constraint of $2000mJ$

For the average case performance outputs given in Figure 7.2, the rule based, monotone and jumping threshold methods ensure a similar competitive ratio through the end of horizon but the rule based threshold approach eludes from others approximating to the optimal solution as the user efficiency characteristics become more similar. These three methods on average case analysis satisfies the the lower bound on the competitive ratio (1.51) that a fraction based online KP heuristic should confirm as stated in [62]. Similarly, the genetic algorithm reveals a worse performance compared with the other methods as discussed earlier. However, over a similar set of user sequence its performance augments as observed since the training of the strategy over generations become more concrete eliminating many irrelevant steps in the fitness evaluation process.

To cover all of the performance analysis and see the throughput maximization performance of proposed techniques, Figure 7.3 is provided assuming harvested energy is between $[0, 250mJ]$ coming at random unknown intervals. The throughput performances show that the decision process implemented via rule based optimization

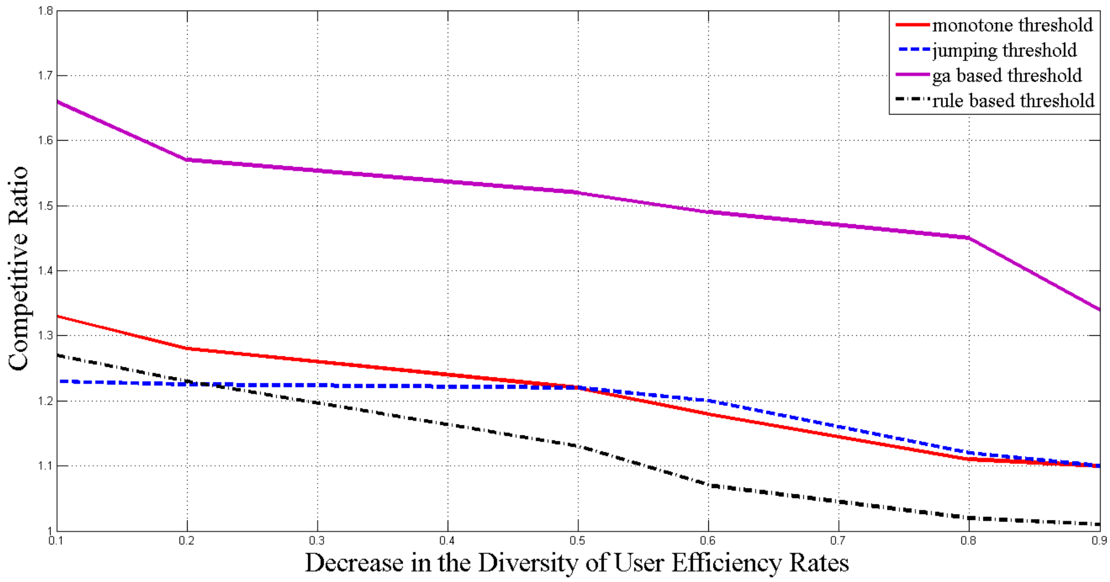

Figure 7.2: Performance Evaluation of Different Online Threshold Heuristics vs. Diversity in Users Characteristics : 'Average Case Competitive Ratio', Monte Carlo Simulation of 1000 runs over a Randomly Generated User Sequence of $N = 1000$ Users under $k = 10$ Energy Harvests of Different Amounts between $[0, 250mJ]$ Modelled on a 24-Hour Daily Period with APOM Capacity Constraint of $2000mJ$

gives the most satisfactory outcome as discussed earlier. However, all other heuristics are performance-wise comparable considering different user sequence characteristics and required transmission rates. It should also be noted that even this randomized throughput results stayed at a much higher level in terms of transmission rates compared with service requirements for 3G communication.

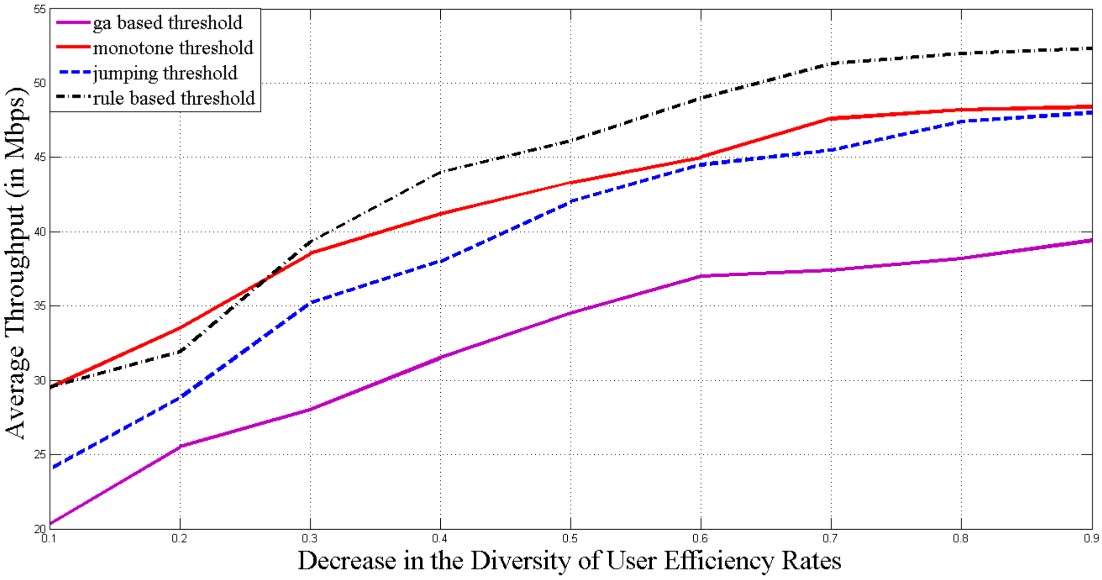

Figure 7.3: Throughput Performance Evaluation of Different Online Threshold Heuristics vs. Diversity in Users Characteristics, Monte Carlo Simulation of 1000 runs over a Randomly Generated User Sequence of $N = 1000$ Users under $k = 10$ Energy Harvests of Different Amounts between $[0, 250mJ]$ Modelled on a 24-Hour Daily Period with APOM Capacity Constraint of $2000mJ$

CHAPTER 8

CONCLUSION

In this thesis, we addressed the problem of online user admission for a mobile internet service provider, which is inspired by the emerging interest of industry initiatives toward providing Internet access to deprived areas. First, the problem setup is modelled as a very well-known combinatorial optimization problem, *Knapsack Problem*. Then, the offline optimum solutions are examined as well as online heuristics for this model. Due to energy replenishment capability of the service provider, the standard static capacity knapsack formulation has been changed and some online heuristics are proposed. These solutions turned out to be applicable to other instances of online knapsack problems with incremental capacity since AP is capable of energy harvesting, which corresponds to incremental dynamic capacity as well.

For a throughput maximization decision problem, obtaining a *threshold type* scheme turned out to be advantageous for online models. We considered adaptive threshold based policies, where a user is admitted if its utility to weight ratio exceeds a certain threshold, where the threshold also varies depending on availability of energy and closeness to the next energy harvesting instant. We proposed monotonic, and piecewise monotonic threshold functions, based on a previous literature. Next, we developed two different threshold functions using Rule Based approach and Genetic Algorithm. The competitive ratios of the algorithms were measured using Monte Carlo simulations. Experimental results demonstrate that the proposed decision methods using different threshold functions for the resource allocation problem of the energy harvesting APOM are efficient in achieving close to optimal competitive ratios as well as low computational complexity.

As a further study, the strategies proposed in this paper can be extended to a multiple mobile station case for improved efficiency in practical uses. Route planning for stations, their intercommunication protocols and the optimum station settlement may also be the subjects of other researches themselves. Optimum path planning combined with our concept, even better performances can be attained. In addition, different models may be applied to APOM scenario problems, where the channel characteristics are implemented with a real life compatible interference model. Also, energy replenishments might be interpreted stochastically. As well as channel gains, the energy replenishment can also be stated as a Markov Process. Finally, the deterministic plan for this model and stochastic policy can be compared. Yet, there may still be further extensions to the problem apart from applying different possible models. The main idea behind this problem is obviously an innovative approach for communication networks and once practically used, it is very likely for such a system to spread over the world in the coming years especially in space studies and military projects in addition to civilian applications.

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APPENDIX A

COMPETITIVE RATIO DERIVATION

Proof of Theorem 1. *Following the steps given in [62], for any input sequence of* σ *after some time including energy harvests, let the algorithm terminate filling* Z *fraction of the total capacity (total amount of energy harvests until that instant). Let* S *and* S^* *denote the set of selected users by the Monotone Threshold method and the offline optimal algorithm respectively. In equations A.1 and A.2, weight and value of the common items in both sets are assigned to the variables* W *and* V*. Then, the proof of the deterministic competitive ratio is given as follows:*

$$\sum_{i \in (S \cap S^*)} w_j \triangleq W \tag{A.1}$$

$$\sum_{i \in (S \cap S^*)} v_j \triangleq V \tag{A.2}$$

An upper bound is needed to be defined on the total value of optimal algorithm. Therefore, since all the users to be selected by the optimal algorithm but not by the Monotone Threshold Algorithm have value over weight ratios smaller than the threshold at that instant and threshold is an increasing function, we have an upper bound as:

$$OPT(\sigma) \leq V + \psi(Z)(B - W) \tag{A.3}$$

$$\frac{OPT(\sigma)}{A(\sigma)} \leq \frac{V + \psi(Z)(B - W)}{V + v(S \setminus S^*)} \tag{A.4}$$

Using the threshold function we may define upper bounds for the common total value parameter V *and remaining total value of optimal algorithm as* V_1 *and* V_2 *respec-*

tively.

$$V \geq \sum_{i \in (S \cap S^*)} \psi(z_j) w_j \triangleq V_1 \tag{A.5}$$

$$v(S \setminus S^*) \geq \sum_{i \in (S \setminus S^*)} \psi(z_j) w_j \triangleq V_2 \tag{A.6}$$

$$\frac{OPT(\sigma)}{A(\sigma)} \leq \frac{V + \psi(Z)(B - W)}{V + v(S \setminus S^*)} \tag{A.7}$$

$$\leq \frac{V_1 + \psi(Z)(B - W)}{V_1 + v(S \setminus S^*)} \leq \frac{V_1 + \psi(Z)(B - W)}{V_1 + V_2} \tag{A.8}$$

$$\frac{OPT(\sigma)}{A(\sigma)} \leq \frac{\psi(Z)B}{\sum_{i \in S} \psi(z_j) w_j} \leq \frac{\psi(Z)}{\sum_{i \in S} \psi(z_j) \Delta z_j} \tag{A.9}$$

Then, the assumption of encountering very small weights with respect to the capacity is used and Δz_j is defined as follows:

$$\Delta z_j \triangleq z_{j+1} - z_j = w_j / B forall j \tag{A.10}$$

$$\sum_{i \in S} \psi(z_j) \Delta z_j \cong \int_0^Z \psi(z) dz \tag{A.11}$$

$$= \int_0^c L dz + \int_c^Z \psi(z) dz \tag{A.12}$$

$$= \frac{L}{e} \frac{(Ue/L)^z}{ln(Ue/L)} = \frac{\psi(z)}{ln(U/L) + 1} \tag{A.13}$$

Finally, when the obtained result of Eqn A.13 is substituted for the denominator of Eqn A.13, we have a deterministic competitive ratio given as:

$$\frac{OPT(\sigma)}{A(\sigma)} \leq ln(U/L) + 1 \tag{A.14}$$