USER CENTRIC AND NETWORK CENTRIC APPROACHES FOR RESOURCE AND EMERGENCY ALERT OPTIMIZATION IN WIRELESS NETWORKS

by

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ABSTRACT OF THE DISSERTATION

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With the advent of HetNets and small cells as a viable solution to enable new 5G applications like ultra-reliable low latency communications (URLLC), the problems of user association and resource allocation in wireless HetNets have drawn a lot of attention in recent years. Due to the inherent interdependencies of these two problems, we cannot optimize one without considering its impact on the other one. Hence, we should jointly optimize them, which often results in formulating NP-hard optimization problems. To address such complexity, we have to design proper low complexity heuristic methods. In this thesis, we investigate two different approaches to solve this joint optimization problem, namely, network centric approach using a centralized optimization model based on Expected Utility Theory (EUT), and user centric approach using a distributed interactive game theoretic model based on Prospect Theory (PT). Network centric approaches often rely on solving centralized optimization problems. In this thesis, we first show that the centralized optimization of user association and resource allocation in HetNets is reducible to the well-known 0-1 Knapsack problem, and hence is NP-hard. Then, to reduce the computational complexity, we propose a machine learning aided heuristic model to efficiently solve it. In particular, a multi-tier network
with a single macro base station (MBS) and multiple overlaid small cell base stations (SBSs) is considered that includes users with different latency and reliability constraints. Modeling the latency and reliability constraints of users with probabilistic guarantees, the joint problem of user offloading and resource allocation (JUR) in a URLLC setting is formulated as an optimization problem to minimize the cost of serving users for the MBS. Since the JUR optimization is NP-hard, we propose a low complexity learning based heuristic method (LHM) which includes a support vector machine-based user association model and a convex resource optimization (CRO) algorithm. To further reduce the delay, we propose an alternating direction method of multipliers (ADMM) based solution to the CRO problem. Simulation results validate the efficiency of the proposed LHM method. Since network centric models are based on Expected Utility Theory (EUT), they are not capable of capturing the subjectivity of end-user decisions and its effects on the performance of wireless networks, especially under the presence of uncertainty in the network services and parameters. To explicitly address subjectivity, we use PT to study the impact of end-user decisions on service provider (SP) bidding and user/network association in a HetNet with multiple SPs while considering the uncertainty in the service guarantees offered by the SPs. Using PT to model end-user decision making that deviates from EUT, we formulate user association with SPs as a multiple leader Stackelberg game where each SP offers a bid to each user that includes a data rate with a certain probabilistic service guarantee and at a given price, while the user chooses the best offer among multiple such bids. We show that when users underweight the advertised service guarantees of the SPs (a behavior observed under uncertainty), the rejection rate of the bids increases dramatically which in turn decreases the SPs utilities and service rates. To overcome this, we design a two-stage learning-based optimized bidding framework for SPs. In the first stage, we use a support vector machine (SVM) learning algorithm to predict users’ binary decisions (accept/reject bids), and then in the second stage we cast the utility-optimized bidding problem as a Markov Decision Problem (MDP) and use a reinforcement learning (RL)-based dynamic programming algorithm to efficiently solve it. Simulation results and computational complexity analysis validate the efficiency of the proposed bidding framework.
We also investigate resource management for mobile networks during emergencies such as natural disasters and show that the current wireless emergency alerts (WEAs) are not efficient to increase users’ compliance with received alerts guidelines. WEAs motivate users to refrain from overloading the mobile network with non-necessary traffic during emergency situations where the capacity of the cellular network has been dramatically reduced due to damage to the communications infrastructure. In these situations, enabling people who are either trapped or in distress in isolated areas with limited network access, and allowing them to communicate with rescue and recovery teams in their neighborhoods is critical for saving them. In this thesis, we present a Cognitive Wireless Emergency Alert System (CWEAS) that introduces a cognition cycle to the current Integrated Public Alert and Warning System (IPAWS) and preserves bandwidth and protects against mobile network outage during emergencies, by using customized alerts and traffic prediction models that consider realtime monitoring information of the network, users and the environment.
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Chapter 1
Introduction

With the emergence of 5G ultra-dense heterogeneous networks (HetNets), as a design solution to cope with the increasing demand from mobile users for higher data rates and increased reliability, user to BS association in such networks has drawn a lot of attention in recent years [1,2]. In terms of design and control, all user to BS association models could be classified into two categories of network centric models, and interactive user centric models. In the network centric approaches, the user to BS association decisions are entirely made at the network/BSs side, using centralized optimization techniques, with or without the input information from users. However, in the interactive user centric models, users are also involved in the decision process in a way that BSs compete with each other to serve the users located within their coverage area, and users choose the best serving BS among all such candidates, that could better serve the user demands.

Traditionally, before the development of HetNets, each mobile user were covered by a few BSs, and users coverage/received signal strength was the main issue. Hence, mostly network centric approaches were employed to associate each user to the BS from which it could receive the strongest signal with the highest SNR, and perform the required handoff procedure between current and destination BSs. Recently, with the emergence of new app types in 5G like URLLC and IoT besides of traditional eMBB apps and considering their diverse QoS requirements in one hand, and the network economics aspects of wireless services in another hand, the user to BS association paradigm is shifting toward more distributed user centric approaches, as users no longer need to be served always by the BS which offers a higher data rate, or better SNR. For example, for some IoT apps with event driven sporadic traffic, data rate is of less importance as compared to power consumption, and for URLLC apps reliability and delay criteria are
more critical than data rate. Hence, ideally users should be able to choose their serving BS based on their dynamic app requirements, in an interactive and dynamic fashion, unlike static SNR based approaches.

In such a scenario where users could choose from multiple service providers (SPs), SPs will have to dynamically compete with each other to get the users to connect to their network by offering attractive service guarantees and prices. Therefore, user/network association and smart data pricing are extremely important from both user and SP perspectives [3–5]. Earlier work in the literature on both user/network association [6–24], as well as pricing [25–29], has primarily relied on models based on EUT.

Due to uncertainties in channel and traffic conditions, when the advertised data rates offered by SPs can only be met with probabilistic guarantees, then these probabilities are not necessarily the same from user and SPs perspectives owing to the subjective biases of human decision making. This disparity can result in the rejection of SP offers as shown in our previous work [30]. In fact, it was shown in [30] that when users underweight the advertised service guarantees of the SPs (a behavior observed under uncertainty), the rejection rate of the bids increases dramatically which in turn decreases the SPs utilities and service rates.

In this thesis, we use Prospect Theory [31], a Nobel prize winning theory that explains real-life decision-making and its deviations from EUT behavior, to study user decisions in wireless HetNets. To do so, we first formulate the user to BS association problem in HetNets as a Stackelberg game between SPs and user, in which WiFi and cellular SPs as the leaders of the game make offers to the user, and the user as a follower makes a decision about the received offers. Then based on the user response to received offers, the SPs optimize their bids to maximize their utility. By considering a convex pricing function for the SPs and a concave payoff function for the users, we compare the utility of both user and SPs under EUT and PT. We derive all possible pure strategy and mixed strategy NEs for the proposed Stackelberg game. We also provide the conditions under which the existence of such NEs are guaranteed, for both EUT and PT cases. To see the effects of heterogeneity of the SPs, we compare the results for both symmetric and non-symmetric SP models. To reduce the rejection rate
of SPs offers, we design a bandwidth expansion solution by which SPs could retain users and compensate the underweighting of advertised service guarantees by offering extra bandwidth to users. However, the applicability of bandwidth expansion solution is relied on this assumption that SPs know exactly how users would perceive their advertised service guarantees, while in reality SPs won’t have access to such information as users will only communicate their final binary decisions to SPs. Hence, SPs won’t know anything about users’ internal decision making model, unless they use learning algorithms to develop models for predicting user decisions.

To overcome this issue, we design an interactive two-stage learning-based optimized bidding framework for SPs. In the first stage, we use a SVM learning algorithm to predict users’ binary decisions (accept/reject bids), and then in the second stage we cast the SPs utility-optimized bidding problem as a Markov decision problem (MDP), and propose an iterative dynamic programming algorithm to efficiently solve it. Simulation results and computational complexity analysis validate the efficiency of the bidding framework.

The novel contributions of this work are: (i) Using PT to capture the effects of user perception of uncertainty in service guarantees and decision making; (ii) Showing the inefficiencies of the widely adopted EUT model of user decision making and its negative effects on the SPs’ expected utility and revenue; (iii) Proposing a two-stage learning-based framework for SPs to learn users’ decisions under uncertainty in the first stage via SVM learning, and optimize bids in the second stage using RL to maximize revenue; and (iv) Proposing an efficient low complexity dynamic programming based algorithm to solve the formulated RL problem, and find utility optimized bids for SPs.

Simulation results reveal that using the proposed dynamic programming-based optimized bidding (DPOB) method, the achievable sum utility of users and SPs increases on average by factors of 2.77, and 3.27, respectively, as compared to the EUT model. Also, it is observed that the average bandwidth consumption of SPs under DPOB is higher than EUT, as DPOB compensates the under estimation of service guarantees by offering greater bandwidth to users. However, since SPs charge the users proportionally, when users accept their bids, the overall utility of SPs increases under DPOB, despite
increasing their service cost. Moreover, it is shown that the DPOB algorithm converges to the optimal solution much faster than other exhaustive search methods, due to its iterative pruning feature which facilitates its speed in finding the utility optimized bid for each user, among all feasible bids.

The rest of this thesis is organized as follows. In chapter 2, we review the literature and related works. In chapter 3, we present a network centric optimization model for joint user association and resource allocation in wireless HetNets, and propose a learning based heuristic method to efficiently solve it. In chapter 6 we introduce an interactive Stackelberg game model as a user centric approach to study the effects of end-users behavior on the performance of wireless HetNets, using Prospect Theory. In section 5, we design a two-stage learning-based optimized bidding framework for SPs to learn the end users behavior using support vectors machine learning, and optimize their bids based on that using a dynamic programming based heuristic algorithm. We summarize the findings of this thesis and conclude in chapter 7.
Chapter 2

Background and Related Work

Numerous studies have been done in recent years to address user association in HetNets [3]. Due to the inherent interdependencies between user/cell association and resource allocation problems in HetNets and their direct impacts on each other, these two problems are usually jointly addressed and optimized with respect to a given performance parameter [6,7]. The diverse range of performance criteria considered in the user/network association schemes proposed for HetNets spans from load balancing [8–10], to energy efficiency [11–14], interference management [15], coverage maximization [16], and latency minimization [17]. Also, in terms of the methodology, the range of approaches proposed for user/network association in HetNets spans from optimization methods [12], to game theoretic solutions [14,17–21], evolutionary algorithms [22], estimation methods [23] and learning algorithms [24].

In terms of methodology, the range of approaches include evolutionary game models [32,33], auction based models [34], matching theory based methods [35], non-cooperative and competitive game models [36,37], Stackelberg and Bayesian methods [38] semidefinite relaxation and randomization models [39], Lagrange decomposition methods [40], and other approaches [41–43]. However, most of these mechanisms essentially are borne out of EUT based approaches. When a service provider (SP) controls the access of end-users to the offered services via differentiated and hierarchical monetary pricing, then the performance of the network is directly subject to end-user decision-making that has shown to deviate from EUT in many cases, and is better captured by models based on PT [31,44–46].

Moreover, several works investigated the role of network economics on user/network association and allocation of network resources, via supply and demand-based smart
pricing models [25-29]. For example, in [25] an iterative double-auction mechanism is proposed to offload traffic from macro BSs to third party small cell access points. A cost-aware adaptive bandwidth management mechanism for empowering users to make traffic offloading decisions is proposed in [26]. The effects of users social learning on service provider’s dynamic pricing policies is investigated in [27]. In [28] the duopoly competition between mobile network operators for the mobile data plans with time flexibility is characterized using a three stage game model. In [29] a framework for realization of time dependent pricing for multimedia data traffic is proposed to modify users’ behavior and prevent congestion. The role of PT in wireless data pricing has been explored in [44, 45] where users use their subjective biases in evaluating objective probabilistic parameters, and has been observed via human subject studies in [46]. In [47], a stochastic learning based method for resource scheduling in a virtualized RAN setting is proposed, in which a centralized network controller auctions channels at the beginning of each auction period, and SPs compete with each other to get access to those channels in order to serve their covered users efficiently, and optimize their utility. However, this work also uses EUT based utility models and does not account for subjective user bias in evaluating network uncertainties, as auction happens only between network entities, and users are not directly involved in making decisions in the auction.

In contrast to the earlier works, in this dissertation, using PT, we address both user/network association and data pricing with emphasis on end-user behavior and decision making under uncertainty. In chapter 6 we model the HetNet with probabilistic service guarantees and PT based decision making using the approach in [30] where it was observed that the underweighting of the service guarantees by the users results in an increased rejection of the SP bids. To overcome this, a heuristic solution based on expanding the bandwidth available to the SPs bids was proposed in [30]. However, it required the SPs to have knowledge of how the users perceive the uncertainty in the service guarantees, while in reality, SPs don’t have access to such information. The focus of the learning based optimized bidding method presented in chapter 5 is to overcome the bid rejection problem via a completely different approach, namely a
two-stage learning-based optimized bidding framework for SPs. In the first stage, we use a SVM learning algorithm to predict users' binary decisions, and then in the second stage we cast the utility-optimized bidding problem as a Markov Decision Problem and propose a RL-based dynamic programming algorithm to efficiently solve it.
Chapter 3

Network Centric Approach: A Centralized Optimization Model

3.1 Introduction

The emergence of delay-sensitive applications such as intelligent transportation systems, and patient monitoring applications makes it necessary to redesign classical resource allocation techniques in wireless heterogeneous networks (HetNets) and support ultra-reliable and low latency communications (URLLC) [48]. URLLC introduces new challenges to the design of next-generation cellular networks where the traffic consists mainly in short packet transmission and the related hard constraints in terms of latency and reliability. In fact, any delay in the transmissions of the order of microseconds could make the packets useless and hence must be dropped. Coupled with the ultra-density of future cellular networks that are expected to support billions of Internet of things (IoT) devices, time-sensitive applications will require a large amount of network resources such as power and bandwidth. Thus, the optimization of such scarce resources represents a crucial challenge for wireless service providers, as they need to support URLLC in one hand, and reduce their cost in using network resources on the other.

Several works in the literature have addressed the problem of resource allocation in cellular networks for both bandwidth-intensive applications and URLLC traffic [49–54]. Most of these works have considered a cellular network model with a single base station (BS) that serves two types of users namely eMBB and URLLC users, and proposed techniques to jointly satisfy the delay and reliability constraints of URLLC users, while optimizing the allocation of resources for the cellular BS. The authors in [49] proposed an optimal resource allocation strategy for uplink transmissions to maximize the delay-sensitive area spectral efficiency as a performance metric while guaranteeing
the constraints on reliability. In [50], the authors proposed a method for maximizing energy efficiency for URLLC under strict QoS constraints on both end-to-end delay and overall packet loss. In [51], the authors investigated the potentials of using unlicensed spectrum for enabling ultra reliable and low latency communications. The work in [52] presented a network slicing based resource allocation framework to provide reliable and low latency communications to users with such demands. In [53] a load balancing user association scheme for millimeter wave networks is proposed.

Although interesting, all these works consider a network composed of a single cell while currently deployed networks are heterogeneous with different types of base stations. Thus, none of these works have studied the opportunity of offloading users to potential small cells as a possible way for increasing reliability of the transmissions. Moreover, they do not account for the impact of the serving cost on the allocation of resources and user offloading at the service providers. User offloading and resource allocation are two effective and highly correlated techniques for enabling URLLC in wireless HetNets, and due to their interplay, they must be jointly optimized while considering the monetary impact on the service providers.

The main contribution of the model presented in this chapter consists in jointly considering user offloading and resource optimization to enable URLLC in HetNets. In our model, hard latency and reliability constraints of URLLC users are modeled with probabilistic guarantees and relaxed based on Markov’s inequality. In particular, we formulate the joint user association and resource optimization (JUR) problem as an optimization problem which is NP-hard and computationally intractable for large HetNets. We reduce the complexity of the JUR problem by casting it into two sub-problems and then proposing an efficient learning-based heuristic method (LHM) to solve them. The first sub-problem is the user-cell association problem for which we reformulate it as a classification problem and solve it using a support vector machine (SVM)-based learning algorithm. We use the results of JUR optimization to train the SVM classifier, and since the results of JUR problem are optimized, the training error will be minimized this way. Once we trained the SVM, we can use it to determine user associations for future users. The second sub-problem is the resource allocation
problem for which we propose a low complexity iterative algorithm. After solving user association problem using the trained SVM classifier, the JUR problem will be simplified by removing binary user association variables from it and it will be reduced to a convex optimization problem. To solve such convex optimization problem for the MBS, we propose a low complexity iterative solution based on the alternating direction method of multipliers (ADMM). Simulation results show that the proposed heuristic method significantly decreases the spectrum access delay for users (by $\sim 93\%$) as compared to JUR problem, while maintaining the full service rate. By offloading $75\%$ of users to SBSs, it also reduces the MBS’s bandwidth and power consumption costs in serving users by $33\%$ as compared to the method with no offloading referred to as the Direct Serving Method (DSM). The rest of this chapter is organized as follows. Section 3.2 introduces the network and system models, and the JUR optimization problem is formulated in section 3.3. Section 3.4 presents the proposed learning-based heuristic method which includes a SVM-based user association model and a low complexity iterative algorithm for resource optimization. Simulation results are presented in section 3.5, and we conclude this chapter in section 3.6.
3.2 Network and System Models

3.2.1 Network Model

We consider a HetNet model which includes one macro cell BS (MBS) and several overlaid small cell BSs (SBSs), and a mix of users with different URLLC applications who are randomly distributed under the coverage area of the MBS. We assume that the MBS is primarily responsible for serving all users, however it can offload some users to overlaid SBSs if such BSs offer to serve users located under their coverage with a price which is less than the cost of serving them directly by the MBS. Figure below shows our network model, in which MBS uses high power transmissions (denoted with gray links) to serve users who are located in the cell edge boundaries, while SBSs can serve such users who are located under their coverage area with low power transmissions (denoted with yellow links), and hence with less cost.

Figure 3.1: HetNet Model with URLLC Applications.
3.2.2 System Model

In our system model, we assume that MBS periodically optimizes its decisions on user offloading and resource allocations, and at the beginning of such optimization intervals an auction will happen between MBS and SBSs, in which each SBS \( k \) bids to serve each user \( i \) under its coverage by calculating the cost of serving such user considering its delay, reliability and data rate constraints. We assume in each transmission request, each user includes its requirement in terms of latency, data rate and reliability which could be different from other user’s requirements. The total price offered by the SBS \( k \) to serve user \( i \) is defined as \( \Phi_{k,i}^* \), which is given by

\[
\Phi_{k,i} = \Phi_{k,i}^s + \Phi_{k,i}^r,
\]

(3.1)
as the summation of two terms; the first term \( \Phi_{k,i}^s \) is the cost of bandwidth and power resources used by SBS \( k \) to serve user \( i \) and satisfy its constraints, and the second term \( \Phi_{k,i}^r \) is the amount of reward asked by SBS \( k \) to serve user \( i \). This offered price has to be paid by the MBS to the SBS \( k \), if MBS offloads user \( i \) to the SBS \( k \). The objective function of the MBS is to minimize its overall cost in serving and offloading all users in the HetNet, and is given by

\[
\min_{(\mu_i, w_i, p_i)} \sum_{i \in U} \mu_i(c_p p_i + \gamma c_w w_i) + (1 - \mu_i)\Phi_{k,i}^*,
\]

(3.2)
in which \( p_i \) and \( w_i \) denote the amounts of power and bandwidth required by the MBS to serve user \( i \), respectively. And \( \mu_i \) is the binary user association variable for user \( i \), with \( \mu_i = 1 \) if users \( i \) is associated to the MBS, and \( \mu_i = 0 \) if user \( i \) is offloaded to the best serving SBS who offers the minimum price to serve this user among all other SBSs. Also, \( c_p \) and \( c_w \) are the MBS unit costs for power and bandwidth, respectively, \( \gamma \) is the regularization parameter which models the trade-off between power and bandwidth costs, \( U \) denotes the set of all users, and \( \Phi_{k,i}^* \) is the price offered by the best serving SBS to serve user \( i \) and is given by

\[
\Phi_{k,i}^* = \min_k \Phi_{k,i}.
\]

(3.3)
We assume the overall spectrum access delay for each user \( i \), \( d_i \), is given by

\[
d_i = d_c + (1 - \mu_i)d_o,
\]

(3.4)
which is the summation of MBS computation delay $d_c$, and offloading delay $d_o$ in case user $i$ is offloaded. So, $d_c$ accounts for the delay in making user associations decisions by MBS, and is a function of the computational complexity of the optimization problem used by MBS for user association and resource allocation, and its processing power, hence it is assumed to be fixed for all users. However, offloading delay is only considered for offloaded users and is assumed to be equal to $3 \times RTT$ as three $RTT$ is required for transmissions of bidding, bid selection, and acknowledgment messages between MBS and selected SBS. Denoting $r_i$ as the service rate of user $i$, it is given by

$$r_i = w_i \log(1 + p_i h_i^2 / N_0).$$  

(3.5)
as a function of its allocated power, $p_i$, bandwidth, $w_i$, channel gain, $h_i$, and noise power, $N_0$. We assume each user $i$ has a threshold for its acceptable delay, denoted as $d_{th,i}$, and the delay constraint for each user is defined by setting an upper bound, $\delta_d$, for the violation probability of its delay constraint as defined in

$$Pr[d_i \geq d_{th,i}] \leq \delta_d.$$  

(3.6)

Also, the data rate constraint for each user $i$, can be defined as the probability of satisfying its requested data rate, $r_{th,i}$,

$$Pr[r_i \geq r_{th,i}],$$  

(3.7)

and, the reliability constraint for each user $i$ is defined by setting an upper bound for its data rate constraint’s violation probability,

$$Pr[r_i \leq r_{th,i}] \leq \delta_r.$$  

(3.8)
3.3 Joint User Offloading and Resource Optimization (JUR)

After defining the objective function for MBS in (4.2), and delay and reliability constraints for users in (4.6), and (4.8), respectively, the joint user association and resource optimization (JUR) problem for the MBS can be formulated to minimize the cost of serving users for the MBS while satisfying their delay and reliability constraints. The JUR problem formulation is given by

$$\min_{(\mu_i, w_i, p_i)} \sum_{i \in U} \mu_i (c_p p_i + \gamma c_w w_i) + (1 - \mu_i) \Phi^*_{k,i}, \quad (3.9a)$$

subject to:

$$\Pr[d_i \geq d_{th,i}] \leq \delta_{d,i}, \forall i \in U, \quad (3.9b)$$

$$\Pr[r_i \leq r_{th,i}] \leq \delta_{r,i}, \forall i \in U, \quad (3.9c)$$

$$0 \leq p_i \leq P_{max}, \forall i \in U, \quad (3.9d)$$

$$0 \leq \sum_{i \in U} w_i \leq W_{max}, \quad (3.9e)$$

$$\mu_i - \mu_i^2 = 0, \forall i \in U, \quad (3.9f)$$

in which $p_{max}$ is the maximum power spectral density that can be used by MBS to serve any user, and $W_{max}$ is the total bandwidth available at the MBS. The constraints in (3.9d) and (3.9e) ensure that the allocated power and bandwidth to each user is within the acceptable range for them, respectively, and the constraint in (3.9f) ensures that user association variable for each user $i$ is a binary integer variable. Solving the optimization problem defined in (3.9a)-(3.9f) gives the optimal solution to the JUR problem, however this is a binary integer non-linear programming problem, which is NP-hard and computationally intractable for HetNets with large number of users. In fact, in [34] we showed that a simplified version of this problem is reducible to the Knapsack problem which is well known NP-hard problem, thus JUR optimization is also NP-hard and not scalable for large HetNets. Hence, we need to find low complexity alternative solutions to the JUR problem.
3.4 Proposed Heuristic Method

To increase the efficiency of resource allocation for the MBS, we replace the NP-hard JUR problem with a two phase low complexity heuristic solution, in which we first solve the user association problem using a Support Vector Machine (SVM)-based user association (SUA) model, and then we optimize the MBS’s power and bandwidth allocation using a convex resource optimization (CRO) algorithm.

3.4.1 SVM-based User Association (SUA)

Since the user association variables in JUR optimization ($\mu_i, \forall i \in U$) are binary variable and optimization problems with binary variables are often NP-hard, in this section we propose a learning based heuristic solution to user association problem, to remove such variables from JUR optimization problem. In fact, since MBS’s decisions on user association for all users are binary, to either serve them or offload them to SBSs, the user association problem in HetNets can be seen as a classification problem, to classify users between MBS and SBSs, which can be efficiently solved for large HetNets using SVMs. Assuming we have the training data from running the JUR problem by MBS in previous time slots, we can train an SVM to learn the user association model from them, and use the trained SVM to predict the user association for the future time slots. To do so, we assume we have a set of labeled data points $(u_i, \mu_i)$ in which $\mu_i$ is the user association value for user $i$, and $u_i = (x_i, d_{th,i}, r_{th,i}, \delta_{d,i}, \delta_{r,i}, SNR_i)$ is the user $i$-th features vector which includes its distance to MBS, data rate threshold, reliability threshold, data rate violation bound, reliability violation bound, and the SNR of its signal at the MBS. The training set $D$ which includes $P$ data points is given by

$$D = \{(u_1, \mu_1), (u_2, \mu_2), \ldots, (u_P, \mu_P)\}.$$ (3.10)
using the training data, we can train a SVM using the below optimization problem:

\[
\min_{w, b, \epsilon} \frac{1}{2} w^T w + c \sum_{i=1}^{P} \epsilon_i,
\]

subject to:

\[
\mu_i (w^T \Phi(u_i) + b) \geq 1 - \epsilon_i,
\]

\[
\epsilon_i \geq 1,
\]

in which \(2/w^T w\) is the width of separating margin, \(c\) is the regularization parameter, \(\epsilon_i\) is the error in misclassifying user \(i\), and \(\Phi(u_i)\) is the Gaussian kernel function used to increase the precision of classification in problems with non-linearly separable data points, by capturing the correlations between different data points. It maps the features vector of each user \(u_i\) into a point in higher dimensional transformed feature space. For any two \(m\)-dimensional feature vectors \(u_i\) and \(u_j\), the kernel function is defined as

\[
\Phi_{(u_i,u_j)} = e^{-\gamma ||u_i - u_j||^2}, \gamma = 1/2\sigma^2 \geq 0.
\]

After deriving the classification vector \(w\) and parameter \(b\) from the optimization problem defined in (3.11a)-(3.11c), we construct the classifier function

\[
f(u_i) = (w^T u_i) + b = \begin{cases} 
\geq 0, \ i.e. \ \mu_i = 1, \\
\leq 0, \ i.e. \ \mu_i = 0,
\end{cases}
\]

and use it to predict the association of each user \(i\) with given feature vector \(u_i\) as defined in (4.13). Figure shows that for any potential user with the given six features, the SVM classifier function can determine if the MBS should offload it or serve it directly.

### 3.4.2 Convex Resource Optimization (CRO)

After determining the user associations using the SVM classifier by the MBS, the binary user association variables can be removed from the original JUR problem, and it can be reduced to a convex optimization problem. The non-convex objective function in JUR problem defined in (3.9a) will be reduced to minimizing a linear cost function as defined in

\[
\min_{p_i, w_i} \sum_{i \in U, \mu_i = 1} (c_p p_i + \gamma c_w w_i),
\]
Figure 3.2: SVM-based User Association in HetNets.
which is a convex function in both power $p_i$, and bandwidth $w_i$ variables. Note that MBS is only optimizes its bandwidth and power allocations to those users that are not offloaded to SBSs, and have to be served by MBS. Also, the non-convex constraint defined in (3.9f) can be removed since $\mu_i$ variables are no longer optimization variables, and are known to MBS using SVM classifier in previous phase. Since users who are associated to MBS experience the minimum delay which is the fixed computation delay of MBS, and none of them experience offloading delay, the delay constraint can also be removed in resource optimization problem for the MBS. Also, using the Markov’s inequality bound for the reliability constraints, we have

$$Pr[r_i \geq r_{th,i}] \leq \frac{E[r_i]}{r_{th,i}},$$  \hspace{1cm} (3.15)

and, accordingly we can write

$$Pr[r_i \leq r_{th,i}] = 1 - Pr[r_i \geq r_{th,i}] \geq 1 - \frac{E[r_i]}{r_{th,i}}.$$  \hspace{1cm} (3.16)

Hence, we can rewrite the reliability constraint defined in (3.9c) as

$$1 - \frac{E[r_i]}{r_{th,i}} \leq \delta_{r,i},$$  \hspace{1cm} (3.17)

which can be simplified as

$$-E[r_i] + r_{th,i}(1 - \delta_{r,i}) \leq 0.$$  \hspace{1cm} (3.18)

It should be noted that according to (4.5), knowing the transmission power, $p_i$ and bandwidth $w_i$, the expected service rate of user $i$, $E[r_i]$, is a function of expected channel gain and noise, and denoting expected channel gain and noise as $\bar{h}_i$ and $\bar{N}_0$, respectively, it can be calculated by

$$E[r_i] = w_i \log(1 + p_i\bar{h}_i^2/\bar{N}_0).$$  \hspace{1cm} (3.19)

Since $E[r_i]$ is a concave function in $(w_i,p_i)$, hence $-E[r_i]$ and accordingly the reliability constraint defined in (5.1) are convex. The convex resource optimization (CRO) problem
for MBS can be formulated as

$$\min_{p_i, w_i} \sum_{i \in U, \mu_i = 1} (c_p p_i + \gamma c_w w_i),$$

subject to:

$$- E[r_i] + r_{th,i}(1 - \delta_{r,i}) \leq 0,$$

$$0 \leq p_i \leq p_{max},$$

$$0 \leq \sum_{i \in U} w_i \leq W_{max},$$

which can be solved using CVX, in much less time than JUR problem. If some URLLC users have stricter delay constraints such that they cannot even wait for the computational delay, $t_c$, of solving the CRO problem before receiving their service, then MBS has to find heuristic methods to reduce the time complexity of solving this problem. One way to find the solution to the CRO optimization problem in less time is to use the method of Lagrange multipliers, since all its objective and constraints functions are differentiable and continuous in both $p_i$ and $w_i$ optimization variables.

Defining the power vector $p = (p_1, p_2, \ldots, p_N)$, $0 \leq p_i \leq P_{max}, \forall i$, and the bandwidth vector $w = (w_1, w_2, \ldots, w_N)$, $0 \leq \sum w_i \leq W_{max}, \forall i$, and power and bandwidth cost function $f(p) = \sum_i c_p p_i$, and $f(w) = \sum_i \gamma c_w w_i$, the objective of the CRO problem is to find the optimal solution $(p^*, w^*)$ such that

$$(p^*, w^*) = \min_{p, w} \{ f(p) + f(w) | E[r_i] \geq r_{th,i}(1 - \delta_{r,i}), \forall i \}. \quad (3.21)$$

The deviation of the offered reliability to each user $i$ and the minimum bound for the reliability of this user for any amount of allocated power, $p_i$, and bandwidth, $w_i$, is defined as

$$g(p_i, w_i) = E[r_i] - r_{th,i}(1 - \delta_{r,i}), \forall i,$$

where, we must have $g(p_i, w_i) \geq 0$ to satisfy the reliability constraint of each user $i$ that is associated to the MBS. However, since $g(p_i, w_i)$ has a direct relation with both of the power and bandwidth cost functions, to minimize the cost we need to satisfy the reliability constraint of each user $i$ with minimum possible value for $g(p_i, w_i)$, which
means that for the optimal solution, we want the this value to converge to zero. However, it is extremely important that the value of $g(p_i, w_i)$ stays positive while approaching to zero, since for negative values of it the reliability constraint of user $i$ will be violated. To guarantee this, we use a log barrier function for reliability in our penalized Lagrangian function for the method of multipliers to make sure that $g(p_i, w_i)$ will never turn into a negative value. By introducing the Lagrangian variable $\lambda_i$ for each user $i$ to model the cost of deviation from the required threshold for reliability, the penalized Lagrangian function for each user $i$, is given by

$$L(p_i, w_i, \lambda_i) = f(p_i) + f(w_i) + \lambda_i \ln(g(p_i, w_i)) + \frac{\rho}{2} \|\ln(g(p_i, w_i))\|. \tag{3.23}$$

Note that if $g(p_i, w_i) \leq 0$, then $\ln(g(p_i, w_i))$ is undefined, hence $L(p_i, w_i, \lambda_i)$ can only be evaluated in the interior of the feasible region for reliability constraint. Denoting $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_N)$ the Lagrangian function considering all the users will be given as

$$L(p, w, \lambda) = \sum_{\forall i \in U} L(p_i, w_i, \lambda_i), \forall i \in U. \tag{3.24}$$

We denote the values of $p$, $w$, and $\lambda$ variables at each step $k$ of the Lagrangian method of multipliers as $p^k$, $w^k$, and $\lambda^k$, respectively. Starting from some initial values for these variables from their feasible regions, at each step $k$ we fix the values for two of these parameters in the Lagrangian function by using their current values, to find the optimal value for the third variable, by minimizing the Lagrangian function with respect to that variable. This update procedure is given in

$$\begin{cases} p^{k+1} = \text{Arg min}_p L(p, w^k, \lambda^k), \\ w^{k+1} = \text{Arg min}_w L(p^{k+1}, w, \lambda^k), \\ \lambda^{k+1} = \lambda^k + \rho \ln(g(p^{k+1}, w^{k+1})). \end{cases} \tag{3.25}$$

in which $\rho$ is the dual update step length. We continue this iterative updates until converging to a state in which the values of optimization variables do not change anymore. Note that the Lagrangian function is continuous and differentiable with respect to all three variables $p$, $w$, and $\lambda$, hence we can simply take a derivative from the Lagrangian
function in each iteration to find its optimal value quickly w.r.t any variable when the values of other two variables are given. Using this method, in a few iterations we can find the optimal value for the Lagrange dual problem, and since the primal optimization problem is convex, the duality gap is zero, which means the optimal solution to the Lagrange dual problem is also the optimal solution to the primal optimization problem.
3.5 Simulation Results

To evaluate the efficiency of our proposed heuristic method, we consider a HetNet scenario in which there is one MBS located in the center of a cell with the radius of 2000 ft, and there are 8 overlaid SBSs with shorter coverage ranges of 600 ft within that cell who can serve the cellular users under their coverage. We also assume that there are 300 URLLC users who are randomly distributed within the cell, each with different data rate, reliability and delay constraints. We solved the joint user association and resource allocation problem for the MBS using both JUR and LHM, by implementing these methods in Matlab. For better comparison, and to show the effects of user offloading on reducing the MBS’s cost, we also implemented the Direct Serving Method (DSM) in which MBS serves all the users directly without offloading any of them to SBSs. In DSM, MBS optimizes its bandwidth and power allocations to minimize its serving cost using the cost function defined in (4.14). We compare the performance parameters of these three methods in Table 3.5.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>DSM</th>
<th>JUR</th>
<th>LHM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalized Run Time</td>
<td>0.281</td>
<td>1</td>
<td>0.068</td>
</tr>
<tr>
<td>Avg Cost Per User</td>
<td>102.6990</td>
<td>66.3524</td>
<td>68.6456</td>
</tr>
<tr>
<td>Serving Rate</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Total Offloaded Users</td>
<td>0</td>
<td>226</td>
<td>222</td>
</tr>
</tbody>
</table>

As we can see from this table, in JUR method 226 users (75.33 % of total 300 users), and in LHM 222 users (74 % of total 300 users) have been offloaded to the overlaid SBSs, respectively which means that SVM classifier has successfully identified 98.23 % of the users that must be offloaded in order to minimize the cost of MBS. Offloading of these users reduces the MBS’s average energy and bandwidth cost per user from 102.6990 unit cost (UC) in DSM method to 66.35 UC and 68.64 UC in JUR and LHM methods, respectively which leads to the reduction of MBS’s average energy and bandwidth consumption cost by nearly 36%, 33%, respectively as compared to DSM. As we can see in Table 3.5, although the offloading rate and the average cost per user in both JUR and LHM are nearly the same, but the LHM’s running time is much
shorter than the time required by the JUR method. In fact, using the proposed learning based heuristic method to reduce the computational complexity of JUR, we reduced the resource allocation delay for the MBS from 54.03 sec in JUR (which is an NP-hard method) to only 3.68 sec in LHM, which leads to the 93% reduction in spectrum access delay for URLLC users.

Fig. 3.3 compares the MBS’s average energy and bandwidth consumption cost to serve each user in JUR, LHM and DSM. As shown in this figure, due to the offloading of users from MBS to SBSs in LHM and JUR methods, the MBS’s serving cost per user is much less in these methods as compared to DSM, and it is nearly the same in both LHM and JUR methods since the SVM classifier used in LHM heuristic has successfully identified and offloaded users from MBS to SBSs as in the JUR method with less than 2% of users having different base station associations in LHM as compared to JUR. The reason for the gap between MBS’s cost in serving users in LHM and JUR as compared to DSM is that SBSs usually have better channel conditions and hence consume less power and bandwidth to serve URLLC users under their coverage area, and offloading users located under the coverage area of SBSs has less cost for MBS as compared to serving them directly.

To see the effects of load on the service rate of MBS using each of the JUR, LHM and DSM schemes, we change the number of users in our HetNet from 300 users to 500
users, by increasing the number of users with 20 new users in each step. We define the service rate as the percentage of URLLC users who are getting a service that satisfies their delay and reliability constraints. The Fig. 3.4 compares the service rates of MBS using DSM, JUR, and LHM in different load situations. As we can see, by increasing the load or number of users in the HetNet, MBS is unable to serve all the users using DSM method, and the service rate goes below 50% when the number of users exceeds 600 users, while in both JUR and LHM by exploiting the cooperation between MBS and SBSs, and offloading users to less congested SBSs, the full service rate can still be achieved as long as the load is less than the capacity of the HetNet.
3.6 Conclusion

In this chapter, we have considered a HetNet model with one MBS, multiple SBSs and URLLC users with different latency and reliability constraints, and jointly optimized user associations and resource allocation for the MBS. Modeling the latency and reliability constraints of users with probabilistic guarantees, we first formulated an optimization method for joint user association and resource allocation (JUR) in HetNets, and showed that it is NP-hard. In order to reduce the time complexity of the JUR method, we proposed a learning based heuristic method (LHM) to cast the initial optimization problem into a simple SVM-based user association model and a convex resource optimization (CRO) problem. To further reduce the delay for the users, we proposed an ADMM-based solution to the CRO problem. Simulation results validated the efficiency of the proposed method, and showed that it can reduce the MBS’s energy and bandwidth consumption costs considerably by $\sim 33\%$, while also reducing the spectrum access delay for cellular users by $\sim 93\%$ which is attractive for URLLC.
Chapter 4
User Centric Approach: An Interactive Game Theoretic Model

4.1 Introduction

The models presented in the previous section, and in general all network centric user association and resource allocation models, are based on the EUT model, which is unable to explain users real life decisions under uncertainty. In this chapter, we study the impact of end-user’s subjective bias toward probabilistic network parameters like service guarantees, when making decisions (accept/reject SP offers), on the performance of the system. To do so, we consider an interactive user centric model for association and resource allocation in HetNets, in which users receive multiple data service offers from SPs, each of which is defined by an advertised data rate with a probabilistic service guarantee at a given cost.

We use Prospect Theory [31], a Nobel prize winning theory that explains real-life decision-making and its deviations from EUT behavior, to study user decisions in wireless HetNets. We first formulate the user association problem in HetNets as a multiple leader Stackelberg game between SPs and user, in which WiFi and cellular SPs as the leaders of the game make offers to the user, and the user as a follower makes a decision about the received offers. Then based on the user response to received offers, the SPs optimize their bids to maximize their utility. By considering a convex pricing function for the SPs and a concave payoff function for the users, we compare the utility of both user and SPs under EUT and PT. We derive all possible pure strategy and mixed strategy NEs for the proposed Stackelberg game. We also provide the conditions under which the existence of such NEs are guaranteed, for both EUT and PT cases. To see the effects of heterogeneity of the SPs, we also compare the results for both symmetric and
non-symmetric SP models. To the best of our knowledge, this is the first work which address PT effects on user association in HetNets.
4.2 System Model and Problem Formulation

4.3 Network Model

To study user association in HetNets, we developed a two-tier HetNet scenario which includes $L$ wireless users that are randomly distributed within the coverage area of $K$ base stations. As shown in Fig. 4.1, in our HetNet model there is one macrocell LTE BS located in the center of the area and $K - 1$ overlaid small cell WiFi access points who are competing with each other to serve the users in the HetNet. We assume each user in the HetNet receives several bids from service providers (SPs) in both cellular and WiFi tiers, where each bid includes a data rate with a certain probabilistic service guarantee and at a given price. Upon receiving such bids, the user makes a binary decision to accept or reject each of the received bids.
4.4 Stackelberg Game for User Association in HetNets

In our HetNet model, each user receives $K$ different bids from all $K$ base stations, i.e., one bid from the cellular BS and $K - 1$ bids from the WiFi BSs. To enable multi radio dual connectivity (MR-DC) on UEs pushed by 3GPP, we assume each user can be simultaneously connected to both cellular and WiFi SPs to receive the data service. Specifically, we assume that each user can only be associated to the cellular SP and the best serving WiFi SP for that specific user, which is the SP who offers a bid with highest utility among all WiFi SPs. Note that since all WiFi SPs use the same pricing function, the SP with better channel conditions consumes less amounts of resources to serve the user and hence offers the bid with the highest utility among all WiFi SPs. Hence, we model user association problem in this work as a Stackelberg game with two leaders and one follower, where SPs act as the leaders who make service offers to the user, and the user serves as a follower who accepts or rejects the received bids. Since we have $L$ users in our HetNet model, to solve the user/network association association problem in a distributed manner, we need to solve $L$ Stackelberg games each with three players including WiFi SP and cellular SP as the leaders and one user as the follower. Assuming each BS’s maximum bandwidth budget per user is fixed and the same for all users covered by that BS, these $L$ Stackelberg games are independent, and hence we consider and solve only one of these Stackelberg games without loss of generality. Note that finding the optimal bandwidth/power allocation for SPs is a NP-hard problem [34] and not the focus of this work. In the remainder of this chapter, we focus on one of these games. Using the index $w$ for user’s preferred WiFi SP and the index $c$ for cellular SP, we denote the bids of WiFi and cellular SPs with triples $(r_w, p(r_w), bw_w)$, and $(r_c, p(r_c), bw_c)$, respectively, in which the first term shows the advertised data rate, the second term is the proposed price for the offered data rate, and the third term is the amount of bandwidth that will be allocated to the user by each SP. Overall, in this dissertation all variables with the subscript $w$ are associated with the WiFi SP and all variables with the subscript $c$ are associated with the cellular SP. User decisions are binary, which means the user either accepts a bid or rejects it, and there is no probabilistic decision by user. We denote user
decisions on cellular and WiFi SPs bids with $d_c$ and $d_w$ respectively, which are binary variables. So, the tuple $(d_c, d_w)$ represents user’s strategy with regard to the received bids, hence, the user has four possible strategies $(0, 0)$, $(0, 1)$, $(1, 0)$ and $(1, 1)$. Fig. 4.2 illustrates the Stackelberg game model between cellular and WiFi SPs and mobile user. All three players have a cost function and a benefit function, and their utility functions are simply the difference of the cost and benefit functions. We represent user’s utility function under the EUT model as

$$U_{user,EUT}(d_c, d_w) = H(R_{Joint,EUT}) - c_{user}(d_c, d_w),$$

where $H(R_{Joint,EUT}) = \delta(R_{Joint,EUT})^{1/\theta}, \delta > 0, \theta > 1$, is the user’s benefit function which is a concave function of the user’s expected aggregate data rate under the EUT model, $R_{Joint,EUT}$. Note that since the benefit function is a concave function of the expected data rate, increasing the user’s data rate does not necessarily increase the user’s payoff proportionally. Also, $c_{user}(d_c, d_w) = d_c p(r_c) + d_w p(r_w)$ is the user’s cost function which shows the aggregate price that must be paid by user to the SPs for each $(d_c, d_w)$ strategy. The user’s expected aggregate data rate is defined by

$$R_{Joint,EUT} = r_c g_c(r_c, bw_c) d_c + r_w g_w(r_w, bw_w) d_w,$$

where $g_c(r_c, bw_c)$ is the service guarantee of the bid received from the cellular SP, and denotes the probability of having the user experienced data rate after accepting the cellular SP offer, $R_c$, equal or higher than the advertised data rate by cellular SP, $r_c$. 
while the amounts of bandwidth allocated to the user by the cellular SP is $bw_c$. Without loss of generality, using $R_c = bw_c \log_2 (1 + pt|h|^2/N_0bw_c)$ from the Shannon formula, where $pt$ is the SP transmit power, $h$ is the channel gain, $N_0$ is the noise power spectral density, the service guarantee is given by

$$g_c(r_c,bw_c) = \Pr(R_c \geq r_c|bw_c) = \exp \left(-\frac{2^{r_c/bw_c} - 1}{pt|h|^2/N_0bw_c}\right), \quad (4.3)$$

where for a fixed advertised data rate $r_c$, allocating a larger bandwidth $bw_c$ to the user, yields a higher service guarantee, and for a fixed allocated bandwidth $bw_c$, advertising a larger data rate $r_c$ to the user results in a lower service guarantee [46]. Similar definition holds for $g_w(r_w,bw_w)$ which is the service guarantee of the bid received from WiFi SP. Once the user chooses its best response strategy, $(d^*_c, d^*_w)$, the SPs will respond with their best response strategies to maximize their own utilities. The utility of the WiFi SP, $U_{SP,w}$, is defined as

$$U_{SP,w} = d_w p(r_w) - C_{SP,w}(r_w, bw_w), \quad (4.4)$$

and the utility of cellular SP, $U_{SP,c}$ is defined as

$$U_{SP,c} = d_c p(r_c) - C_{SP,c}(r_c, bw_c), \quad (4.5)$$

where, the first term in both of the above equations is the SPs’ expected payoff from the user, and the second term is their incurred service cost. The SPs’ payoff from the user is equal to the offered price in their bids if the user accepts their bids, otherwise their payoff from the user is equal to zero. In this work, we assume both SPs use convex pricing functions, as $p(r_w) = \alpha_1(r_w)^{\beta_1}$, and $p(r_c) = \alpha_2(r_c)^{\beta_2};(\alpha_1, \alpha_2 > 0)$, $(\beta_1, \beta_2 > 1)$, where $\alpha_1$ and $\beta_1$ are payoff parameters for the WiFi SP, and $\alpha_2$ and $\beta_2$ are payoff parameters for the cellular SP. We also assume the SPs use linear cost functions, as $C_{SP,w}(r_w, bw_w) = c_1(r_w) + c_2(bw_w)$, and $C_{SP,c}(r_c, bw_c) = c_3(r_c) + c_4(bw_c)$, $(c_1, c_2, c_3, c_4 > 0)$, where $c_1$ and $c_2$ are constant cost coefficients for the WiFi SP, and $c_3$ and $c_4$ are constant cost coefficients for the cellular SP. To satisfy the user’s minimum data rate constraint, the SPs must ensure that their offered data rate is higher than the minimum data rate required by the user, $r_{\text{min}}$. Thus, the data rate constraints for the
WiFi and the cellular SPs will be defined as below, respectively:

\[ r_w g_w(r_w, b_w) \geq r_{\text{min}}, \]
\[ r_c g_c(r_c, b_c) \geq r_{\text{min}}. \]

Note that the reason we define strict data rate constraints, in (4.6) and (4.7), is to enable ultra reliable and low latency applications in 5G HetNets, like URLLC applications, for which delay is extremely critical with a hard deadline. Therefore, the associated utility for user would be zero if the successful transmission is not completed within the given deadline.
4.5 User Optimization Problem

Upon receiving the bids from the SPs, the user will run an optimization algorithm to find its best strategy with regard to the received bids. We assume the user’s payoff function from the received data is a concave function, as defined in Eq. 4.1, in which the user’s utility is not linearly increased with increasing the data rate. It means that as long as the minimum data rate constraint is satisfied, the user is not willing to pay extra price with linear relation to the extra data rate offered by SPs. To find its best response strategy, \((d_c^*, d_w^*)\), user will run the following optimization problem (denoted as \(Max1\)):

\[
\text{Max1 Problem: User’s Utility Maximization.} \\
\max_{d_c, d_w} \left[ \delta(R_{Joint,EUT})^{1/\theta} - d_w \alpha_1 (r_w)^{\beta_1} - d_c \alpha_2 (r_c)^{\beta_2} \right] \tag{4.8}
\]

subject to

\[
R_{Joint,EUT} \geq r_{min} \tag{4.9}
\]

\[
\delta(R_{Joint,EUT})^{1/\theta} \geq d_w \alpha_1 (r_w)^{\beta_1} + d_c \alpha_2 (r_c)^{\beta_2}, \tag{4.10}
\]

\[
d_c, d_w \in \{0, 1\} \tag{4.11}
\]

As shown above, the user has two major constraints for bid selection. The first constraint, shown in Eq. 4.9, is the user’s data rate constraint which ensures the expected data rate for the user is higher than its minimum required data rate, \(r_{min}\). The second constraint defined in Eq. 4.10 is the user’s utility constraint which guarantees a positive utility for the user from its strategy. Note that, according to user’s objective function defined in Eq. 4.8, users prefer offers with the highest possible data rate, and the lowest possible price. However, since SPs use a convex pricing function for the pricing of their data rate offers, the offers with very high data rates come with exponentially increasing prices too, and hence the users expected utility from such offers is not necessarily higher than the offers which only satisfy the minimum data rate for the user. This is because the extra price burden of offers with higher data rates outweighs the users extra gain resulting from such offers.
4.6 SPs Optimization Problems

When the SPs receive user’s decision with regard to their bids, they choose their best response strategy. The the best response strategy \((r^*_w, bw^*_w)\) for the WiFi BSs is obtained by solving the optimization problem below (denoted as Max2):

**Max2 Problem:** WiFi SP’s Utility Maximization.

\[
\max_{r_w,bw_w} \left[ d_w \alpha_1(r_w)^{\beta_1} - (c_1 r_w + c_2 bw_w) \right] \tag{4.12}
\]

subject to

\[
0 \leq bw_w \leq bw_{w,\text{max}}, \quad (4.13)
\]

\[
0 \leq r_w \leq r_{w,\text{max}}, \quad (4.14)
\]

\[
r_wg_w(r_w,bw_w) \geq r_{\text{min}}, \quad (4.15)
\]

in which, \(bw_{w,\text{max}}\) is the maximum amount of bandwidth that can be allocated to the user by WiFi SP, and \(r_{w,\text{max}}\) is the user’s maximum achievable data rate from WiFi SP considering the gain of the channel between WiFi SP and the user, and also \(bw_{w,\text{max}}\). We assume the SPs use a proportionally fair bandwidth allocation algorithm to determine the maximum amount of bandwidth that can be allocated to each user, and also assume this amount of bandwidth is enough to serve the user and satisfy its required minimum data rate constraint. Considering \(bw_{w,\text{max}}\), the user’s maximum achievable data rate from WiFi SP, \(r_{w,\text{max}}\) is given by:

\[
r_{w,\text{max}} = bw_{w,\text{max}} \log(1 + P_w h^2_w / N_0), \tag{4.16}
\]

where, \(P_w\) is the transmit power of WiFi SP, \(h^2_w\) is the gain of the channel between user and WiFi SP, and \(N_0\) is the noise power. Similarly, the cellular SP runs Max3 optimization problem, which is defined exactly similar to Max2, except the index \(w\) is replaced with the index \(c\) and the parameters \(\alpha_1, \beta_1, c_1, c_2\) are replaced with the parameters \(\alpha_2, \beta_2, c_3, c_4\), respectively. In Theorem 1, we prove that for both WiFi and cellular SPs, the best response strategies derived from Max2 and Max3 optimization problems, satisfy the minimum data rate constraint with equality.

**Theorem 1.** Assuming there is always a feasible solution, the WiFi and cellular SPs best response strategies derived from Max2 and Max3 problems, respectively, will always
satisfy the minimum data rate constraint in the boundary of its feasibility region, i.e. we always have $r_w^* g_w(r_w^*, bw_w^*) = r_{min}$, and $r_c^* g_c(r_c^*, bw_c^*) = r_{min}$.

**Proof.** We prove this by contradiction for the WiFi SP. Assume $(r_w^*, bw_w^*)$ is the optimal solution for $Max_2$ problem, and $bw_w^*$ is not a marginal bandwidth, i.e. $r_w^* g_w(r_w^*, bw_w^*) \neq r_{min}$. Considering Eq. 4.15, we can infer that $r_w^* g_w(r_w^*, bw_w^*) > r_{min}$ (1). In this case $\exists bw_w'_{w}$ such that $r_w^* g_w(r_w^*, bw_w') = r_{min}$ (2). From (1) and (2), and considering the direct relation between $g_w(r_w^*, bw_w^*)$ and $bw_w^*$, we can infer that $bw_w'_{w} < bw_w^*$. Now, considering the WiFi SP’s utility function given in Eq. 4.12 and due to its reverse relation with the advertised bandwidth, $bw_w$, we can infer that $U_{SP,w}(r_w^*, bw_w') > U_{SP,w}(r_w^*, bw_w^*)$ which is in conflict with the initial assumption that $(r_w^*, bw_w^*)$ is the optimal solution for $Max_2$ problem. So, the proof is complete. The same proof is valid for the cellular SP. □
4.7 Modeling User Behavior via PT Probability Weighting Effect (PWE)

To model the effects of PT on user decision making, we assume that users use their subjective biases in evaluating the bids made by the SPs. Specifically, we consider the probability weighting effect (PWE) of PT to model how the users evaluate the advertised probabilistic service guarantees which are part of the SPs bids. We use the Prelec function [55] to model the PWE under PT. Abbreviating the SPs probabilistic service guarantees as $g$, the weighted version of such probabilities from the users perspective, $w(g)$, is given by the Prelec function as

$$w(g) = \exp(-(-\ln(g))^{\alpha}), \quad (0 < \alpha < 1).$$

Therefore, end-users make decisions to accept or reject the received offers from the SPs by perceiving the objective probability, $g$, to be the subjective probability, $w(g)$, where $\alpha$ is the Prelec function parameter that describes the deviation of $w(g)$ from $g$.

![Comparing Advertised vs Subjective Service Guarantees in EUT vs PT model](image)

Figure 4.3: Probability Weighting Effect (PWE) in EUT vs PT with Prelec parameter $\alpha = 0.7$.

Fig. 4.3 compares the SPs advertised probabilities and the users subjective probabilities in both PT and EUT models. In this figure, users subjective probabilities under PT model are given by the Prelec function with parameter $\alpha = 0.7$, while in the
EUT model the advertised and subjective probabilities are assumed to the same, i.e. \( w(g) = g \). As we can see from Fig. 4.3, the Prelec function is a regressive and s-shaped function which is concave in \( 0 < g < 1/e \) region and convex in \( 1/e < g < 1 \) region, and \( w(g) > g \) in the former domain while \( w(g) < g \) in the later. Under this PWE model, we can infer that the users overestimate the service guarantees of the received offers if the advertised service guarantees are less than \( 1/e = 0.37\% \), and they underestimates them if the advertised service guarantees are higher than 0.37%. Assuming that SP networks are well designed to offer service guarantees higher than \( 1/e \), we focus on the underestimating of service guarantees by the users under PT. It is also justified by the fact that end-users in real world wireless networks typically perceive the quality of their service as lower than that advertised by the SPs [56,57].

Under the PT model, instead of exact advertised service guarantees, weighted service guarantees will be used by the user to estimate the expected joint data rate from SPs, and the expected utility. Therefore, the user’s expected aggregate data rate under the PT model, denoted as \( R_{\text{Joint},PT} \), is given by

\[
R_{\text{Joint},PT} = r_c \ w(g_c(r_c, bw_c)) \ d_c + r_w \ w(g_w(r_w, bw_w)) \ d_w, \tag{4.18}
\]

which is different from the user’s expected aggregate data rate under the EUT model, defined in Eq. (4.2), due to PWE of PT. Accordingly, the user’s utility function under the PT model, denoted as \( U_{\text{user},PT} \) is given as

\[
U_{\text{user},PT}(d_c, d_w) = H \left( R_{\text{Joint},PT} \right) - c_{\text{user}}(d_c, d_w). \tag{4.19}
\]
4.8 Nash Equilibria Strategies under EUT vs PT

According to Theorem 1, any underestimation of the advertised service guarantees by the user will result in the violation of data rate constraints defined in MAX2 and MAX3 optimizations, and hence lead to the rejection of received offers from each individual SP. Moreover, since the user’s expected utility is also a function of the aggregate data rate, under estimation of service guarantees by the user, will change its expected utility as well. Hence, user decisions under PT could deviate from user decisions under EUT. Note that each user only accepts bids that satisfy both minimum data rate and positive utility constraints defined in MAX1 optimization, and since under estimation of service guarantees by the user could result in violation of at least one of those conditions, a user rejects more bids under the PT model, which in turn also affects the Nash Equilibria of the Stackelberg game between the SPs and users. We derive the Nash equilibria strategies considering the users two bid selection constraints. Any SP bid that satisfies users positive utility and minimum data rate constraints will always be always accepted by the user, and if such bid leads to a positive utility for SP, then it is a potential NE strategy for the Stackelberg game. Note that in Table 4.1, which summarizes the NE under EUT model, since there is no difference between the perceived service guarantees and the advertised service guarantees (all perceptions are objective), we only check the positive utility constraint for the user to characterize different NE strategies. However, in the Table 4.2 which summarizes the NE under PT model, due to underweighting of service guarantees, the minimum data rate is not necessarily satisfied at the user side, and that’s why we have both positive data rate, and positive utility conditions to specify each NE strategy. A characterization of the Nash Equilibria under the EUT and the PT models follows directly from Theorem 1, and can be found in [30].

Table 4.1 summarizes the Nash Equilibria strategies of the user in the Stackelberg game for EUT model, for both symmetric and asymmetric SP models. Table 4.2 summarizes the user’s Nash Equilibria strategies under PT model, for both symmetric and asymmetric SP models. In the symmetric model, all SPs are assumed to use identical cost, benefit and utility functions, and we have \( r_w^* = r_c^* = r^*, \) \( bw_w^* = bw_c^* = bw^* \).
\( \beta_1 = \beta_2 = \beta_s \), and \( \alpha_1 = \alpha_2 = \alpha_s \). In the asymmetric model, some SPs could be superior to others and offer bids that induce higher utilities for users. In this work, we assume the WiFi SP is superior than the cellular SP since it has better channel conditions and hence consumes less resources to serve a user with a given data rate, and hence is able to offer a lower price to the user as compared to cellular SP. As it is shown in Table 4.1

\[
\beta_1 = \beta_2 = \beta_s, \quad \alpha_1 = \alpha_2 = \alpha_s.
\]

In the asymmetric model, some SPs could be superior to others and offer bids that induce higher utilities for users. In this work, we assume the WiFi SP is superior than the cellular SP since it has better channel conditions and hence consumes less resources to serve a user with a given data rate, and hence is able to offer a lower price to the user as compared to cellular SP. As it is shown in Table 4.1

<table>
<thead>
<tr>
<th>User’s NE Strategy Under EUT - Symmetric SPs</th>
<th>User’s NE Strategy Under EUT - Asymmetric SPs</th>
</tr>
</thead>
<tbody>
<tr>
<td>((d^<em>_c, d^</em><em>w) = (0, 0)) if (\delta \leq \frac{(r^*)^{\beta_1}}{(r</em>{\min})^{1/\theta}} \alpha_s, U_{user,EUT} = 0)</td>
<td>((d^<em>_c, d^</em><em>w) = (0, 0)) if (\delta &lt; \frac{(r</em>{w^*})^{\beta_1}}{(r_{\min})^{1/\theta}} \alpha_s, U_{user,EUT} = 0)</td>
</tr>
<tr>
<td>((d^<em>_c, d^</em>_w) = (0, 1)), with ( p = 0.5 )</td>
<td>((d^<em>_c, d^</em><em>w) = (0, 1)) if (\delta \leq \frac{(r</em>{w^<em>})^{\beta_1}}{(r_{\min})^{1/\theta}} \alpha_1 \leq \frac{(r^</em>)^{\beta_1}}{(2)^{1/\theta} - 1} \frac{(r_{\min})^{1/\theta}}{\alpha_1})</td>
</tr>
<tr>
<td>(\frac{(r^<em>)^{\beta_2}}{(r_{\min})^{1/\theta}} \alpha_s \leq \delta \leq \frac{(r^</em>)^{\beta_2}}{(2)^{1/\theta} - 1} \frac{(r_{\min})^{1/\theta}}{\alpha_s})</td>
<td>(U_{user,EUT} = \delta(r_{\min})^{1/\theta} - \alpha_1 (r_{w^*})^{\beta_1})</td>
</tr>
<tr>
<td>(U_{user,EUT} = \delta(r_{\min})^{1/\theta} - 2\alpha_s (r^*)^{\beta_2})</td>
<td>(U_{user,EUT} = \delta(r_{\min})^{1/\theta} - 2\alpha_s (r^*)^{\beta_2})</td>
</tr>
</tbody>
</table>

Table 4.1: Summary of the User’s NE Strategies Under EUT Model

and Table 4.2, under the PT model, both \((1, 0)\) and \((0, 1)\) Nash Equilibrium strategies which are feasible under the EUT model become infeasible under the PT model, due to underestimation of advertised service guarantees by the user. The results in [30] reveal that when users underweight the SPs advertised service guarantees, the rejection rate of the SP bids, and consequently the resulting utility and revenue for SPs decreases dramatically. To overcome this, we discuss next a learning-based optimized bidding mechanism for SPs.
<table>
<thead>
<tr>
<th>User’s NE Strategy Under PT- Symmetric SPs</th>
<th>User’s NE Strategy Under PT- Asymmetric SPs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\left( d_{c}^<em>, d_{w}^</em> \right) = (0, 0)$</td>
<td>$\left( d_{c}^<em>, d_{w}^</em> \right) = (0, 0)$</td>
</tr>
<tr>
<td>if $\delta &lt; \frac{2(\gamma^<em>)^{\beta_s}}{\left(2r^</em> w(g(r^<em>,bw^</em>))\right)^{1/\theta} \alpha_s}$</td>
<td>if $\delta &lt; \frac{\alpha_1(r_w^<em>)^{\beta_1} + \alpha_2(r_c^</em>)^{\beta_2}}{\left(r_c^* w(g_c(r_c^<em>,bw_c^</em>)) + r_w^* w(g_w(r_w^<em>,bw_w^</em>))\right)^{1/\theta}}$</td>
</tr>
<tr>
<td>or $[2r^* w(g(r^<em>,bw^</em>))] &lt; r_{min}$</td>
<td>or $[r_c^* w(g_c(r_c^<em>,bw_c^</em>)) + r_w^* w(g_w(r_w^<em>,bw_w^</em>))] &lt; r_{min}$</td>
</tr>
<tr>
<td>$U_{USER,PT} = 0$</td>
<td>$U_{USER,PT} = 0$</td>
</tr>
<tr>
<td>$\left( d_{c}^<em>, d_{w}^</em> \right) = (1, 1)$</td>
<td>$\left( d_{c}^<em>, d_{w}^</em> \right) = (1, 1)$</td>
</tr>
<tr>
<td>if $\delta \geq \frac{2(\gamma^<em>)^{\beta_s}}{\left(2r^</em> w(g(r^<em>,bw^</em>))\right)^{1/\theta} \alpha_s}$</td>
<td>if $\delta \geq \frac{\alpha_1(r_w^<em>)^{\beta_1} + \alpha_2(r_c^</em>)^{\beta_2}}{\left(r_c^* w(g_c(r_c^<em>,bw_c^</em>)) + r_w^* w(g_w(r_w^<em>,bw_w^</em>))\right)^{1/\theta}}$</td>
</tr>
<tr>
<td>and $[2r^* w(g(r^<em>,bw^</em>))] \geq r_{min}$</td>
<td>and $[r_c^* w(g_c(r_c^<em>,bw_c^</em>)) + r_w^* w(g_w(r_w^<em>,bw_w^</em>))] \geq r_{min}$</td>
</tr>
<tr>
<td>$U_{USER,PT} = \delta \left(2r^* w(g(r^<em>,bw^</em>))\right)^{1/\theta} - 2\alpha_3(\gamma^*)^{\beta_3}$</td>
<td>$U_{USER,PT} = \delta \left(r_c^* w(g_c(r_c^<em>,bw_c^</em>)) + r_w^* w(g_w(r_w^<em>,bw_w^</em>))\right)^{1/\theta}$</td>
</tr>
</tbody>
</table>

Table 4.2: Summary of the User’s NE Strategies Under PT Model.
4.9 Proposed Bidding Strategy under PT: Bandwidth Expansion

In previous section, we inferred that under PT if the user underestimates the advertised service guarantees, it is more likely for the user to reject the SPs offers by choosing \((0, 0)\) strategy. This can reduce the utility of SPs if they do not redesign their bidding strategies. So, in order to help the SPs to cope with user decisions under PT, and increase the chance of their offers to be accepted by the user, we propose a new bidding strategy for the SPs under PT based on bandwidth expansion [46]. As mentioned before, under PT user replaces its subjected service guarantee, for example \(w(g_c(r^*_c, bw^*_c))\) for the cellular SP, with the service guarantee advertised by the SPs, \(g_c(r^*_c, bw^*_c)\). And if the advertised service guarantee is higher than \(1/e\), the user will underestimate it, which means we have \(w(g_c(r^*_c, bw^*_c)) < g_c(r^*_c, bw^*_c)\). In such a situation if the SPs offer the same bid as in EUT, the user will reject their bids as the data rate constraint of the user will not be satisfied by such offers under PT. So, for SPs to convince the user to accept their bids, one way is to increase their offered bandwidth such that despite the user’s under estimation of the service guarantee, still the expected data rate for the user under PT is higher than its minimum data rate threshold, \(r_{\text{min}}\). If we denote \(BW^{*}_{c,PT}\), and \(BW^{*}_{w,PT}\) as the amount of BW required by the cellular and the WiFi SPs, respectively to convince the user to accept their offers under PT, assuming their offers got accepted under EUT, for the cellular SP bid we must have:

\[
BW^{*}_{c,PT} \geq g_c^{-1}(\lambda_c, r^*_c) \quad (4.20)
\]

where

\[
\lambda_c = w^{-1}(g_c(r^*_c, bw^*_c)) \quad (4.21)
\]

in which, \((r^*_c, bw^*_c)\) is the cellular SP bid under the EUT model. In fact the cellular SP must expand its offered bandwidth so as to offer \(r^*_c\) data rate with the service guarantee of \(\lambda_c\), where \(w(\lambda_c) = \tilde{g}_c(r^*_c, bw^*_c)\). This way, the extra bandwidth offered by the cellular SP compensates the under estimation of the service guarantee by user under PT. Same conditions must hold for the WiFi SP.
4.10 Simulation Results

In this section, we provide several simulation results to validate the efficiency of our model. We consider a HetNet scenario similar to the one presented in Fig. 4.1, in which there are $L$ randomly distributed users that are covered by 9 BSs. There is one cellular SP in the center of a macro cell and 8 overlaid WiFi SPs. We assume that the maximum coverage radius for WiFi SPs is 300 ft, while, all users are located within the coverage range of the cellular SP and can get served by it. We use Hata propagation model for urban environments to capture the effects of path loss on the user-BSs links. The table below contains the description and values of different parameters we have used in our simulations.

Fig. 5.5 compares the sum utility of BSs under these three scenarios while we change the number of users (load) from $L = 50$ to $L = 500$.

When the number of users is less than 150, PT outperforms EUT in terms of SPs sum utility. The reason is that when the load is low, SPs offer higher data rates to users, hence, even with low service guarantees they can satisfy the user's minimum data rate constraint. And due to probability weighting effect (PWE) under PT, when
the advertised service guarantees are lower than $1/e = 0.37\%$, the user overestimates service guarantees, which leads to a higher acceptance rate for the SP offers under PT as compared to EUT. By increasing the acceptance rate, the SPs’ sum utility is also increased. However, by increasing the number of users, the SPs advertised data rates will decrease as they assign less BW to each user. They have to increase their service guarantees to satisfy the user’s data rate constraint. Hence, the user’s acceptance rate and consequently the SPs utilities decrease dramatically by increasing the number of users beyond $L = 150$. However, using bandwidth expansion feature under PT, the SPs are able to retain most of their subscribed users with some extra cost. When the number of users goes beyond 400, which is the max network capacity under our setting, most of the SPs are not capable of satisfying user’s data rate constraint as their BW budget per user will diminish by increasing the load. Therefore, the number of users associated to BSs and consequently the SPs sum utility decreases when $L$ is higher than 400. Fig. 4.6 compares the sum utility of users under EUT, PT and PT with BW
expansion for different load situations. As we expected, there are two turning points in this diagram. The first point is where the number of users goes beyond 150 users, which results in a considerable dropping of user association rate and the sum utility of users under PT. While by enabling bandwidth expansion under PT as its shown in Fig. 4.6, sum utility of users will be increased by increasing the number of users as more users will be associated to SPs until the number of users get close to the network capacity which is 400 users in our setting. After that, the user association rate reduces again as bid selection constraints for many users cannot be met by SPs considering their limited resources.

To see how much extra costs the SPs have to incur to retain their users under PT using bandwidth expansion, we compare the average bandwidth consumption of users in EUT vs PT with bandwidth expansion feature in Fig. 4.7. When the SPs advertised service guarantees are less than $1/e = 0.37\%$ threshold, which occurs when the number of users are less than 150, the SPs are not required to consume any extra BW to retain
their EUT users under PT. However, by increasing the number of users beyond 150, the number of users who receive an offer with a service guarantee higher than 0.37% will increase. So, to retain those users under PT, the SPs have to offer extra BW to satisfy user’s bid selection constraints. The amount of extra BW that the SPs have to provide for the users under PT raises by increasing the load, as the SPs’ service guarantees increase in this situation. So, user’s underestimation of service guarantees become more intense. Note that we used the Perlec function with parameter $\alpha = 0.7$ to capture PWE under PT. By using lower values for $\alpha$, the gap between these two curves become larger as the number of users is increasing. The simulation results under PT show that the SPs can retain most of their subscribed users under EUT by offering some extra bandwidth to them to compensate negative effects of the user’s underestimation of their advertised service guarantees. Although bandwidth expansion increases the SPs’ cost, however as long as their expected payoff from user is higher than their cost, its justifiable for them to perform bandwidth expansion to retain their users.
4.11 Conclusion and the Issues Associated with Bandwidth Expansion

In this chapter, we studied the impact of end-user behavior on SP bidding and user/network association in a HetNet with multiple SPs while considering the uncertainty in the service guarantees offered by the SPs. We formulated user association with SPs as a multiple leader Stackelberg game where each SP offers a bid to each user that includes a data rate with a certain probabilistic service guarantee and at a given price, while the user chooses the best offer among multiple such bids. Using PT to model end-user decision making that deviates from EUT, we showed that when users underweight the advertised service guarantees of the SPs, the rejection rate of the bids increases dramatically which in turn decreases the SPs utilities and service rates.

In this chapter, we studied the problem of user association in wireless HetNets under PT, where all covering WiFi and cellular SPs offer data services to users who are free to accept or reject any of the received offers. We formulated user association with SPs as a multiple leader Stackelberg game where each SP offers a bid to each user that includes a data rate with a certain probabilistic service guarantee and at a given price, while the user chooses the best offer among multiple such bids, and extracted all potential NEs for this game under both EUT and PT. The NE existence analysis reveals that some of the feasible NEs under EUT become infeasible under PT when users underestimate the advertised service guarantees by the SPs. Using PT to model end-user decision making that deviates from EUT, we showed that when users underweight the advertised service guarantees of the SPs, the rejection rate of the bids increases dramatically which in turn decreases the SPs utilities and service rates. To avoid such a utility loss for the SPs under PT, we proposed a new bidding strategy by which the SPs are able to cope with the underestimation of their service guarantees by the user under PT, if they know exactly how users would perceive the advertised service guarantees. Our simulation results demonstrate that using such a bidding strategy, the SPs are able to retain most of their lost EUT users under PT by incurring some additional costs, and hence reduce their utility loss under PT.

The key assumption for the bandwidth expansion solution is that we assume SPs
know how users perceive and potentially underweight their advertised service guarantees, however, in reality SPs don’t have access to such info about users internal decision making model. In fact, users only share their binary decisions with SPs, and SPs wont be able to estimate the exact Prelec parameter used by users, unless they develop learning algorithms to dynamically learn the users decision making model based on their past decisions. In the next chapter, we propose a two stage learning based framework to address this issue.
Chapter 5
User Centric Approach: A Learning-based Optimization Model

5.1 Learning-based Optimized Bidding Method for SPs

To find the utility-optimized bids, we propose a two-stage learning method for SPs where in the first stage, SPs learn a classifier function for predicting binary user decisions, via SVM learning. Then in the second stage, SPs find the utility-optimized bids using a RL-based bidding algorithm in which the classifier function obtained in the first stage using SVM is used to evaluate the value of each potential bid by predicting the user decision with regard to that bid. A heuristic solution based on expanding the offered bandwidth in the SPs bids was proposed in [30]. However, it requires the SPs to have knowledge of how the users perceive the uncertainty in the service guarantees, while in reality, SPs don’t have access to such information.

5.1.1 SVM-based Classifier for Predicting User Decisions

Using a record of previous user decisions in response to different offered services, and noting the binary nature of user decisions in our work, we can efficiently train a SVM classifier to predict user decisions with regard to any future bid. Note that the Prelec parameter governing each user’s decision making under the PT model is unknown to the SPs and there is no training data for SPs to train a classifier which predicts the Perlec parameter used by each user. In fact, the only information SPs receive from each user is its binary decisions (accept/reject). Therefore, we design a classifier to predict user decisions and not the underlying Prelec parameter used by each user in evaluating
the received bids. The set of training data, here denoted as $D$, is given by

$$D = \{(x_1, y_1), (x_2, y_2), \ldots (x_P, y_P)\}, \quad (5.1)$$

which includes $P$ entries of labeled data samples $(x_i, y_i)$, where the feature vector $x_i = (r_i, p(r_i), bw_i)$ represents the bid $i$ features including its advertised data rate, the offered price, and offered bandwidth, respectively, and $y_i$ represents the previous binary decision of user in response to bid $i$. Using the gathered training data, the SVM classifier parameters, $q$ and $b$, can be derived by solving the optimization problem given in (5.2)-(5.4) using the SVM learning algorithm. In the SVM optimization objective function given in Eq. (5.2), $2/q^T q$ is the width of the separating margin between two groups of accepted and rejected bids which is supposed to be maximized by minimizing its inverse, and $\epsilon_i$ is the amount of error in classifying each data point $i$, which is supposed to be minimized, and $c$ is a regularization parameter that defines the trade-off between these two objectives. The inequality constraint in Eq. (5.3) enforces $q^T \phi(x_i) + b \geq 1 - \epsilon_i$ for all accepted bids and $q^T \phi(x_i) + b \leq -(1 - \epsilon_i)$ for all rejected bids, as it combines these two constraints.

**SVM Learning Optimization.**

$$\min_{q,b,\epsilon} 1/2 q^T q + c \sum_{i=1}^{P} \epsilon_i, \quad (5.2)$$

subject to:

$$y_i (q^T \phi(x_i) + b) \geq 1 - \epsilon_i, \quad (5.3)$$

$$\epsilon_i \geq 0. \quad (5.4)$$

The constraint in Eq. (5.4) ensures that the amount of classification error for each data point $i$, $\epsilon_i$, is either zero for correctly classified points, or a positive value for misclassified points. After finding the SVM classifier parameters $q$ and $b$ from solving the SVM optimization, we can define the SVM classifier function $f(x_i)$ as

$$f(x_i) = q^T x_i + b = \begin{cases} 
\geq 0, & \text{i.e. } d(x_i) = 1, \text{ accept,} \\
\leq 0, & \text{i.e. } d(x_i) = 0, \text{ reject,} \end{cases} \quad (5.5)$$

to predict the user’s binary decision with regard to any given bid $x_i$, denoted as $d(x_i)$. 
5.1.2 RL-based Optimized Bidding

To find the utility-optimized bids for SPs, we formulate the SPs optimized bidding problem as a Markov Decision Problem (MDP) with the tuple \((S, A, P_{SA}, \gamma, R)\) in which \(S\) denotes the set of states, \(A\) defines the set of actions in each state, \(P_{SA}\) is the set of state-action transition probabilities, \(\gamma\) is the discount factor, and \(R\) is the reward function. The SP bidding MDP can be solved using any standard reinforcement learning algorithm like Q-learning. In the proposed MDP, each state \(s_i \in S\) is defined by a triple \(s_i = (r_{si}, bw_{si}, d_{si})\) in which the first two elements \((r_{si}, bw_{si})\) denote the bid associated with the state \(s_i\), and the third element \(d_{si}\) denotes the user decision with regard to this bid. The set of states \(S\) is given by

\[
S = \{ s_i \mid s_i = (r_{si}, bw_{si}, d_{si}), \; i \in \{1, 2, \ldots 2MN\} \}, \tag{5.6}
\]

where we have discretized both the data rate, \(r\), and bandwidth, \(bw\), by considering \(M\) possible values for \(r\), and \(N\) possible values for \(bw\). Moreover, since user decisions are binary, \(d_{si} \in \{0, 1\}\), we have a discrete state space for the SP bidding problem with overall \(2MN\) states. Considering the SP random actions, rewards, and transitions, we can cast the SP bidding problem as a MDP. The set of possible actions in each state, \(A\), is given by

\[
A = \{a_1, a_2, \ldots, a_{MN} \mid a_j = (r_{aj}, bw_{aj})\}, \tag{5.7}
\]

in which each action \(a_j = (r_{aj}, bw_{aj})\) is in fact a feasible bid that the SP can offer to the user. Taking each action \(a_j\) in a given state \(s_i\) results in a transition from state \(s_i\) to the new state \(s'\), with new data rate, bandwidth, and user decision coordinates of \((r_{s'}, bw_{s'}, d_{s'})\). The destination state \(s_{s'}\) for each state-action pair will be specified by the state-action transition probabilities \(P_{SA}\) which is given as

\[
P_{SA} = \{Pr(s' \mid s_i, a_j), \forall s_i, s' \in S, \forall a_j \in A\}, \tag{5.8}
\]
with

\[
Pr(s'|s, a) = \begin{cases} 
Pr(d_a = 1), & \text{for } s' = (r_{aj}, bw_{aj}, 1), \\
Pr(d_a = 0), & \text{for } s' = (r_{aj}, bw_{aj}, 0), \\
0, & \text{for } s' \neq (r_{aj}, bw_{aj}, 1) \land s' \neq (r_{aj}, bw_{aj}, 0),
\end{cases} \tag{5.9}
\]

where \(d_a\) is the binary user decision with respect to the bid offered in action \(a\), and \(Pr(d_a = 1)\) is the probability that the user accepts the bid offered in action \(a\), while \(Pr(d_a = 0)\) is the probability that the user rejects this bid. The state-action reward function \(R(s, a)\) which defines the reward that can be achieved from taking action \(a\) in the state \(s\), depends on the user decision with regard to the bid offered in action \(a\) as it determines the resulting destination state, and is defined as

\[
R(s, a) = \left( \sum_{s' \in S} Pr(s'|s, a)[d_{s'}(p(r_{s'}) - c(r_{s'}, bw_{s'})) - [d_s(p(r_s) - c(r_s, bw_s))] \right), \tag{5.10}
\]

which is the expected gain/loss associated with the resulting transition from taking action \(a\), and is given by the difference of the expected utility in destination state \(s'\) and the expected utility in initial state \(s\). Using (5.9), the reward function is simplified as

\[
R(s, a) = Pr(d_a = 1)[p(r_{aj}) - c(r_{aj}, bw_{aj})] - [d_s(p(r_s) - c(r_s, bw_s))]. \tag{5.11}
\]

The value function \(V_\pi(s)\) defines the value of each policy \(\pi : S \rightarrow A\) in each state \(s\) as

\[
V_\pi(s) = R(s, \pi(s)) + \gamma \sum_{s' \in S} Pr(s'|s, \pi(s)) V_\pi(s'), \tag{5.12}
\]

in which \(\gamma\) is the discount factor, \(0 < \gamma < 1\), and \(\pi(s)\) is the action that according to policy \(\pi\) should be taken in state \(s\). The goal of the MDP is to find the optimal policy \(\pi^*\) which determines the best action in each state which maximizes the expected reward of the SP.

### 5.1.3 Dynamic Programming-based Optimized Bidding (DPOB)

To find the utility-optimized bids, SPs can use the SVM classifier built in the previous section, to predict user decisions with regard to any given bid, before sending
any offer to the user. However, since advertised bandwidth and data rate are both continuous quantities, and any combinations of a bandwidth and data rate corresponds to a new bid, we have infinite potential bids, and finding the optimal one using SVM is computationally intractable. To reduce the computational complexity and find the utility optimized bids for SPs in less time, we discretize both the data rate, $r$, and bandwidth, $bw$, by considering $M$ possible values for $r$, and $N$ possible values for $bw$, which gives us $M \times N$ potential bids, overall.

Moreover, due to the Pareto dominance relations between potential bids, and considering the rationality of user as a rational player, if a user rejects any SP action/bid $a_i$, it will also reject any other SP action/bid $a_j$ that results in a lower expected utility for that user, considering the rationality of users and their objective to maximize their expected utility. Note that SP actions are actually the bids that SP offers to the user, hence we use these two terms interchangeably. In fact, if a user rejects the SP action $a_i = (r_{ai}, bw_{ai})$, it will also reject any other action $a_j = (r_{aj}, bw_{aj})$ if $(r_{ai} \leq r_{aj}) \land (bw_{ai} \geq bw_{aj})$, since $a_i$ Pareto dominates $a_j$ from the user’s perspective, under such conditions. Likewise, when a user accepts any SP action $a_i$, the offering SP is not willing to take a new action $a_j$ if $a_j$ results in a lower utility for the SP. In fact, if user accepts any bid $a_i = (r_{ai}, bw_{ai})$, the offering SP will not offer any new bid $a_j = (r_{aj}, bw_{aj})$ to the user if $(r_{ai} \geq r_{aj}) \land (bw_{ai} \leq bw_{aj})$ since action $a_i$ Pareto dominates action $a_j$ from the SP’s perspective, under such conditions. Note that based on the utility functions of the users and SPs defined in section 4.4, when other parameters in a given bid remain the same, increasing the advertised data rate will increase the utility of SPs and decrease the utility of users, while increasing the allocated bandwidth increases the utility of users and decreases the utility of SPs. The Pareto dominance relations between different actions in the discrete state space for optimized bidding, helps SPs to update the set of feasible actions in each iteration after taking a new random action, by removing the infeasible actions from the list of actions in the newly visited state while executing the RL algorithm. The proposed dynamic programming-based algorithm for optimized bidding is given in Algorithm 1. Note that Algorithm 1 could be initialized with any random state/bid in the discrete state space of the bidding problem, and hence it is
**Algorithm 1 Dynamic Programming-based Optimized Bidding (DPOB) Algorithm**

**Input:** \{Set of states: \( S \), Initial state of the system: \( \bar{s} = (r^{*}_{EUT}, bw^{*}_{EUT}, d_{\bar{s}}) \), Set of actions: \( A \)\}

**Initialize** \( SP_{Utility} = d_{\bar{s}} [p(r_{\bar{s}}) - c(r_{\bar{s}}, bw_{\bar{s}})], \ a^{*} = (r^{*}_{EUT}, bw^{*}_{EUT}) \)

**while** \( A \neq \emptyset \) **do**

\[
\begin{align*}
&\text{choose a random action } a_{j} = (r_{a_{j}}, bw_{a_{j}}) \text{ from the set } A \\
&\text{build the associated vector } x = (r_{a_{j}}, p(r_{a_{j}}), bw_{a_{j}}) \\
&\text{find } d(x) \text{ using SVM classifier in Eq. (5.5)} \\
&\text{calculate } R(\bar{s}, a_{j}) \text{ using Eq. (5.11)} \\
&\text{if } R(\bar{s}, a_{j}) \geq SP_{Utility} \text{ then} \\
&\quad \text{Set } SP_{Utility} = R(\bar{s}, a_{j}) \\
&\quad \text{Set } a^{*} = (r_{a_{j}}, bw_{a_{j}}) \\
\end{align*}
\]

**end**

**Update set of actions:**

\[
\begin{align*}
&\text{if } d(x) = 1 \text{ then} \\
&\quad \text{Update } A: \text{ remove all actions } a_{k} \text{ from } A \text{ if } (r_{a_{k}} \leq r_{a_{j}}) \land (bw_{a_{k}} \geq bw_{a_{j}}) \\
&\text{end} \\
&\text{if } d(x) = 0 \text{ then} \\
&\quad \text{Update } A: \text{ remove all actions } a_{k} \text{ from } A \text{ if } (r_{a_{k}} \geq r_{a_{j}}) \land (bw_{a_{k}} \leq bw_{a_{j}}) \\
&\text{end} \\
\end{align*}
\]

**end**

**Output:** \( a^{*}, SP_{Utility}. \)

Independent of the Stackelberg game between SPs and the user. However, instead of starting from a totally random state, here we initialize the DPOB algorithm with a state that its first two elements represent the SPs’ Nash Equilibrium strategy in the Stackelberg game derived from MAX2/MAX3 optimizations under EUT model, here denoted as \( \bar{s} = (r^{*}_{EUT}, bw^{*}_{EUT}, d_{\bar{s}}) \), to boost the performance of the algorithm and converge to the optimal solution faster. The magnitude of such performance gain depends on the divergence between objective and subjective service guarantees for each user. Since these two parameters are closely related according to (4.17), the average performance observed from initializing the DPOB algorithm with SP’s NE strategy under the EUT model is always better than the case in which we initialize it with a totally random state. We now state the following Theorem on the benefits of iteratively pruning the set of actions \( A \) in the DPOB algorithm.

**Theorem 2.** Assuming user accept/reject decisions are equally likely for any random bid, the DPOB algorithm converges to the optimal solution with a logarithmic average convergence time of \( \mathcal{O}(\log_{1.33} |A|) \).
Proof. We first show that DPOB algorithm converges to the optimal solution. We prove this by contradiction. Assume \( a_{j^*} \in A \) is the optimal action/bid in the MDP such that it maximizes the SP's utility, i.e. \( a_{j^*} = \text{argmax}_{a_j \in A} [R(\bar{s}, a_j)] \), assuming \( \bar{s} \) to be the initial state of the MDP. Since the DPOB algorithm continues until \( A = \emptyset \), i.e. there is no feasible action in the set of actions \( A \), the optimal action \( a_{j^*} \) will be visited by the algorithm unless this action gets removed from the set of actions, during iterative pruning of this set in the DPOB algorithm. In that case, there must exists an action \( a_k \in A \) which Pareto dominates \( a_{j^*} \) and results in higher utility for the SP as compared to \( a_{j^*} \), which is in contrast with initial assumption that \( a_{j^*} \) is the optimal action for the SP. Now we have to show that DPOB algorithm converges to the optimal solution with a logarithmic average convergence time of \( O(\log_{1.33} |A|) \). Assume \( a_l \in A \) and \( a_{j^*} \in A \) are the actions with the lowest and the highest resulting utilities for the SP, respectively. If SP bids \( a_l \) and user accepts that, still all the other actions are feasible for the SP, i.e. no action will be removed from the set \( A \), while if SP bids \( a_{j^*} \) and user accepts that, all other actions become infeasible as \( a_{j^*} \) Pareto dominates all other actions, which means the set of actions \( A \) becomes empty after taking this action. However, in general if we assume the random user decisions (accept/reject) with regard to each bid, and the random action/bid selected by the SP among all feasible actions, are both uniformly distributed random variables (with equally likely outcomes), after taking any random action \( a_j \), on average for half of the remaining feasible actions/bids like \( a_k \) we either have \( (r_{a_k} \leq r_{a_j}) \land (bw_{a_k} \geq bw_{a_j}) \), or \( (r_{a_k} \geq r_{a_j}) \land (bw_{a_k} \leq bw_{a_j}) \), which means that either the action \( a_j \) Pareto dominates them, or they Pareto dominate \( s_j \), due to the symmetry of the actions space in terms of Pareto dominance relation with \( a_j \). Hence, regardless of the user decision, one of these two groups of actions, which include on average one fourth of the total actions in \( A \), will become infeasible and hence will be removed from \( A \). If user accepts \( a_j \), those actions that \( a_j \) Pareto dominates them will be removed as they result in a lower utility for SP, and if user rejects \( a_j \), those actions that Pareto dominate \( a_j \) for SP will be removed since there is no chance for them to get accepted by the user. Hence, on average the initial set of actions \( A \) shrinks by one fourth of its size after each iteration of the algorithm, and hence the complexity of finding the
optimal bid is of $O(\log_{1.33} |A|)$, where $|A| = MN$ is the total number of feasible actions for the SP.

Note that if we cast the DPOB algorithm as a tree-based search algorithm in a binary tree with $|A|$ leaves, then $O(\log_{1.33} |A|)$ estimates the depth of such binary tree, in which at each level of the tree the branch that includes $1/4^{th}$ of the leaves below that level will be pruned, and the second branch that includes $3/4^{th}$ of the leaves below that level will be traversed, up until we arrive at the optimal solution located at the leaf node with the maximum depth in the tree. According to Theorem 2, the complexity of the proposed DPOB algorithm is $O(\log_{1.33} |A|)$. As a comparison and also for the purpose of benchmarking, we now discuss the complexity of standard RL algorithms such as value iteration and Q-learning. The complexity of the value iteration to find the optimal solution from any initial state, is of $O(\log |S|^2|A|)$ in which $|S|$ is the number of states and $|A|$ is the number of actions, which is much higher than the DPOB complexity. The reason for the high complexity of the value iteration method is that we have to verify the possibility of going from any source state to any destination state via any action, to find the optimal policy/action from any initial state. Also, Q-learning as a model-free RL algorithm has a complexity of $O(|S||A|)$ to find the optimal solution from any given initial state, as it explores all the possible actions in each state, until arriving at the optimal solution [58].

Thus, the computational gain of DPOB as compared to model free RL algorithms is noteworthy since it reduces the network access delay for users by leveraging learning tools like SVM at the SP side, which is attractive for SPs to enable and support delay critical applications in 5G HetNets.
5.2 Simulation Results

In this section, we provide simulation results to validate the efficiency of the proposed learning based bidding algorithm. As shown in Fig. 5.1, we consider a HetNet scenario in which there are \( L \) randomly distributed mobile users, that are covered by 9 BSs including one cellular BS (CBS) with the coverage radius of 1000\( ft \) located in the center of a macro-cell and 8 overlaid small-cell long-range WiFi BSs (WBSs) with maximum coverage radius of of 300\( ft \). Each WBS competes with the CBS to offer data service to each mobile user located in a coverage area common to them. We use the Hata propagation model for urban environments [59] to capture the effects of path loss on each of the radio links. Table 5.1 details the parameters used in the simulation of the HetNet environment modeled here.

![Figure 5.1: Simulated HetNet Scenario.](image)

Fig. 5.2 compares the sum utility of the SPs under three scenarios: (i) EUT- expected: where there is no difference between the users objective and subjective perceptions of the SPs service guarantee, (ii) EUT- achievable: where the users subjectively weight the
Table 5.1: Simulation Parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L=50$-$500$</td>
<td>Number of users</td>
<td>$BW_{w} = 5$ MHz</td>
<td>Total bandwidth- WiFi</td>
</tr>
<tr>
<td>$K=9$</td>
<td>Number of BSs</td>
<td>$N_{w} = -80$ dBm</td>
<td>Noise power- WiFi channels</td>
</tr>
<tr>
<td>$X_{dim} = 2000$ ft</td>
<td>X dimension of the area</td>
<td>$SSID_{w} = 15%$</td>
<td>SSID overhead ratio- WiFi</td>
</tr>
<tr>
<td>$Y_{dim} = 2000$ ft</td>
<td>Y dimension of the area</td>
<td>$G_{w} = 7.4$ dBm</td>
<td>WiFi antenna gain</td>
</tr>
<tr>
<td>$R_{c} = 1000$ ft</td>
<td>Cellular coverage range</td>
<td>$r_{min} = 300$ Kbps</td>
<td>Users required min data rate</td>
</tr>
<tr>
<td>$R_{w} = 300$ ft</td>
<td>WiFi coverage range</td>
<td>$c_{1} = 1 \times 10^{-3}$</td>
<td>Unit data rate cost- WiFi</td>
</tr>
<tr>
<td>$T_{c} = 43 dBm$</td>
<td>Transmission power- cellular BS</td>
<td>$c_{2} = 2 \times 10^{-3}$</td>
<td>Unit bandwidth cost- WiFi</td>
</tr>
<tr>
<td>$f_{c} = 1800$ MHz</td>
<td>Operating frequency- cellular</td>
<td>$c_{3} = 2 \times 10^{-3}$</td>
<td>Unit data rate cost- cellular</td>
</tr>
<tr>
<td>$N_{c} = -104.4$ dBm</td>
<td>Noise power- cellular channels</td>
<td>$c_{4} = 40 \times 10^{-3}$</td>
<td>Unit bandwidth cost- cellular</td>
</tr>
<tr>
<td>$BW_{c} = 20$ MHz</td>
<td>Total bandwidth- cellular</td>
<td>$\alpha_{1} = 5$</td>
<td>Pricing coefficient- WiFi</td>
</tr>
<tr>
<td>$G_{c} = 21$ dBm</td>
<td>Cellular antenna gain</td>
<td>$\alpha_{2} = 10$</td>
<td>Pricing coefficient- cellular</td>
</tr>
<tr>
<td>$h_{c} = 32$ m</td>
<td>Cellular BS height</td>
<td>$\beta_{1} = 1.1$</td>
<td>Pricing exponent- WiFi</td>
</tr>
<tr>
<td>$T_{w} = 26$ dBm</td>
<td>Transmission power- WiFi BS</td>
<td>$\beta_{2} = 1.1$</td>
<td>Pricing exponent- cellular</td>
</tr>
<tr>
<td>$f_{w} = 2.4$ GHz</td>
<td>Operating frequency- WiFi</td>
<td>$\delta = 100$</td>
<td>Payoff coefficient- user</td>
</tr>
<tr>
<td>$\alpha = 0.7$</td>
<td>Prelec function parameter- PT</td>
<td>$\theta = 1.1$</td>
<td>Payoff exponent- user</td>
</tr>
<tr>
<td>$M=100$</td>
<td>Quantized points for data rate</td>
<td>$N = 100$</td>
<td>Quantized points for bandwidth</td>
</tr>
</tbody>
</table>

SPs service guarantees with the Prelec probability weighting function parameterized by $\alpha$, and (iii) DPOB- achievable: where the learning algorithm is used to predict the users responses to bids. In this figure, in each of the cases, the total number of users (load) in the HetNet changes from $L = 50$ to $L = 500$. As we can see, when the number of users is lower than 200, since the advertised data rates are high and low service guarantees in the range of $[0, 1/e]$ are advertised by SPs to satisfy users data rate constraints, users overestimate the value of the SPs bids due to PWE of PT described in Eq. (18). When the total number of users is more than 200, since the advertised data rates are low, the SPs bids include high service guarantees in the range of $[1/e, 1]$ which results in the underestimation of such bids by the users and their subsequent rejection. Thus the deviation of users behavior from EUT affects the network adversely in the region corresponding to underweighting of the service guarantees. It can also be seen that the proposed DPOB algorithm uniformly improves performance in both low and high load situations, by taking (a) advantage of learning the end users decision making, and (b) optimizing the SPs bids based on the learned information to maximize the users acceptance rate of the offered bids. In fact, as seen in Fig. 5.2, the achievable sum utility of SPs under DPOB increases on average by a factor of 3.27 as compared to EUT.
Further, the gap between DPOB and EUT is bigger in low load situations. The reason is that when the total number of users is low, the SPs allocate more bandwidth to each user and hence their advertised data rates are much higher, which in turn results in a very high price for their bids considering the convex pricing functions used by SPs. This situation results in a rejection of bids by the users since their payoff function is a concave function of the data rate, making the SPs offers unattractive. In the case of DPOB, the ability to learn user actions (accept/reject) by evaluating all feasible bids, allows the SPs to make only those bids that are still affordable to the users.

Fig. 5.3 compares the sum utility of users under the mentioned three scenarios. As we can see again, the proposed DPOB algorithm uniformly outperforms EUT model in terms of users sum utility, due to offering more affordable bids to users which increases user’s acceptance rates and utilities, accordingly. Moreover, we observe that users sum utility under all three models increases with increasing the number of users, before reaching the max network capacity under our setting when $L = 400$. The reason is that when the load is low, users receive bids with advertised data rates much higher than their required minimum data rate, and due to SPs convex pricing and users concave payoff functions, such bids result in low utility for users, while by increasing the load, the gap between advertised data rates of SPs and required data rates of users shrinks, which increases the users utility accordingly. As seen in Fig. 5.3, the achievable sum utility of users under DPOB increases on average by a factor of 2.77 as compared to the EUT model.

We can also see in both Fig. 5.2 and Fig. 5.3 that when the number of users is more than 400, which is the max network capacity under our setting, most of the SPs are not capable of satisfying the users data rate constraints since their bandwidth budget per user decreases with increasing load. Therefore, the number of users who accept bids, and are connected to BSs decreases, which in turn reduces both the SPs and users sum utilities.

We also observed (not shown here) that when we use a smaller value for the Prelec parameter, such as $\alpha = 0.5$, which corresponds to a situation where the PWE of PT
is more intense, the performance improvements in sum utilities using DPOB are also greater.

Fig. 5.4 compares the average bandwidth consumption per user for SPs in DPOB vs EUT. As shown in this figure, by increasing the load the average bandwidth consumption of DPOB is slightly higher than EUT as DPOB compensates the effects of the users underestimation of service guarantees by offering more bandwidth to users to convince them to accept the received offers. As we saw in Fig. 5.2, since users pay the price requested by SPs when they accept any SP offer, the overall utility of SPs is more under DPOB as compared to the EUT model, despite having higher service cost per user using
DPOB.

![Graph comparing EUT vs DPOB](image)

**Figure 5.4:** Average Bandwidth Consumption per User in EUT vs. DPOB.

Fig. 5.5 compares the time complexity of the proposed DPOB algorithm vs. the Q-learning algorithm, while using both algorithms to find the utility-optimized bids for SPs. As predicted by Theorem 2, the DPOB algorithm converges much faster than the Q-learning algorithm, and as the figure shows the normalized run time of the DPOB is much less than Q-learning. It is also observed that the reduction in the complexity is more affected by the number of states in the MDP ($MN = 10,000$ in this example), and not the number of users. Note that the number of iterations required for the convergence of DPOB is ($\log_{1.33} MN \approx 32$). On the other hand, the Q-learning needs to build Q-tables with dimensions of 10,000 for convergence. Thus, DPOB is attractive for supporting delay critical applications in HetNets.
Figure 5.5: Time Complexity Reduction of DPOB algorithm vs. Q-learning algorithm.
5.3 Conclusion

In this chapter, we studied the impact of end-user behavior on SP bidding and user/network association in a HetNet with multiple SPs while considering the uncertainty in the service guarantees offered by the SPs. We formulated user association with SPs as a multiple leader Stackelberg game where each SP offers a bid to each user that includes a data rate with a certain probabilistic service guarantee and at a given price, while the user chooses the best offer among multiple such bids. Using PT to model end-user decision making that deviates from EUT, we showed that when users underweight the advertised service guarantees of the SPs, the rejection rate of the bids increases dramatically which in turn decreases the SPs utilities and service rates.

In this chapter, to prevent the rejection of SP bids by the user as a result of underweighting the advertised service guarantees, we proposed a two-stage learning-based optimized bidding framework for SPs. In the first stage, we used a SVM learning algorithm to predict users' binary decisions, and then in the second stage, we cast the SP utility-optimized bidding problem as an iterative dynamic programming problem and proposed the DPOB algorithm to efficiently solve it. Simulation results and computational complexity analysis validated the efficiency of the proposed learning based bidding algorithm, and showed that the DPOB algorithm could improve the social welfare of the system for both users and SPs as compared to EUT-based bidding algorithms.

Regarding the benefits of applying prospect theory in this work, it helped us to accurately model and explain the deviation of service guarantees (the only uncertain parameter in our system model) from the perspective of subjective end-users (humans) and SPs, and also helped SPs to efficiently react to this deviation. In fact, if SPs could estimate the Prelec parameter that characterizes user behavior, it could be used directly at the SP to optimize the bids and compensate for the underweighting of service guarantees based on that.
6.1 Introduction and Motivation

In the previous sections, we have discussed the optimized user centric and network centric resource allocation methods for normal situations. However, during emergencies and natural disasters where the cellular network capacity could dramatically shrink, we have to redesign methods for the allocation of scarce cellular resources in order to connect the trapped mobile users to the first responders and volunteer in the area, to facilitate rescue and recovery operations. During the disasters like hurricanes that endanger lives, wireless emergency alerts (WEAs) are sent to users in affected areas to update them about the latest environmental situations, and ask them to follow specific guidelines that could enhance their safety and security. In such situations, to prevent network outage it is extremely critical for mobile users to not overload the cellular network with non-necessary bandwidth-intensive traffic. However, unfortunately recent studies show that most people will not fully comply with the received alerts guidelines during emergencies, which ask them to refrain from non-necessary cell phone usage until further notice. Hence, to increase users’ compliance and provide network access for users who are in need for help, we have to design an alert system which is adaptive and reconfigurable based on the realtime information on the users’ behavior, mobile network situation, and environmental status variations.

However, in the current Integrated Public Alert and Warning System (IPAWS), which is responsible for generating and disseminating alerts, there is no monitoring mechanism to measure the effectiveness of alerts and their associated user’s compliance level, and also IPAWS is not dynamically reconfigurable based on realtime captured
information of the environment, users and the mobile network.

To address these issues, in this thesis, we present a Cognitive Wireless Emergency Alert System (CWEAS) architecture that is able to predict and prevent mobile network outage during emergencies, using prediction models and machine learning tools that consider real-time monitoring information of the network capacity, users traffic and environmental status changes. We assume cellular network operators are able to identify the source and classify the incoming mobile traffic into 12 different categories of applications with different priorities, based on the observed traffic patterns and using deep packet inspection techniques which evaluate the headers of IP packets carrying applications data. DPI techniques could capture information like incoming packets source, their associated transport protocol, port number, or application. The designed CWEAS is able to protect scarce network resources from non-essential use, by decoupling the low priority non-essential users traffic from high priority public safety traffic. CWEAS is backward compatible with the current IPAWS architecture as it complements IPAWS by adding a cognitive control cycle to it by which the real-time monitoring information of the system will be utilized to make it more adaptive and efficient. The main objective of CWEAS is to provide network access and prevent network outage during emergencies, through boosting users’ compliance by disseminating more customized and effective WEAs, and also using complementary net access control mechanisms to make sure the network traffic will not exceed the available capacity. The results of a survey we performed on mobile users and the simulation results both validate the necessity and efficiency of the proposed CWEAS architecture.
6.2 Review of WEAs Evolution

The initial version of WEA messages called WEA 1.0 used to support the transmission of alerts across three different classes namely presidential alerts, imminent threat alerts, and child abduction emergency/AMBER alerts became functionally available after 2012 [63]. WEA 1.0 alerts that used to trigger a unique sound and vibration on receiving smart phones were used for broadcasting tornado, flash flood, dust storm, hurricane, typhoon, extreme wind, and tsunami warnings by means of broadcasting 90 character text-only messages to large geographical areas that were believed to be at risk. Later studies showed that the 90 characters’ limit of WEA 1.0 alerts that were absent of graphic elements, and their coarse broadcast domain had reduced the effectiveness of such alerts [64, 65]. Since its inception, and based on stakeholder experience and technological advancements, there have been continual enhancements to the WEA system to meet public safety needs. After Federal Emergency Management Agency (FEMA) received many public complaints on frequency of overnight WEA alerts with perceived little impact, the second version of WEA messages, WEA 2.0, was initially announced in 2016 and became fully operational in May 2019 after going through several rounds of upgrades. During such upgrades, the alert message length limit increased from 90 characters in WEA 1.0 to 360 characters in WEA 2.0, new alert classes for public safety were established, alert message prioritization become available, transmission of embedded references and multimedia content via alerts become feasible, Spanish language alert messages were supported, and state/local WEA alert testing feature and consumer opt-in capabilities for receiving WEA alerts were added in WEA 2.0 [66].

Finally, the latest version of such alerts called WEA 3.0 is proposed on May 2019 to better integrate WEA modules with other components in the Integrated Public Alert and Warning System (IPAWS) architecture, and define broadcast domains of WEA alerts more precisely by narrowing geo-targeting requirements. For example, WEA 3.0 specifications are assumed to be met only when an alert is delivered to 100% of users in a target area with no more than 0.1 of a mile overshoot, to prevent course broadcasts and increase the effectiveness of alerts. In WEA 3.0, each type of alert will be delivered
only to areas and users that match with predefined specifications for that type of alert. Depending on the alerts type, the IPAWS central controller could route alerts to be broadcast via different communications mediums, including radio transmissions, mobile networks, or satellite communications. Based on WEA 3.0, different authorities at federal, state or local levels could initiate and trigger a wide range of alerts from different categories like weather emergencies, public safety, or security related alerts. In summary, WEA 3.0 introduces two new capabilities, including 24-hour alert message retention at mobile devices in a consumer accessible format, and device-based geo-fencing (DBGF) for enhanced geo-targeting of WEA alert messages. According to DBGF, a mobile device must be capable of receiving coordinates defining one or more geometric shapes (circle, polygon) sent by the alert originator, and must be able to compare its location against the alert area defined by that shape, with the 0.1 of a mile overshoot allowance taken into consideration.
6.3 Current IPAWS Architecture

As mentioned in the previous section, WEAs are disseminated to users via IPAWS. The current IPAWS architecture and the interdependencies between different modules within this unified architecture, which is managed by Federal Emergency Management Agency (FEMA), is illustrated in Fig. 6.1.

IPAWS Architecture

![IPAWS Architecture Diagram]

Figure 6.1: Integrated Public Alert and Warning System (IPAWS) Architecture.

As shown in Fig. 6.1, the IPAWS architecture includes 4 vertical layers, namely Alerting Authorities, Alert Aggregator/Gateway, Alert Disseminators, and People/End Users. The first layer from the left specifies the alert initiator authority at the local, state, or national level. All the alerts initiated in the first layer will be routed to the centralized alert aggregator/gateway in the second layer which is managed by IPAWS Open Platform for Emergency Networks (IPAWS OPEN). The responsibility of IPAWS OPEN is to classify and process received alerts based on their type and scope and forward them to the appropriate alert dissemination system in the third layer. WEA
system is one of the modules in the third layer of IPAWS architecture that broadcasts the received alerts from the IPAWS gateway to mobile devices in the fourth layer located within the target area defined for each WEA alert, via wireless communications mediums and links. The third layer of IPAWS is in fact the broadcast layer which delivers different emergency alerts to users via different communications mediums including wired, wireless, radio, or satellite communications depending on the alerts type, scope, and required technology for their propagation and delivery.

According to WEA 3.0, once the alerts are received at the mobile phones antennas, the alerts will be initially processed according to a logical processing diagram given in Fig. 6.2, and the appropriate action will be taken for each received alert message which could be discarding the alert in case of duplicate reception of the same alert, presenting the alert to application layers for processing and storing it at the same time, or storing the alert without presenting it to application layers if it does not pass the WEA 3.0 required checks to be presented to the application layer.

![Figure 6.2: Alert processing at mobile devices after reception](67)
6.4 Cognitive Wireless Emergency Alert System (CWEAS)

As we saw in the previous section, IPAWS architecture is only able to deliver the alerts like wireless emergency alerts to users during emergencies; however, after delivery of such alerts, there is no mechanism in IPAWS to see if users are actually complying with received alerts, or if the alerts themselves are effective and informative enough to enhance users’ compliance and motivate them to follow the suggested guidelines or not. Considering the harmful impacts of disregarding the alert guidelines by mobile users on the rescue and recovery operations during natural emergencies which could put some lives in danger, in this thesis we present a novel cognitive wireless emergency alert system (CWEAS) architecture, to resolve such issues and enhance the efficiency of WEAs.

CWEAS is an adaptive and self-reconfigurable system which takes into account the current status of the mobile network, environment, and users to optimize its performance and ensure network access for trapped people in affected areas and enables them to get connected to the first responders and volunteers in the area if needed. CWEAS is also backward compatible with IPAWS and could be easily integrated with the current IPAWS architecture, as it actually extends IPAWS by adding a cognitive cycle to it to make it more effective and adaptive based on the realtime information of the mobile network, users, and the environment. The major two enhancements of CWEAS as compared to IPAWS is that first, it is able to dynamically change the alert messages wording and make them customized for a given target audience/population. Second, it leverages intelligent congestion control and access control mechanisms at the network side to manage communication resources in the mobile network, predict and prevent network outage, and facilitate communications between public safety agents and trapped people in affected areas. To predict the system’s future state based on its current status, CWEAS could leverage traffic prediction models and machine learning tools like regression learning. The functional architecture of the proposed CWEAS model and the interdependencies between its modules is illustrated in Fig. 6.3.

As we can see in Fig. 6.3, the CWEAS includes 7 modules in total, out of which
the four blue modules entail the functionalities of IPAWS architecture, one module for each layer, and the other 3 green modules, namely Realtime Monitoring System (RMS), Learning & Prediction Unit (LPU) and Dynamic Alert Optimizer & Network Access Control (DAO-NAC) are the proposed added modules in CWEAS architecture which form a cognitive cycle with the Users module, to dynamically update and reconfigure CWEAS to make it more effective based on the realtime monitoring information of the users, network and environment.

RMS module dynamically monitors the system’s status and captures the real-time variations in the environment, user’s traffic, and mobile network load and capacity. It also classifies the observed streams of data in some categories based on their source/destination user or IP address, associated application and port number, traffic priority, and associated transport protocol, using deep packet inspection (DPI) techniques and inspecting the headers of each data packet. It also measures the user’s compliance level and their reaction to received alerts to see how effective each alert is, and if users follow the suggested guidelines in the alert or not. Besides of users and mobile network status, it also monitors the variations of the underlying natural emergency like flooding or hurricanes, and sends all the raw monitoring data to the Learning and Prediction Unit.
(LPU) for further processing. LPU receives the raw monitoring data on three domains including network, environment and users, and feeds them into its prediction models to predict the future state of the system in each domain precisely, using machine learning tools. More specifically, it predicts if a mobile network outage is likely to happen in the near future based on the current information or not. It also predicts the effects of each possible action, like changing the alert type or blocking access for a given application type, on the systems performance as a whole. After processing the raw monitoring data, and extracting useful information about the current and future status of the system and the effects of each possible action on systems performance, LPU sends all of these information to the DAO-MAC module for the alerts and network access optimization.

DAO-NAC includes two complementary sub-modules, each with a given responsibility, namely DAO and NAC sub-modules. DAO is responsible for generating customized, informative and effective alerts based on the monitoring information on the performance of different alerts, network capacity and load, and also demographic information of the population in the affected areas, to increase their cooperation and compliance level and facilitate rescue and recovery operations. Hence, for each group of users a customized alert messages will be chosen from a variety of both persuasive alerts as well as punitive alerts which remind users of the potential penalties for noncompliance to public safety guidelines, in order to maximize their compliance and reduce non-essential traffic. However, our survey results show that users compliance to alerts is different per alert types, but it is never complete, meaning users’ compliance level may not be enough to save the network from outage due to excessive non-essential load from users, despite optimizing alerts. Hence, some network access control methods are implemented by the NAC sub-module to make sure that the network remain accessible to facilitate the communications between the people in need and the first responders and volunteers in the affected area. To make sure the total network load is below a given threshold, the NAC sub-module sorts the application types based on their priority, and if needed it starts blocking access for the users who are congesting the network with non-essential low priority traffic, until the load goes below a given threshold required.

Such periodic and adaptive mechanisms implemented in the proposed cognitive
cycle within CWEAS which rely on the feedback information from the system, will definitely enhance the efficiency of public safety operations over time, by allocating more communications resources to public safety operations and also sending more customized and informative alerts to the users in affected areas. However, taking advantage of such system requires extensive field studies to understand the types of applications that mobile users of different age are using in everyday life, and also their reaction to different types of alerts. To this end, in the next section, we present the results of a case study survey we performed on Amazon Mechanical Turks (MTurks) during which around 898 users from different parts of the US participated.
6.5 Survey on Designing WEAs to Reduce the Cellular Traffic

To increase mobile users compliance with emergency guidelines, we need to design effective alerts, and to do so we have to design several types of alerts and then monitor and measure the mobile users’ response after receiving each of these alerts, in order to find the most effective ones for each category of people/residents, in each emergency situation, and under different mobile network load conditions.

6.5.1 Designing 7 different emergency alerts

In our survey we designed 7 different emergency alerts with different wordings described in Fig. 6.4, namely Basic Information, Altruistic, Multimedia, Negative Feedback, Positive Feedback, Reward, and Punitive alerts, to record users feedback after receiving any of the mentioned alerts, in a hypothetical emergency situation. These alerts would help us to understand and measure the effectiveness of WEAs with different objectives ranging from pure persuasive and altruistic alerts to punitive alerts.

As we can see in this figure, the basic information alert just passes the information about the emergency and asks users to not use their cellphones until further notice. Reward and Punitive alerts would add a financial benefit or punishment for complying with or disregarding the alert guideline to not use cellphones until further notice, respectively. Positive reinforcement alert reiterates the positive impact of complying with alert guideline on facilitating the rescue and recovery of victims. Negative reinforcement alert highlights the negative impacts of disregarding alert guidelines which could add to the sufferings and loss of victims. Multimedia alert includes a picture of rescue operations to gain more attention from users and increase their compliance. Finally, Altruistic alert tests humane behaviors of users by telling them how they could personally help rescue the people in need by not using cellphones.

6.5.2 Classifying cellphone apps into 12 categories

To estimate mobile users’ daily data traffic, we classify all cellphone apps in terms of their bandwidth consumption into 12 categories, and then we ask users how much
Figure 6.4: 7 Different wireless emergency alerts used in the survey.

time they use each category of apps in a daily basis. As shown in Fig. 6.5 we divide these 12 categories of mobile apps into three classes of high, medium and low data rate apps based on their instantaneous data rate, which is also associated with the amount of network resources they consume per unit time.

We also classify mobile apps in terms of their network access priority considering both users preferences and apps data rates, so as to block low priority apps traffic in emergency situations where the network is congested and overloaded with non-essential traffic, and mobile network access is critical for saving trapped people via connecting them to the first responders and volunteer in the area.
6.5.3 Survey on average mobile users daily traffic, and the effectiveness of designed alerts

To estimate mobile users average daily traffic, and also to measure the effectiveness of the 7 designed alerts on the reduction of users unnecessary traffic across 12 designated categories, we performed a survey in Amazon Mechanical Turk (MTurk), which is a crowdsourcing website for performing online surveys, during which we recorded the responses of 898 participants who took part in the survey. Participants were all smartphone owners, residents of the United States, and fluent English speakers, among them, 51% were men and 49% were women, with ages ranging from 18 to 65+ with a majority of the responders in the ranges 25-34 (33.96%), and 35-44 (33.49%). Further details on users’ demographic information, the recruitment process, and the survey procedures could be found in [68].

In designing the survey questions, we followed three primary objectives including: (1) to test users understanding of mobile apps bandwidth consumption as it has been shown that it could impact their compliance with received alerts asking them to reduce their cellphone usage, (2) to record and estimate average mobile users daily traffic in order to do network capacity planning and design access control mechanisms during emergencies to prevent network outage, and (3) to monitor and measure the effectiveness of each of

<table>
<thead>
<tr>
<th>Apps Category</th>
<th>Data Rate (Kbps)</th>
<th>Bandwidth Consumption Rank</th>
<th>Net Access Priority Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>video streaming</td>
<td>530</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Send/upload videos</td>
<td>180</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Social media</td>
<td>80</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Video call</td>
<td>70</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Audio Call</td>
<td>19.05</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Music</td>
<td>14.51</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>Send/upload photos</td>
<td>14.22</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>Web browsing</td>
<td>4.27</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Gaming</td>
<td>3.41</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>Other phone Apps</td>
<td>2.67</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>GPS</td>
<td>0.79</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>SMS</td>
<td>0.02</td>
<td>Low</td>
<td>High</td>
</tr>
</tbody>
</table>

Figure 6.5: 12 categories of apps used by mobile users.
the 7 alert types designed to reduce cellular traffic during emergencies, by recording users response to questions about their cellphone usage across 12 application categories before and after receiving one of the 7 alert types.

We first asked users to describe the bandwidth consumption of each of the applications by classifying them into three categories of high, medium, or low bandwidth-consuming apps, using the relative number of text messages associated with each category as a well known reference, to help them understand the notion of bandwidth or data rate as technically illiterate users may not know about these concepts, necessarily. Fig. 6.6 shows the percentage of mobile users who correctly understand the bandwidth consumption of each app type, across all 12 apps categories.

![Mobile Users Understanding of Apps Bandwidth Consumption](image)

Figure 6.6: Mobile Users Understanding of Apps Bandwidth Consumption.

As we can see from this figure, for all apps categories, the majority of users were unable to correctly identify apps data rate and bandwidth consumption, which very well could be one of the reasons explaining their low compliance with the emergency alerts, as we can see in the following section, especially considering users lack of information on the bandwidth intensive apps like video streaming.

Fig. 6.7a shows the mobile users’ average daily usage time per task, in which web browsing, listening to music, using social media, and video streaming are the most frequently used tasks. Also, the mobile users’ average daily traffic per task is shown in
Fig. 6.7b, which is the multiplication of app usage durations by the apps data rates given in Fig. 6.5.

![Graph showing Daily Usage Time and Traffic per App Category](image)

(a) Average Daily Usage Time (min)

(b) Average Daily Traffic (MB)

Figure 6.7: Mobile Users Average Daily Usage Time and Traffic per App Category.

After asking about users understanding of apps data rates and capturing their usage patterns, we test the effectiveness of the designed alerts in reducing non-essential cellular traffic, by randomly showing one of the designed alerts in Fig. 6.4 to each user, and asking about their usage patterns in a hypothetical natural disaster situation after receiving the alert messages. To measure users’ compliance with alerts, we define
absolute compliance as a situation where users agree to stop using their cellphones until further notice, while partial compliance refers to a situation where users refrain from using a particular task, but they could still use their cellphones for other tasks. Fig. 6.8 shows both the absolute and partial compliance of users with the received alerts across different app categories.

As we can see in Fig. 6.8a, users observed compliance with each of the seven designed alerts is different due to their different wordings and objectives; however, in general, the absolute compliance of users with alerts is low and on average only 18.88% of users would comply with the received alert guidelines to refrain from cellphone usage until further notice. There are several reasons that could explain the low compliance of users with alerts which is seen in other research experiments as well [69–74], including: (1) the addiction of mobile users to cellphone usage in this era which makes it extremely hard for them to abandon cellphone usage; (2) seeking news using cellphone apps specifically social media apps, which are used by many users as major sources of getting news and updates during natural disasters, and (3) lower altruistic behaviors in individualist cultures in western countries as opposed to more socially oriented eastern cultures in Asian countries. We also observe in this figure that persuasive alerts result in higher compliance rate as compared to punitive alerts, as we can see the positive reinforcement alert which tells users they could personally help to save the lives of endangered people resulted in the highest compliance, while punitive alert which tells users they might lose network access if they continue to congest the network with non-essential traffic has resulted in the lowest compliance rate.

Although absolute compliance rates are low for almost all the alert types, as we can see from Fig. 6.8b, the partial compliance rates across different apps are moderately higher, even though users may stop using one app but still continue to use other apps in partial compliance. As predicted, the lowest partial compliance observed is for the social media, audio calls, and web browsing apps, which are all the apps that users would use to get updates and news about the situation or share their feelings and concerns with their friends and family.

Regardless of the reasons for users low compliance rates, it is clear that only relying
on users compliance would not be necessarily enough to save the network from outage as a result of excessive traffic, and hence we need to implement traffic admission control policies at the network side as a complementary measure to maintain network access for mobile users during disasters. In the next section, using simulation results, we show how we can use network access control mechanisms as a complementary measure with alerts to maintain the load below a given threshold which is necessary to prevent network outage.
Figure 6.8: Absolute and Partial Compliance of Alerts across Different App Categories.

(a) Alerts Absolute Compliance

(b) Alerts Partial Compliance per App
6.6 Simulation Results

In this section, we present simulation results to show the impact of several parameters on the outage probability of cellular networks during emergencies. We evaluate the effectiveness of alerts in reducing non-essential traffic as well as the impact of network access control mechanisms to maintain the realtime traffic below a given threshold, assuming the number of active cellular users is varying. We consider a cellular network model in which a cellular LTE base station located at the center of the cell serves a varying number of active mobile users, that are randomly located within the cell area with a radius of 2 Km. We assume the cellular LTE BS is reusing 20 MHz of licensed spectrum across its three sectors, and overall it’s designed to provide the max capacity of 900 Mbps, with 300 Mbps capacity across each sector.

To see the effects of the load (number of active mobile users) on the aggregate cellular traffic and outage probability, we consider two different scenarios, with a constant and varying number of mobile users. Also, in both scenarios, we assume each active cellular user is randomly running to one of the 12 categories of apps listed in Fig. 6.5, and also randomly receiving one of the 7 alert types in Fig. 6.4 during a hurricane asking him to refrain from cellphone usage until further notice to facilitate rescue and recovery operations. We also assume the users full and partial compliance levels are in accordance with the observed survey results presented in Fig. 6.8. We assume during the natural disaster (hurricane), due to damages to the cell tower components, like its antenna elements or power amplifier, and also due to bad channel conditions resulting from storm and rain, the capacity of the cellular network is shrunk to 300 Mbps. Hence, to provide network access and prevent an outage, we have to maintain the aggregate cellular traffic below this threshold, using both alerts and access control mechanisms that block non-essential traffic by blocking low priority apps traffic according to Fig. 6.5, using DPI techniques, until the total traffic goes below the 300 Mbps threshold needed to connect mobile users to first responders and volunteers in the area.

The field measurements and cellular traffic patterns observed in residential areas in China presented in [75] show that the peak cellular traffic during busy daily hours
from 10 am to 10 pm is almost uniformly distributed, due to a large number of users and central limit theorem, which suggests that the traffic will converge to its average. Hence, in the first scenario, we assume the number of active mobile users is a Gaussian distributed random variable with the mean of 7000 users and standard deviation of 54.77 users, which makes the variance to be around 3000 users. Note that we assume the population of the area is 10000 users, however on average 7000 of them are active simultaneously during the peak traffic hours.

Under such assumptions, Fig. 6.9 shows the variations of cellular traffic over time and compares its fluctuation in four different scenarios including when there is no alert, when we use positive feedback or punitive alerts only, and when we use both positive feedback alert and complimentary access control mechanisms together. As we can see,

![Figure 6.9: Cellular traffic variations over time with or without alerts & access control.](image)

the aggregate traffic of users in normal days without alerts fluctuates between 500 Mbps to 600 Mbps, which is much higher than the available reduced capacity during the natural disaster. Also, we can see that although alerts could lower the total traffic depending on their effectiveness, ranging between positive feedback alert as most effective and punitive alert as least effective alerts, but they are still not enough to lower the traffic below the required 300 Mbps to prevent network outage. Hence, as we can see, we should use access control mechanisms along with the most effective alerts, according to the CWEAS architecture proposed, to maintain the total load below the required
300 Mbps, to provide network access to users. Otherwise, the limited available network resources would be exhausted under congestion, and outage is inevitable.

In the second scenario, to see the effects of active mobile users density on the congestion and network traffic we vary the number of active mobile users from 1000 to 10000 users. The aggregate cellular traffic as a function of load, under different reduced cellular capacities and using different control mechanisms is shown in Fig. 6.10. As we can see, when the cellular capacity is reduced to 300 Mbps and the number of active users exceeds 5600 users, the total traffic would go above the available capacity and after that we need to control the access of users to provide network access to other endangered users. This will happen when number of users exceeds 9000 users, when the reduced cellular capacity is 500 Mbps. In our simulations, when access blocking is needed, we blocked the data traffic belongs to the low priority apps, designated as gaming, music, social media, video streaming, and video uploads, up until the congestion is resolved and the incoming traffic falls below the reduced capacity of cellular network during the hurricane.

![Total Network Traffic Vs Load](image)

**Figure 6.10: Total Network Traffic Vs Load Variations.**

Defining the traffic blocking rate as the ratio of users excessive traffic which is above the capacity and will be blocked by the network to the total users traffic, we can see its variations under three different methods in Fig. 6.11 when the number of active users is 10000.
As shown in this figure, when the reduced capacity we need both access control and alert control mechanisms to prevent traffic blocking and provide access, while when the reduced capacity is high enough like 800 Mbps, only using alert control we can prevent the blocking issue without using any access control mechanism.
6.7 Conclusion

In this section, we proposed an architecture to manage the cellular traffic and provide connectivity during natural disasters, via dynamic WEA and complementary access control mechanisms. To facilitate rescue and recovery operations during emergencies, the proposed mechanisms provide network access to endangered mobile users in order to connect them to first responders and volunteers in the area, even when the capacity of cellular networks is reduced due to damages to the communications infrastructure. We briefly reviewed the evolution of WEAs, and showed that the current IPAWS architecture is not able to dynamically optimize itself based on the observed alerts effectiveness, and the realtime variations in the environmental status, users traffic, and the mobile network capacity. To solve such issues, we proposed the CWEAS architecture, that leverages a cognitive cycle to reconfigure itself based of such variations. We then provided the results of a survey we performed on Amazon MTurk, in which we tested the effectiveness of 7 designed alerts on reducing user’s non-essential traffic across 12 designated cellphone apps. The survey results showed that: (1) sending any of the 7 alerts is better than sending no alert, in terms of reducing users non-essential traffic; (2) the effectiveness of alerts is different depending on their objective and wording, as persuasive alerts are in general more effective than punitive alerts; and (3) despite the positive impact of alerts in reducing cellular traffic, we still need to implement some network access control mechanisms to ensure that the cellular load remains below the shrunk capacity during emergencies, otherwise network outage might be inevitable. We then provided simulation results to verify the results of the survey.
Chapter 7
Conclusions and Potential Extensions

With the development of HetNets and network denitrification as a viable solution to the increasing demand from mobile users for higher data rates and better reliability, the problems of user to BS association and resource allocation in such networks have drawn tremendous attention in recent years. In this dissertation, we presented two user centric and network centric models for joint user to BS association and resource allocation in wireless HetNets. We first showed that the user association and resource allocation optimization problems are inherently interdependent, and hence should be jointly optimized. Then, we formulated the network centric joint optimization problem and proved that it is NP-hard. To address the time complexity issue, we designed a low complexity heuristic method by building a support vector machine classifier for user association, and using an ADMM-based iterative algorithm for resource allocation. The simulation results validated the efficiency of the proposed method.

Moreover, we proposed an interactive user centric framework by which we studied the impact of end-user behavior on SP bidding and user/network association in a HetNet with multiple SPs while considering the uncertainty in the service guarantees offered by the SPs. We formulated user association with SPs as a multiple leader Stackelberg game where each SP offers a bid to each user that includes a data rate with a certain probabilistic service guarantee and at a given price, while the user chooses the best offer among multiple such bids. Using PT to model end-user decision making that deviates from EUT, we showed that when users underweight the advertised service guarantees of the SPs, the rejection rate of the bids increases dramatically which in turn decreases the SPs utilities and service rates. To overcome this, we proposed a two-stage learning-based optimized bidding framework for SPs. In the first stage, we used a SVM
learning algorithm to predict users’ binary decisions, and then in the second stage, we cast the SP utility-optimized bidding problem as an iterative dynamic programming problem, and proposed the DPOB algorithm to efficiently solve it. Simulation results and computational complexity analysis validated the efficiency of the proposed learning based bidding algorithm, and showed that the DPOB algorithm could improve the social welfare of the system for both users and SPs as compared to EUT-based bidding algorithms.

Both of the user centric and network centric resource allocation models presented here are utility based models in which we optimize the utility of users and SPs as the principal objective. While, in emergency situations like hurricanes, during which the capacity of mobile networks could dramatically shrink due to possible damages to cell towers and communications infrastructure, we have to design new methods for resource allocation in mobile networks in order to facilitate rescue and recovery operations. Despite the availability of dedicated channels [60] for the communications between first-responders, previous successful experiences have shown that using the civilians network to get in touch with affected people and trapped individuals who only have access to such networks could facilitate the rescue and recovery operations [61]. Hence, to prevent network outage it is extremely important for mobile users to not overload the mobile network with non-necessary bandwidth-intensive traffic, considering the reduced capacity. However, recent studies have shown that most people will not comply with the received alerts guidelines during emergencies, that ask them to refrain from non-necessary cell phone use. Moreover, in the current Integrated Public Alert and Warning System (IPAWS) which is responsible to generating and disseminating alerts, there is no monitoring mechanism to measure the effectiveness of alerts or user’s compliance level with each alert [62].

To solve these issues, in this thesis, we presented a Cognitive Wireless Emergency Alert System (CWEAS) that is able to predict and prevent mobile network outage during emergencies, using prediction methods that rely on real time monitoring information of the network, users and environment. CWEAS was able to protect scarce network resources from nonessential use, during natural emergencies, by decoupling low priority
user traffic from high priority public safety traffic. It is also backward compatible with
the current IPAWS infrastructure as it extends IPAWS functionalities by adding several
new modules to it to create a cognitive cycle. By performing a survey on mobile users
and providing simulation results based on the survey findings, we showed that CWEAS
could leverage both user centric mechanisms, like customizing alerts wording to increase
users’ compliance level, as well as network centric mechanisms, like controlling the access
of non-compliant users with excessive traffic, to achieve its goal and provide network
access during emergencies.
Bibliography


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