Slicing Enterprise WiFi Networks for Differentiated IoT Service Provisioning

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Tranchement de réseaux WiFi d'entreprise pour l'approvisionnement des services d'IdO différenciés

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RÉSUMÉ

Le nombre croissant de services IdO introduits dans les réseaux sans fil avec leurs diverses exigences et parfois contradictoires ont créé de nouveaux défis pour le contrôle et la gestion de ces réseaux. Le tranchement de réseau est l'une des fonctionnalités les plus recherchées de la 5G pour répondre à ces diverses exigences. Cependant, trancher les réseaux WiFi d'entreprise est difficile à cause de manque des mécanismes de virtualisation du matériel.

Cette thèse propose une nouvelle solution pour le tranchement des réseaux WiFi d'entreprise qui ne nécessitent aucun support de virtualisation dans les points d'accès. Notre solution s'appuie sur un mécanisme d'association dynamique d'utilisateurs qui prend en compte l'utilisation du réseau pour chaque tranche. Afin de prendre les décisions d'association, nous formulons un problème d'optimisation qui maximize le débit total du réseau par rapport aux différentes contraintes de chaque tranche. Ces contraintes incluent les limitations physiques des connexions sans fil, les limitations d'intégrité du système liées aux réseaux WiFi, les exigences IoT et l'utilisation à l'échelle du réseau pour chaque tranche.

En raison de la mobilité des utilisateurs et du changement de trafic dans les réseaux WiFi d'entreprise, cette optimisation de haute complexité doit être résolue en temps réel. De ce fait, nous proposons une heuristique basée sur un jeu d'appariement plusieurs-à-un. Nous adoptons l'algorithme d'acceptation différée pour trouver la solution de correspondance stable tout en tenant compte des exigences de la tranche IoT et du temps nécessaire pour trouver une association appropriée pour les consommateurs existants dans le réseau.

Les résultats de la simulation montrent un potentiel substantiel d'extension des travaux en cours, ce qui peut avoir un impact considérable sur la croissance sociale et économique des réseaux WiFi. Les résultats montrent que la solution proposée se rapproche des résultats optimaux et surpasse les approches RSSI traditionnelles tout en garantissant les exigences des différentes tranches IoT.

Mots-clés: WiFi, IEEE 802.11, tranchement de réseaux d'IdO, réseaux locaux sans fil, association d'utilisateurs, correspondance stable

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ABSTRACT

The increasing number of differentiated IoT services introduced to wireless networks are coming with diverse and sometimes conflicting requirements that brought new challenges for controlling and managing such networks. Network slicing is among the most wanted features of the 5G to address these diverse requirements. However, adopting it for Enterprise WiFi networks is challenging due to the lack of wireless virtualization supports in hardware.

This thesis proposes a new slicing solution for enterprise WiFi networks that requires no virtualization support in WiFi access points. Our solution relies on a dynamic user association mechanism that takes into account the amount of network-wide utilization for each slice. To define the association decisions, we formulate an optimization problem to maximize the total throughput of the network with respect to different constraints of each slice. These constraints include the physical limitations for the wireless connections, system integrity limitations related to the WiFi networks, IoT requirements, and the network-wide utilization for each slice.

Due to highly dynamics of user and traffic in Enterprise WiFi networks, this high-complexity optimization should be solved in a timely manner. We propose a heuristic based on a many-to-one matching game. We adopt the Deferred Acceptance Algorithm to find the stable matching solution while considering the IoT slice requirements and the time required to find proper association for the existing consumers in the network.

Simulation results show substantial potential for extending the current work, which can hugely impact the WiFi networks' social and economical growth. Results show that the proposed solution approximates the optimal results and outperforms the traditional RSSI approaches while guaranteeing the requirements of different IoT slices.

Keywords: WiFi, IEEE 802.11, IoT slicing, WiFi slicing, WLANs, user association, stable matching

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LIST OF ABBREVIATIONS

IoT	Internet of Things
SDN	Software Defined Networking
NFV	Network Function Virtualization
WiFi	Wireless Fidelity
QoS	Quality of Service
5G	Fifth Generation
BYOD	Bring Your Own Device
IEEE	Institute of Electrical and Electronics Engineers
WLAN	Wireless Local Area Network
AP	Access Point
EWLAN	Enterprise WLAN
FPGA	Field-Programmable Gate Array
MAC	Medium Access Control
WNM	Wireless Network Manager
BER	Bit Error Rate
WNV	Wireless Network Virtualization
WLV	Wireless Link Virtualization
KPI	Key Performance Indicator
PDR	Packet Delivery Ratio

LoRa	Long Range
URLLC	Ultra Reliable Low Latency
CCA	Clear Channel Assessment
ISM	Industrial, Scientific and medical
UNII	Unlicensed National Information Infrastructure
ACI	Adjacent Channel Interference
CCI	Co-Channel Interference
SNR	Signal to Noise Ratio
SINR	Signal to Interference plus Noise Ratio
RSSI	Received Signal Strength Indicator
DCF	Distributed Coordination Function
EDCA	Enhanced Distributed Channel Access
DIFS	DCF Inter-frame Space
SIFS	Short Inter-frame spaces
CTS	Clear To Send
RTS	Request To Send
ACK	Acknowledgment
TbF	Time-based Fairness
AbF	Access-Based Fairness
DAA	Deferred Acceptance Algorithm

BDAA	Backward Deferred Acceptance Algorithm
MDAA	Modified Deferred Acceptance Algorithm
CW	Contention Window
DRR	Deficit Round Robin
ADRR	Airtime Deficit round robin
WADRR	Weighted Airtime Deficit round robin
LVAP	Light Virtual Access Point
API	Application Programming Interface

LIST OF SYMBOLS AND UNITS OF MEASUREMENTS

dBm	decibel milliwatt
s	second
m	meter
ms	millisecond
Kbps	megabits per second
Mbps	megabits per second
μs	micro second

INTRODUCTION

Context and motivations

The ever-increasing growth of wireless devices seeking connectivity drives wireless networks to their limits, with users showing more interest in mobility and the introduction of brand-new gadgets and accessories. Therefore, wireless networks are going to face new waves of requests, especially by the manifestation of the Internet of Things (IoT). As forecasted in [Cisco (2018)], the number of IoT devices is rapidly increasing, and the massive traffic generated by these devices will make networks undergo several challenges. Furthermore, the heterogeneity of the devices and a variety of applications with diverse requirements makes IoT a complex environment with heterogeneous demands.

Nowadays networks are expected to be able to support dedicated use-cases and satisfy various requirements, especially with the introduction of 5G and its new capabilities to support diverse and often conflicting services. Such diverse requirements impose new challenges for the wireless network [Caballero, Banchs, de Veciana & Costa-Pérez (2017)] and demand proper techniques for management, policy enforcement, and resource provisioning. However, wireless connectivity is not limited to cellular networks. In terms of exchanged traffic, WiFi is largely considered today's dominant wireless access technology [Cisco (2018)].

There are two main classes of managed WiFi networks:residential and enterprise. Residential networks suffer from the unplanned and individually managed deployment of commodity access points [Zehl, Zubow, Döring & Wolisz (2016)] and with the massive expansion of WiFi networks these consumers are facing an increasing amount of contention and interference. On the other hand, an Enterprise WiFi network contains a plethora of enterprise-grade access points [Schulz-Zander *et al.* (2014)] which are typically managed by a WiFi network controller that monitors and controls those access points. An Enterprise Wireless Local Area Network

(EWLAN) enables seamless and secure connections for the employees of that enterprise. Such network removes the burden of having cable connections and being stuck at a desk. It allows mobility for the employees while maintaining their network connections. It also reduces the implementation and maintenance costs. In addition, it promotes the concept of Bring Your Own Device (BYOD) which allows ubiquitous access for employees to have connectivity on their laptops, smartphones, and tablets. Finally and most importantly, it contributes to IoT connectivity by facilitating the communication of IoT devices within the existing network [Ganji, Page & Shahzad (2019);De bast, Torrea-Duran, Chiumento, Pollin & Gacanin (2019)]. Therefore, we focus on EWLANs where access point placement is already engineered, and the allocation of network resources is performed through a network controller.

As mentioned earlier, meeting IoT requirements is challenging. In a cellular network, slicing is known to be the solution for the aforementioned challenges [Afolabi, Taleb, Samdanis, Ksentini & Flinck (2018)]. The new software-based architecture of the 5G enables operators to instantiate new network slices for a differentiated class of services such as IoT. A network slice is an isolated, self-contained virtual network tailored for applications with specific requirements [Ordonez-Lucena *et al.* (2018)]. Slicing is performed through logical and physical separation of network resources employing softwarization and network virtualization, which enables the operators to present the network functions as software programs running on the off-the-shelf products. This new representation brings extra flexibility and scalability to the network. For example, applications that are highly sensitive to delays can be served on the edge whilst high computations are performed in regional centers and the core of the network. In this process, users are associated with different slices that map the resources based on different characteristics such as coverage, available resources, users' SLAs, and operator policies.

One of the key enablers for network slicing is the network virtualization in the wireless domain which offers new opportunities and better abstraction for network infrastructure and the available spectrum [Richart, Baliosian, Serrat & Gorricho (2016)]. It aims to reduce the time and deployment costs in a wireless network while easing the product upgrade procedure in the network. Isolation, control signaling, resource allocation, and user mobility are some of the well-know challenges for wireless virtualization [Liang & Yu (2015)]. [Liang & Yu (2015)] presents motivations and challenges for virtualizing a wireless network. These challenges can vary based on the level of virtualization (i.e flow, antenna, sub-channel, time slot). It is obvious that each level of virtualization has its specific set of requirements. Regardless of the requirements, virtualization has been used for slicing enterprise WiFi networks [Aleixendri, Betzler & Camps-Mur (2019);Coronado, Riggio, Villa1ón & Garrido (2018)] where different hypervisor technologies have been used for implementing the proposed slicing techniques. In general, using virtualization can improve isolation and it enables better means for managing very dynamic scenarios. However, it can increase the number of controlling messages in the network. Also, it requires new implementation techniques which may result in massive changes in the hardware level in terms of maintenance, operation costs, etc.

The main challenge that wireless operators might face is the capacity crisis [Yang, Li, Jin & Zeng (2015)] which is caused by the proliferation of demands for wireless connections. Therefore, slicing a wireless network has been mainly studied in the cellular domain. Considering the two most important aspects of slicing: maximizing infrastructure utilization and providing the service continuity for users assigned to each slice, it enables operators with means for dynamic optimization of the resource utilization according to different service requirements and network conditions. Inspired by slicing in 5G networks, we study the concept of slicing in the EWLANs where Access Points (APs) are considered as the infrastructure and resource pools.

We consider the main principles that lay the foundation of network slicing and discuss how we consider each of these principles. Some of the main principles in network slicing are [Afolabi *et al.* (2018)]:

- Automation: to remove manual intervention in a slice life cycle (creation, deletion, configuration), an on-demand operation process is required to configure and maintain slices. Such operation can be initiated based on some signaling mechanism that places a request to create a slice based on different requirements such as capacity, latency, and starting and ending time of the slice.
- Isolation: this property of network slicing assures performance guarantees and security for each slice even when there are conflicting requirements. We can achieve this property by making a trade-off between multiplexing gain and the level of isolation required. Isolation can be applied in different approaches (i) using different physical resources, (ii) through virtualization, and (iii) through different policies and access rights.
- Customization: to assure resources are allocated in a way that service requirements are fully met. In this regard utilization of resources is customized based on the different requirements of each slice. It can be performed in a network-wide scheme, data plan, and control plan.
- Elasticity: is to reshape the allocated resources to a slice based on different parameters such as SLAs, changes in the environment, number of serving users, etc. It can be performed through policies or scaling the amount of allocated resources.

In our proposal, we consider different components that contribute to the realization of the aforementioned principles. More detailed information is provided in the section 2.5.

Challenges

To recall, in EWLANs, WiFi APs are densely deployed to provide enough resources for the network users. Since the WiFi APs are often low-cost and commodity devices, slicing is challenging due to the lack of virtualization and softwarization supports at the hardware level. Therefore, the existing solutions for WiFi slicing often focus on designing and manufacturing new devices based on Field-Programmable Gate Array (FPGA). Also, there are big differences between 5G and WiFi in terms of management and control. Based on the definition of slicing, a network operator has full control over all the available resources (transmission medium, computing, storage, and memory) [Afolabi *et al.* (2018)]. Using licensed frequency bands, a base station has full control over the transmission medium and how up-link and down-link are being accessed by all the stations. In contrast, the Medium Access Control (MAC) mechanism in WiFi is completely arbitrary and APs do not have full control over the medium [Richart *et al.* (2016)]. The medium itself is a noisy unlicensed frequency with no centralized scheduling for accessing the spectrum. The differences in management and control protocols and the available technological supports make it very challenging to apply the same 5G slicing techniques in the WiFi domain [Richart, Baliosian, Serrat & Gorricho (2020)].

WiFi hardware virtualization has been mainly achieved using a resource abstraction at the AP level. Basically, in most of the previous efforts, WNV is implemented by using a hypervisor at the virtualization layer [Koutlia, Umbert, Riggio, Vilà & Casadevall (2018)] running on top of a Linux kernel where it controls several virtual APs that contains a virtual machine connected to the physical wireless interface [Nakauchi, Shoji & Nishinaga (2012)]. However, using the same wireless network interface for virtual APs has its own drawbacks and challenges [Smith, Chaturvedi, Mishra & Banerjee (2007)]. To address these challenges different approaches have been proposed. Some used variations of Deficit Round Robin (DRR) scheduling like Airtime DRR (ADRR) [Riggio, Miorandi & Chlamtac (2008)] or Weighted ADRR (WADRR) [Koutlia *et al.* (2018)] on top of a decoupling model that considers two sets of available resources in a WiFi network namely physical resources and virtual resources. Physical resources constitute available channels and the APs working on each channel. Virtual resources are an aggregation of physical resources in terms of coverage and available airtime. Such techniques can be implemented by using Extended SSIDs (ESSIDs) in which each AP broadcasts different SSIDs in the network or by using light virtual AP (LVAP) in which each consumer is assigned a unique virtual basic service set ID (BSSID) [Suresh, Schulz-Zander, Merz, Feldmann & Vazao (2012)]. All aforementioned approaches sound promising however, an EWLAN, due to the dense distribution of its APs, may have a very large number of virtual APs that are broadcasting controlling and management frames in the network. This leads to an increase in channel utilization in the network and lower total throughput [Nakauchi & Shoji (2015)]. Also an uneven distribution of consumers with a tendency to change their service types brings a possibility of service disruption where consumers are required to change their ESSIDs. Aside from all the technological issues, implementing such techniques require changing the existing APs in the network which can bring a financial burden on the enterprise and network operation teams.

On the other hand, there are some software-based approaches that emphasize the programmability of the network infrastructure and mainly APs to perform the slicing. In such approach, resources are provisioned by tuning some parameters such as Contention Window (CW) [Joshi, Mukherjee, Yoo & Agrawal (2008)], Transmit Opportunity (TXOP) [Richart *et al.* (2016)], etc, combined with some scheduling techniques that resemble the slicing for the consumers of the EWLAN. The architectures based on this approach provides northbound application programming interfaces (APIs) that enable the implementation of network applications that mimic slicing controlling mechanisms on the network. To name a few, DIRAC [Zerfos *et al.* (2003)], and Dyson [Murty, Padhye, Wolman & Welsh (2010)] are examples of such architecture that can provide this level of programmability. In more recent efforts [Richart, Baliosian, Serrat, Gorricho & Agüero (2019a);Richart *et al.* (2020);Isolani *et al.* (2020)], we can see other software-based approaches to WiFi slicing. In these efforts, modeling the scheduling procedure inside an AP combined with modification of CW and TXOP has been done to obtain proper airtime for each slice. However, these efforts lack network representation, and do not consider how other elements of the WiFi network can affect the slicing procedure.

The definition of EWLANs emphasizes the centrally controlled APs that are densely deployed throughout the network and serve a large number of consumers where enterprises exploit the advantage of centralized management. However, there is a consensus on user association being the fundamental problem in EWLANs [Dwijaksara, Jeon & Jeong (2019)]. In addition, the introduction of IoT services with diverse requirements escalates the hardness of the existing problem. The main requirements of IoT rely on low latency, high security, and high data rates [Wijethilaka & Liyanage (2021)]. Combining user association with these requirements augments the complexity of the problem considering the nature of WiFi. With uneven distribution of WiFi consumers contributing to inevitable collisions on the contention-based medium and resource-limited IoT devices, it is a challenging task to provide an end-to-end connection for IoT devices with acceptable latency and enough data rate for many services such as mission-critical communication or automation applications.

The aforementioned motivations suggest us to propose a new slicing technique for EWLANs that requires no modification on the hardware side. Such a technique must also perform in a near real-time manner to deal with the stochastic behavior of the WiFi where resources are highly determined by the channel characteristics and conditions [Gómez, Coronado, Villalón, Riggio & Garrido (2020)], and how users are associated with the network [Bayhan & Zubow (2017)].

WiFi APs lack virtualization and softwarization support at the hardware level. Thus, dense deployment of access points in EWLANs causes resource allocation challenges. In addition, the advent of IoT and its related services raises the stakes in wireless resource allocation. A new approach is required to deal with these challenges.

Research questions

Network slicing is a promising tool in the 5G networks to deal with the diverse requirements of new services. There is a consensus on using similar approaches in other wireless domains such as enterprise WiFi. On the contrary, current WiFi slicing solutions either require hardware virtualization support or do not consider network representation of the resources. Therefore, in order to implement network slicing on an enterprise WiFi network that takes care of diverse requirements (throughput, delay, etc), we need to address the following research question:

- **RQ.** Would it be possible to design a slicing solution for Enterprise WiFi networks that requires no modification on AP hardware, but performs similarly to hardware virtualization solutions, and at the same time improves the total network throughput?

Objectives of the thesis

The main objective of this thesis is to propose a new solution to implement WiFi network slicing for EWLANs that requires no modification on the access points, taking into account the heterogeneous nature of IoT and underlying services in the network. The main objective can be divided into three sub-objectives (SO).

- **SO1**. Propose a new approach for achieving IoT slicing on WiFi networks by considering IoT services as tenants of an existing EWLAN. The new approach takes into account resource utilization and service continuity in a WiFi network with no virtualization support. It can be achieved through a resource allocation mechanism that can incorporate differentiated IoT requirements into the provisioning process, and an architecture that enables us to collect heterogeneous requirements of the IoT applications.
- **SO2**. Considering the two most essential requirements of slicing, formulate an optimization model based on the new slicing approach that maximizes resource utilization and minimizes the service disruption in a WiFi network.
- **SO3**. Propose an efficient algorithm to obtain the optimized solution in near real-time considering the stochastic nature of WiFi and the possible complexity of the optimization model.

Thesis organization

This thesis includes an Introduction, three chapters, and a conclusion.

The Introduction includes a briefing on network slicing in wireless networks and the challenges in the domain. It also contains motivations for this thesis followed by the thesis objectives.

In Chapter 1 we review the related work on WiFi slicing and similar technologies for IoT networks. We also reviewed different resource provisioning techniques in the WiFi domain such as channel allocation and user association.

Chapter 2 presents our methodology to achieve the thesis objectives. It contains our proposed architecture, a system model based on the proposed architecture, and a mathematical formulation of the resource provisioning problem in WiFi. In addition, it contains our algorithmic solution for solving the optimization problem in near real-time.

In Chapter 3 we present the experimental setup for validating our proposed architecture using simulations and the obtained results.

The conclusion summarizes the thesis findings and presents possible future work.

CHAPTER 1

LITERATURE REVIEW

The emergence of IoT devices and related differentiated services raised many questions in wireless networks as the number of consumers is rapidly increasing and the demand for more resources mandates more efficient techniques for resource provisioning. It becomes even more challenging when we try to meet some specific QoS requirements [Tan, Zhu, Ge & Xiong (2015)] such as bandwidth, throughput, time delay, packet loss rate, etc.

In this chapter, we investigate the available solutions and techniques for slicing a wireless network. We also review the available frameworks that are proposed to deal with newly introduced requirements for IoT networks. Table 1.1 summarizes our literature review on Slicing and other approaches for controlling and managing the resources inside a WiFi network. It contains state-of-the-art on the topics such as slicing in the WiFi domain, channel allocation, user association, and other related approaches.

Regarding our research question, the next section shed a light on the existing slicing solutions for WiFi. We investigate the pros and cons of the existing works that lead a pathway for our proposal.

1.1 Slicing in WiFi networks

Aside from the cellular networks, there is a big interest in performing the slicing on WiFi networks because huge wireless traffic is transferred using WiFi networks. In this regard, Richart et. al conducted a series of experiments and proposed different ideas [Richart *et al.* (2017);Richart2019;Richart20192;Richart2020]. Their proposal identified two approaches for slicing a wireless network: QoS slicing and Infrastructure slicing. In [Richart *et al.* (2017)] they proposed a technique based on Round Robin queuing to assign a share of available airtime to each slice in an AP. They used Proportional Time Deficit Round Robin (PT-DRR) to identify the traffic flows and assign a queue to each flow. The main objectives of this architecture are

Table 1.1 Literature review

Reference	**Feature, Pros and Cons**
WiFi slicing Richart *et al.* (2017) Carmo *et al.* (2018) Richart *et al.* (2020) Aleixendri *et al.* (2019) Isolani *et al.* (2020) De bast *et al.* (2019)	**Feature** Queue-based flow assignmet Scheduling services to flows **Pros:** They can provide isolation, based on slice priority **Cons:** Requires either virtualizations or changes inside the AP
User association Amer, Busson & Lassous (2016) Li *et al.* (2014) Amer, Busson & Lassous (2018b) Bayhan & Zubow (2017) Karimi, Liu & Rexford (2014) Zhao & Hua (2014)	**Feature** Centralized approaches, Fairness-based approaches **Pros:** airtime is considered **Cons:** Only up-link traffic is considered
Combined approaches Oni & Blostein (2015) Li, Luo, Wu & Yang (2017) Gómez *et al.* (2020) Coronado *et al.* (2018) Al-Rizzo, Haidar, Akl & Chan (2007)	**Feature** Cell breathing approaches, SDN-based **Pros:** proposed for dense WLANs Minimize most congested APs **Cons:** Probability of coverage holes

proportionally allocating the available airtime for each slice and inside each slice allocate the airtime fairly among the users of the slice. Figure 1.1 depicts the simplified queuing architecture used in their proposal.

In their next proposal [Richart *et al.* (2019a)] they tried to deploy infrastructure sharing in WiFi networks by allocating the airtime through the packet scheduling technique which benefits from adaptation to different traffic loads. Next, they proposed another approach [Richart, Baliosian, Serrat, Gorricho & Agüero (2019b)] to guarantee the bit rate for each WiFi consumer in an AP through the consumed airtime for each user and information obtained from the hardware driver such as local data rate manager data. They tried to find ratios of time that can be assigned to each slice while guaranteeing an average bit rate for each client. This bit rate depends on the channel capacity which has stochastic behavior and can vary in different channel conditions. They also

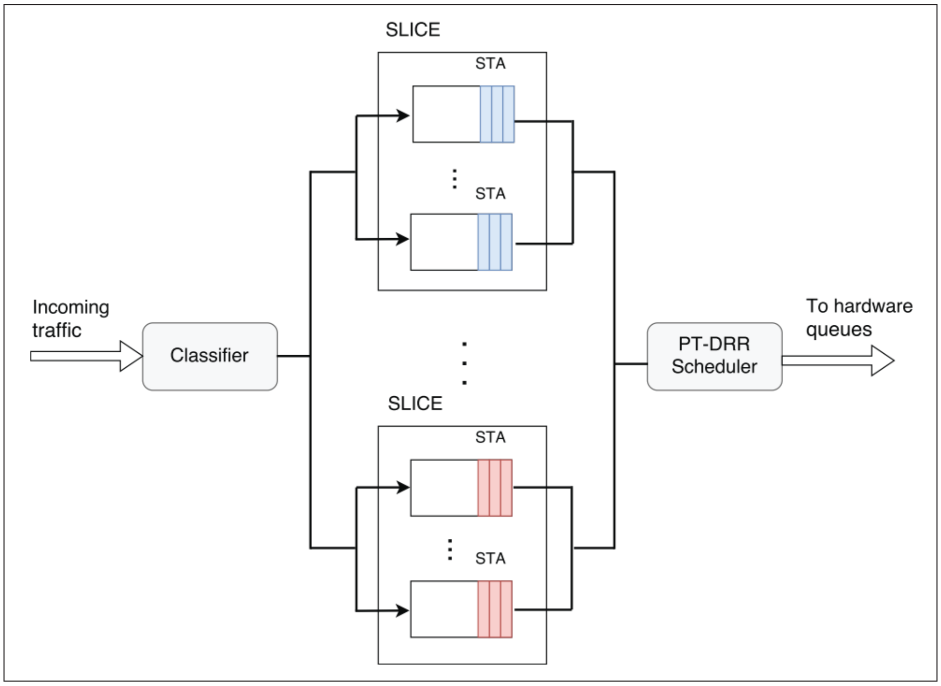


Figure 1.1 Simplified PT-DRR queuing architecture

proposed a QoS slicing technique that deploys different slices based on some performance requirements [Richart *et al.* (2020)]. They calculate the utilized airtime based on the transmission rate and re-transmission in WiFi MAC and later use this information in an adapted queuing mechanism based on a round-robin that assigns a queue for each consumer and each slice in an AP.

There are also other articles that address WiFi slicing in the literature. Carmo et al. [Carmo *et al.* (2018)] proposed a Fog-enabled slice-defined WiFi WLAN-sharing ecosystem which consists of extra virtual functions added to the existing APs. These new virtual functions can provide isolation and flexibility in resource allocation when it comes to affording the Ultra-Dense Networking (UDN) use cases introduced by 5G. Motivated by slicing Radio Access Network (RAN) in 5G, Aleixendri et al. [Aleixendri *et al.* (2019)] proposed another scheduling-based algorithm for slicing a WiFi RAN based on the airtime that consists of both centralized and distributed mechanisms to insure different Service Level Agreements (SLAs) are fulfilled for the tenants in the network. They used an SDN controller that configures a local scheduler in each AP.

These local schedulers are responsible for airtime allocation between the consumers connected to them. Also, they envisaged virtual interfaces with distinguished Service Set Identifier (SSIDs) for each slice. The SDN controller acts as a global scheduler that controls the state of the network.

The next two sections investigate the existing resource provisioning solutions that can be performed without changes in the WiFi APs. Regarding our research question, we are looking for approaches that can help us perform the WiFi slicing without changing the hardware. Therefore, we focus on channel allocation and user association, and the existing efforts in these domains.

1.1.1 Channel allocation

Traditionally channel assignment has been one of the major approaches for resource allocation due to the fact that there is a limited number of channels available for allocation in WiFi networks i.e thirteen $2.4Ghz$ frequency channels in Industrial, scientific, and medical (ISM) and 9 channels in $5Ghz$ Unlicensed National Information Infrastructure (UNII). Therefore several researches showed interest on the channel allocation and assignment [Akl & Arepally (2007);Ribeiro, Souto & Becker (2018);Lim, Jeon & Jeong (2016);Kasasbeh, Wang, Cao & V (2017);Jeunen *et al.* (2018)].

The main issues in channel assignment are Co-Channel Interference (CCI) and Adjacent Channel Interference (ACI). ACI is caused by APs that are using the same frequency channels or some overlapping channels in the network. As a result, the amount of noise and interference is increased in the network when there is an ACI in the network. It is known as the worst type of interference in the network. [Akl & Arepally (2007)] investigate this problem by proposing a distributed solution in which all APs run an optimization problem that aims to minimize the channel interference from neighboring APs. In their investigation, they considered all available channels in $2.4GHz$ and did not limit the algorithm to the existing three orthogonal channels in the ISM band. [Ribeiro *et al.* (2018)] tackle the same problem by emphasizing the growth of IoT devices that are working in the ISM band and how WiFi networks are densely deployed to meet the resource requirements for the new services. They proposed a modular channel assignment approach that takes into account different factors for assigning the channels such as RSSI and signal to interference plus noise ratio (SINR). Their proposal consists of two major modules, an interference analysis module, and a channel assignment module. In this proposal, they collect channel information through beacon frames that are received from neighboring APs and estimate the possibilities of the interference based on factors such as RSSI and SINR. This proposal sounds promising but it needs some modification inside the APs which the authors made by using an open-source operating system called OpenWrt [Ope (2021)].

Aside from ACI, channel utilization can affect the performance of the network. In [Lim *et al.* (2016)] maximum weight matching has been used for channel assignment based on different channel loads provided to a centralized controller through an active or passive scan. In this research, APs and channels were divided into disjoint sets that form a bipartite. The weight of each link is calculated based on the number of APs detected on the channel. [Kasasbeh *et al.* (2017)] proposed a different assignment approach in which they tried to assign channels based on the required throughput and the number of served users in each AP. Using Machine Learning (ML) for channel assignment has been proposed in [Jeunen *et al.* (2018)] in which they perform the channel assignment based on some collected information from the network.

1.1.2 User association

Several management operations exist in the IEEE 802.11 standard that can affect the operation of a wireless network. In a WiFi network, user association can be translated as the way a station is connected to the APs in its vicinity. The most basic approach is to use RSSI which defines the strength of the signal received by a station from other APs. This value can determine if the signal is good enough for a proper wireless connection. This metric is calculated in the station's WiFi device therefore the decisions for the association are taken by the station's WiFi driver and it can vary among different vendors. The shortcoming of this approach is that in dense environments, stations tend to associate with an AP that has the highest RSSI (depicted in Figure 1.2). In such a case, stations do not take into account the amount of channel utilization in the AP and just connect to an AP with the highest RSSI which leads to performance degradation and the unfair distribution of the resources. Therefore user association is a key performance factor in managing a WiFi network.

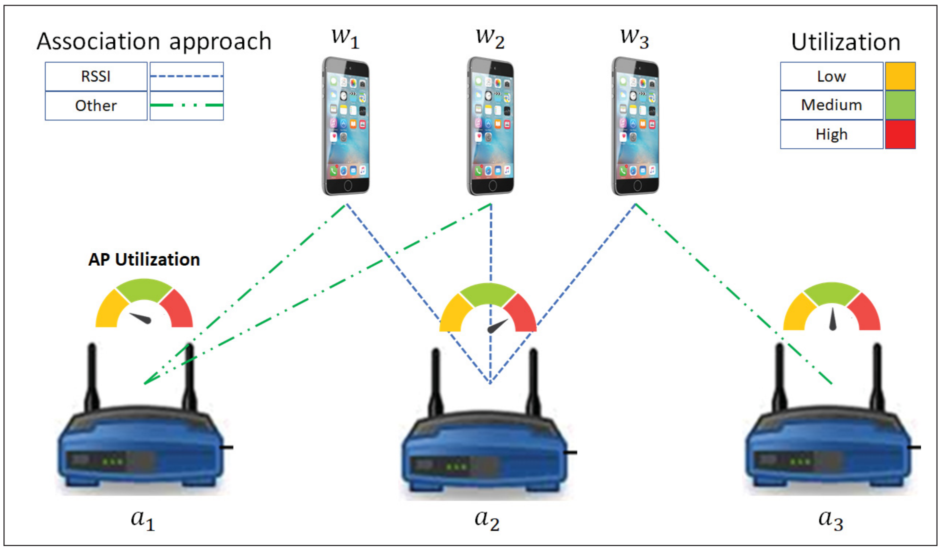


Figure 1.2 RSSI association does not consider AP utilization

In this regard, several pieces of research have been performed to improve the user association in a WiFi network. Authors in [Al-Rizzo *et al.* (2007)] proposed an algorithm that combines user association with channel allocation for minimizing the most congested APs in the network. A game-theoretic model has been proposed for user association in [Ercetin (2008)] where authors investigate the existence of Nash equilibrium in their proposed model due to the fact that in an association process, consumers are not interested in the optimizing the social welfare and they perform selfishly. They also claim that given the decision of other consumers, no other consumer is willing to change his association. They consider airtime as their metric for calculating the amount of congestion in each AP. However, in their model, consumers are the one who does the calculations and decides which APs to connect. In [Ekici & Yongacoglu (2009)] authors proposed a distributed association mechanism that takes into account the APs load and the number of connected devices to each AP. They defined a new metric called "Effective Rate" for each AP that is inversely proportional to the number of connected devices to each AP and their connection data rate. They argue that this metric can be distributed in the network and consumers can use this metric to connect to different APs. [Zhao & Hua (2014)] proposed a game-theoretical model for centralized user association that considers both homogeneous and heterogeneous traffic in an unsaturated network. They argued that airtime cost as a single metric for user association is not enough. They combined airtime cost with the traffic intensity of all nodes. Another game-theoretic solution has been proposed in [Touati, El-Azouzi, Coupechoux, Altman & Kelif (2015)] where authors combine user association with resource allocation on an 802.11 network with heterogeneous nodes that have the same packet size. They used a modified version of the Deferred Acceptance Algorithm (DAA), called Backward Deferred Acceptance Algorithm (BDAA) for their matching game. Their proposed solution contains a load balancing approach followed by an incentive model to encourage their balancing.

Amer et. al performed a series of research [Amer *et al.* (2016),Amer, Busson & Lassous (2018a);Amer *et al.* (2018b)] on different association techniques on how different parameters can affect the performance of a WiFi network. In [Amer *et al.* (2016)] they proposed a centralized solution that tries to optimize the total downlink throughput in the network. In their work, they assumed that the mean frame size sent to all the stations is equal and the number of frames is also equal. They also argued that the total throughput of an AP is equally shared among the stations it is serving. They solve their combinatorial optimization problem with a heuristic based on local search in which they consider the RSSI-based association as their initial step and tried to improve the existing solution in each iteration of the local search algorithm. They extend their work in [Amer *et al.* (2018a)] where they considered a new metric for comparing their algorithm. In this effort, they considered the number of stations that received their desired throughput before and after the optimization. They also stated that fairness in the network can be obtained through two approaches: Access-based Fairness (AbF) and Time-based Fairness (TbF). In AbF approach, the throughput of all the stations connecting to the same AP is the same and it is not affected by the data rate of stations. IN TbF approach, the available access time is shared among users and each station has an identical amount of time to access the medium. Therefore the achievable throughput for each station is highly dependent on its communication characteristics and the physical rate that it can obtain through its connection. In their consecutive work [Amer *et al.*

(2018b)] they proposed a TbF approach in which they consider the throughput requirements of the stations. In their optimization problem, they tried to reduce the highest utilized APs by unloading the utilization through user association. Similarly, Bayhan et. al [Bayhan & Zubow (2017)] proposed a TbF approach in which they tried to maximize the overall throughput of a network by considering proportional fairness for all the stations. They considered the minimum required throughput for each station and also considered the cost for each handover in the network. Like other papers, they also argue that user-driven association can cause performance degradation which leads to lower overall throughput of the network. Also, it can cause issues such as sticky clients (A client does not re-associate until the RSSI level gets too low which causes service disruption) or undesired handovers in the network.

There are some efforts in the literature in which authors combined association with other management techniques such as changing the AP coverage [Li *et al.* (2017)] and Clear Channel Assessment (CCA) threshold adjustment [Oni & Blostein (2015)]. In [Li *et al.* (2017)] authors state that changing the AP coverage area by adjusting the transmission power can force some users to re-associate with their nearby APs however such a technique can make some coverage holes in the network. Therefore, they combined coverage adjustment with user association to perform a load balancing in the AP utilization. In their problem formulation, they tried to minimize the most congested AP by considering the user traffic demand. One of the biggest issues in their approach is that they assumed they know the location of the users which is totally unrealistic. Although users' location can be obtained from techniques such as triangulation [Wikipedia (2021)]. In [Oni & Blostein (2015)] authors proposed another association approach that relies on the uplink SINR of the users. In this approach, a bipartite graph has been used for dividing users and APs, and link weights are defined based on the number of APs in the vicinity of stations. They use RSSI-based association as the initial step for their optimization and proposed a semi-matching approach to improve the RSSI-based association.

Looking at the available literature we can observe that game-theoretic models are suitable models for addressing the association problems [Oni & Blostein (2015);Ercetin (2008);Zhao & Hua (2014);Touati *et al.* (2015)]. Also, we can notice that among all the available parameters in a WiFi network, airtime usage has been highly used for similar problems [Touati *et al.* (2015),Bayhan & Zubow (2017),Ekici & Yongacoglu (2009)]. Therefore we can confidently choose game theory and adapt it for solving our association problem. We can see that among existing solutions, there are few efforts that address centralized association (i.e. Zhao & Hua (2014)). However, the existing solutions do not take into account specific IoT requirements in the network. We also can state that in a vast majority of literature that considers centralized optimal solutions there is no consideration for users' preferences which can cause instability in these solutions [Ercetin (2008)]. On the other hand, in distributed solutions, the cost of Nash equilibrium solutions achieved under selfish optimization of individual users' utility can be much worse than that of centralized outcomes.

CHAPTER 2

METHODOLOGY

In this thesis, we assume a network being segmented into several zones to improve management and control, with several IoT devices in each zone. All IoT devices use WiFi for communication. Therefore, each IoT device can be exposed to several APs. Considering the advantages of the slicing, we proposed an architecture to leverage this paradigm to guarantee heterogeneous requirements for differentiated IoT services in an enterprise network considering other resource-hungry parties in the network such as mobile devices or laptops. We envisage three main components in the proposed architecture: IoT platform, IoT broker, and a WiFi Network Manager (WNM), as depicted in Figure 2.1. We address the user association problem by taking into account the IoT slice requirements that are received from an IoT broker while maintaining the performance of the other mobile users in the network. In the following, we describe different components of our proposed architecture and define the role of each component in the framework.

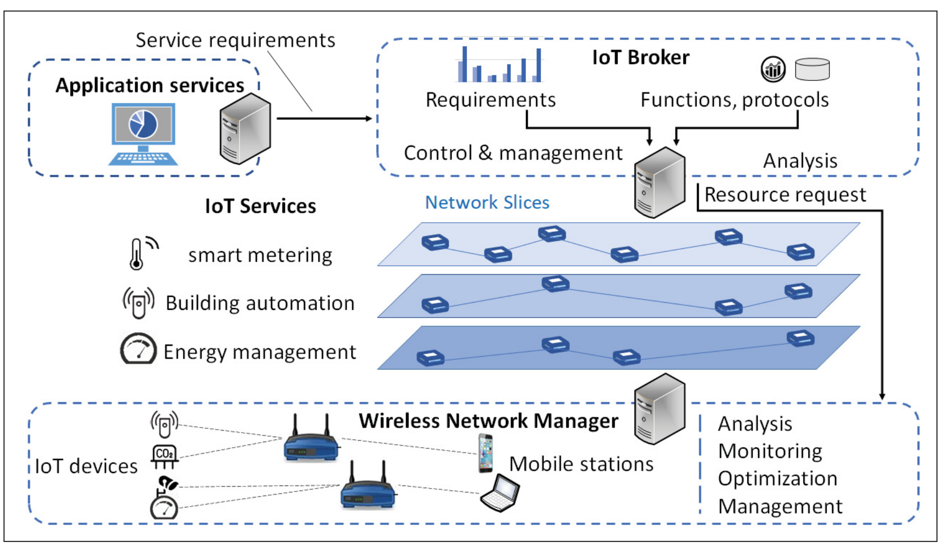


Figure 2.1 Abstract of the proposed architecture consisting of three main components

2.1 Architecture

2.1.1 IoT Platform

Essentially, an IoT platform consists of some IoT applications, various kinds of devices (sensors, actuators, cameras, etc.), and logical communication links. An IoT platform is utilized to bring automation and management among devices to provide IoT applications with the required data to bring a higher level of awareness about the equipped environment. The data that is exchanged among devices and applications through IoT services, that interfacing between two parties using the communication links. Each use-case in an IoT platform can have various requirements in terms of throughput, delay, bit error rate (BER), etc.

In this thesis, we define the IoT platform as an ensemble of services and applications on the enterprise premise for monitoring and controlling some sensory nodes that facilitates the available IoT solutions with means and functionalities to manage and control the underlying IoT devices as the endpoints. In the proposed architecture the endpoints (IoT devices) are connected through the WiFi network. Each of the existing applications and services requires information from the endpoint devices. We use these requirements as inputs for our optimization model. In our proposal service requirements are sent to an IoT broker where the requirements are differentiated per service requirements and mapped into some slices.

2.1.2 IoT Broker

It can be considered as a middle-ware that lies between the IoT devices and different applications and available solutions on the enterprise network. It can be addressed as an integration and processing engine for messages exchanged between the two parties. It provides northbound APIs for IoT applications and carries out data requests to the IoT platform. Such requests are conveyed to the device layer through IoT gateways (APs in this thesis). In the proposed architecture it is responsible for aggregating the QoS requirements from each device. The aggregation is performed based on the most stringent requirements. IoT broker maps these requests to some slices. Devices are placed on each slice based on their requirement similarities. These requirements are sent to the WiFi Network Manager (WNM) for further planning and resource provisioning.

2.1.3 WiFi Network Manager

It is the main component in the architecture that is involved in the process of administering and monitoring the performance and functionality of the network. WNM can be both software and hardware that collects the network data and process it for defining and enforcing the policies and configurations to ensure the correctness of the network functionality while maintaining its performance, reliability, and security. To achieve such autonomy, the MAPE loop (Monitor, Analyze, Plan, Execute) paradigm is being used (Figure 2.2) in which the network is being monitored periodically, and the collected data from the network is being analyzed to diagnose the network states continually. The stored information will be used to plan resource provisioning and system configuration. Resource provisioning takes place inside the WNM as one of its main functionalities. The association decisions are the result of the optimization process in which the slice requirements are incorporated as the constraints of the problem and as the objective function, we try to maximize the total throughput of the network. The output of the optimization problem will determine how IoT devices and mobile users are associated with the network. In our proposal, WNM is composed of three main functional blocks: WiFi monitoring, optimization block, and user management block.

2.1.3.1 Monitoring

WiFi monitoring block works based on two sub-systems, namely ‘data collection’ and ‘data analysis’. A script called ‘Agent’ that runs in each AP will be used to collect data from different APs. Agents collect data such as noise level, channel utilization, list of associated devices, etc. Collected data will be sent to WNM for further resource planning and configuration management. Agents are events generators inside the APs. They are also used to enforce policies and control commands inside the network. As an example, consider a case where new devices are being

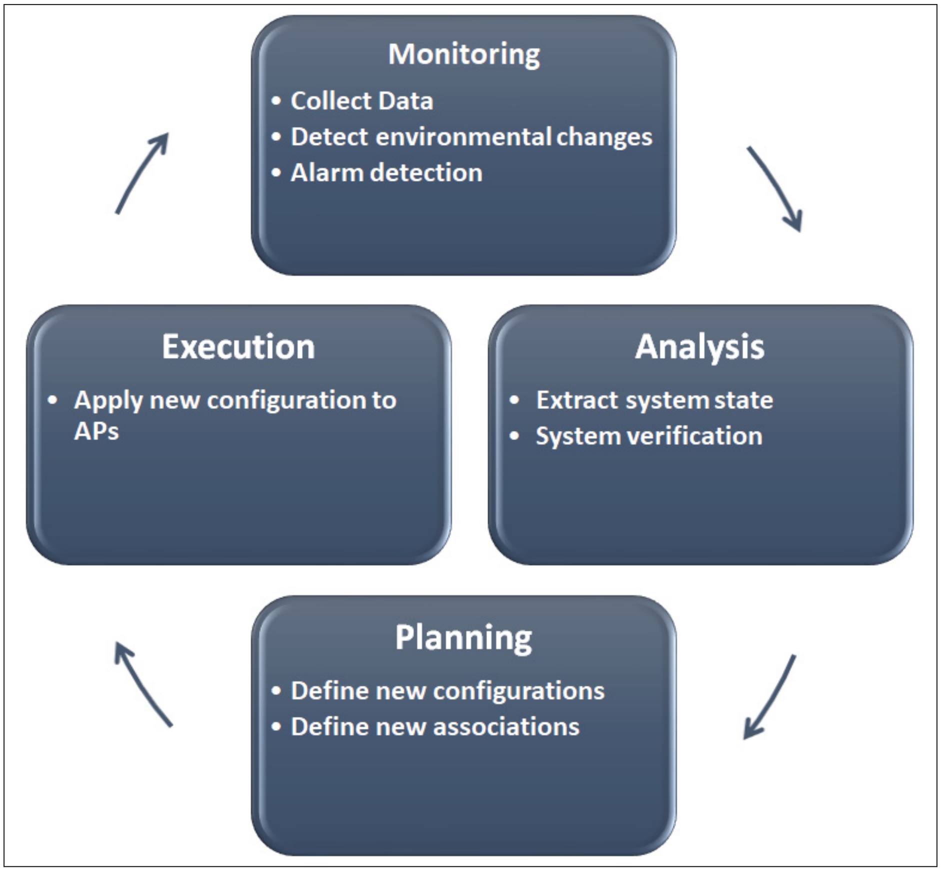


Figure 2.2 MAPE loop for proposed architecture

installed inside a zone and the channel utilization of the nearest AP has gone over the defined thresholds. In such a case, the agent inside that AP sends an alert to the WNM informing the system of possible changes. Based on different alerts WNM might choose to run the optimization to find the optimal configuration followed by some re-associations.

2.1.3.2 Optimization

Collected data from the network enables the system to provide a representation of the network state. To improve system utilization and performance, several optimization techniques are envisaged. Objectives can vary based on the network logic or enterprise policies. To find the optimal configuration for the WiFi network, the optimization functional block uses input data such as signal-to-noise ratio (SNR), noise level, etc., collected from APs to find optimal allocation schemes. Such provisioning can be accomplished by choosing the optimal frequency band, power level, or user association. Regarding the desired objective, various constraints can be added to the optimization problem. The optimization function can be called periodically or upon requests. In event-based scenarios, the optimization function runs upon receiving a notification from the monitoring block. Such intermittent calculation guarantees that unexpected changes in the environment will be considered in provisioning.

2.1.3.3 User management

To perform user association, a functional block is required to enforce policies to make sure IoT devices and mobile users are connected to the network through desired APs. With no predefined rules, WiFi consumers connect to an AP with the strongest signal. The received Signal Strength Indicator based (RSSI-based) approach has been conventionally used in WiFi networks. Using such an approach leads to unfair and unbalanced resource utilization, especially in dense environments. In our proposed approach, the association takes place based on the QoS requirements of IoT devices while meeting the minimum requirements for mobile users. These requirements are identified by the IoT broker functional block and sent to the WNM for planning. Meanwhile, the available resources in the network are calculated based on the data received from APs. The optimization block finds an optimal association scheme to be applied in the network. User management can be achieved using approaches such as using control frames, channel assignment, or MAC filtering.

2.2 System modeling

We consider a set of consumers in the WiFi network including both IoT devices and mobile stations $N = \{1, \cdots, n\}$, connecting to the set of APs ($M = \{1, \cdots, m\}$) in the network. Let $S = \{1, \cdots, s\}$ be the set of slices that the broker has to allocate based on the different application requirements (throughput, delay, etc) planned based on the applications and services that are using the slice. We denote N_s the set of consumers assigned to slice s. A binary variable x defines the association of the consumers to the APs on specific slices (i.e., $x^s_{mn} = 1$ corresponds to the association of consumer n to the access point m).

2.2.1 Physical constraints

In wireless communications, the maximum data rate is highly affected by the amount of SNR. We define the SNR as γ^s_{mn}, and estimate the data rate of device n while connected to AP m based on the Shannon capacity as follows:

$$dr^s_{mn} = \log_2(1 + \gamma^s_{mn}), \quad \forall m \in M, \forall n \in N, \forall s \in S, \tag{2.1}$$

where SNR itself is a relative value based on the signal strength and noise level at the device location. In our proposal, we are using a central approach where the controller has an overview of the network. Therefore, the SNR can be obtained from the controller where it is calculated based on the values obtained from controlling messages and frames exchanged in the network.

In a WiFi network, there are two main factors that affect the throughput of the system. The first one is the consumer's data rate which identifies the quality of the connection between that consumer and the AP. This parameter is highly related to the consumer's SINR. The second factor is the amount of airtime that each station acquires to transceive its data frames. Essentially, consumers with smaller data rates require more airtime to complete their transmissions. Therefore, any connected consumer with higher data rates has to wait to have access to the transmission medium which leads to lower total throughput in the WiFi network [IEEE (2016)].

We estimate the throughput of the consumers based on the number of connections on the AP that serves them (nc_a) and their data rate. The number of serving stations affects the probability of re-transmission for each device [Korowajczuk (2011)]. Figure 2.3 presents how the number of users and their data rate can affect the optimum throughput in an AP. Function $\phi(.)$ calculates the estimated throughput for each device n while connected to the access point m as τ^s_{mn}.

$$\tau^s_{mn} = \phi(nc_m, dr^s_{mn}) \quad \forall m \in M, \forall n \in N, \forall s \in S. \tag{2.2}$$

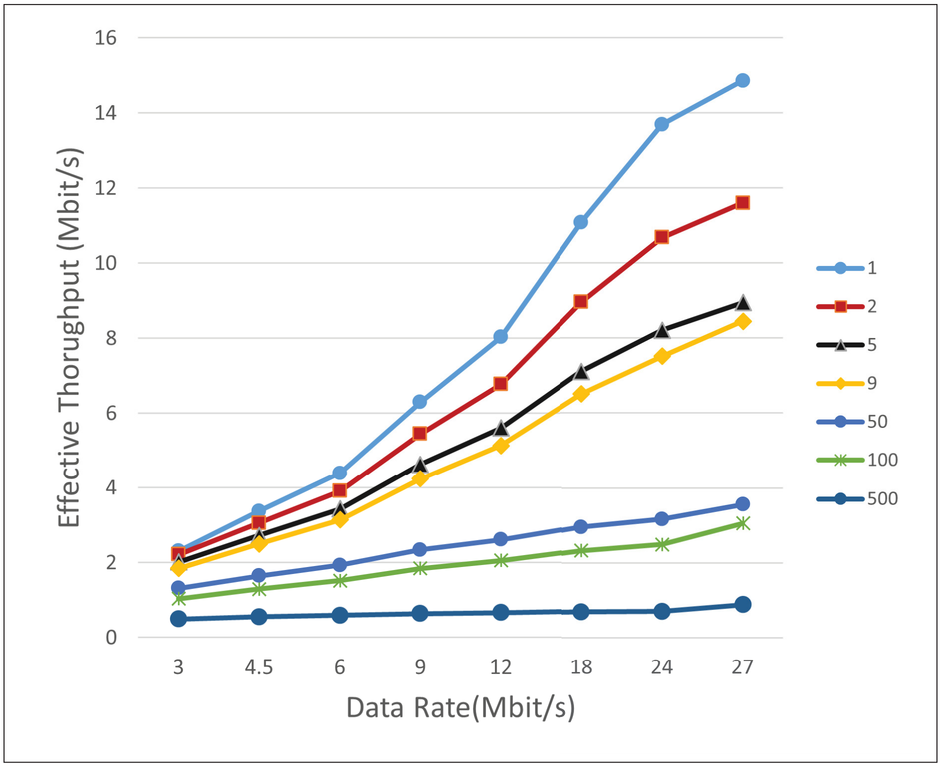


Figure 2.3 How number of users affect the effective optimum throughput in an AP

This estimation calculates the amount of overheads and re-transmissions caused by the 802.11 MAC sub-layer which is based on the Carrier-Sense Multiple Access with Collision Avoidance (CSMA/CA). There are two mechanisms that coordinate transmissions to obtain collision avoidance, Distributed Coordination Function (DCF) and Enhanced Distributed Channel Access (EDCA). To estimate the throughput we consider various parameters such as window size, upload and download ratio, DCF Inter-frame Space (DIFS) and Short Inter-frame spaces (SIFS) duration, different frame sizes such Request To Send (RTS), Clear To Send (CTS), Acknowledgment (ACK) and etc.

2.2.2 Integrity constraints

To maintain the framework's integrity, we need to make sure that each consumer is only connected to a single AP. we formulate

$$\sum_{m \in M} \sum_{s \in S} x_{mn}^s = 1 \quad \forall n \in N, \tag{2.3}$$

This constraint enforces the uniqueness of the connection for all consumers.

2.2.3 IoT slicing constraints.

Let $\underline{T}_s$ and $\overline{T}_s$ show minimum and maximum acceptable throughput values for slice s. Therefore, we can define T_s as the acceptable throughput span for each slice s. We define it as follow:

$$\sum_{m \in M} \tau_{mn}^s x_{mn}^s \geq \underline{T}_s, \quad \forall n \in N_s, \forall s \in S. \tag{2.4}$$

$$\sum_{m \in M} \tau_{mn}^s x_{mn}^s \leq \overline{T}_s, \quad \forall n \in N_s, \forall s \in S. \tag{2.5}$$

Table 2.1 shows an example for different throughput spans on a network.

Table 2.1 Slice throughput requirements

	$\underline{T}_s \leq T_s \leq \overline{T}_s$
Slice 1	1 mbps $\leq T_1 \leq$ 3 mbps
Slice 2	300 kbps $\leq T_2 \leq$ 500 kbps
Slice 3	100 kbps $\leq T_3 \leq$ 150 kbps
Best Effort	0 bps $\leq T_4 \leq$ 5 mbps

Considering the acceptable throughput range for each slice (T_s), we can estimate the airtime utilization of each device (w_{mn}^s) based on its required throughput (Enforced by the IoT broker through for each slice) and the amount of throughput it can achieve.

$$w_{mn}^s = \frac{T_s}{\tau_{mn}^s}, \quad \forall m \in M, \forall n \in N, \forall s \in S, \tag{2.6}$$

therefor we can define a network-wide utilization constraint for each slice where the share of each slice C_s can be enforced by the network administrator or an intelligent subsystem connected to the controller.

$$\sum_{m \in M} \sum_{n \in N} \frac{T_s}{\tau_{mn}^s} x_{mn}^s \leq C_s, \quad \forall s \in S. \tag{2.7}$$

Table 2.2 summarizes all the inputs and variables used in the problem formulation.

Table 2.2 Notations used in the problem formulation

Inputs	Description
M	Set of APs, $M = \{1, \cdots, m\}$
N	Set of consumers, $N = \{1, \cdots, n\}$
S	Set of slices, $S = \{1, \cdots, s\}$
T_s	Acceptable throughput range for slice s
γ_{mn}	Signal-to-noise of consumer n connected to AP m
C_s	Share of slice s in the whole network
Variables	Description
x_{mn}^s	Association variable
τ_{mn}^s	Achievable throughput of consumer n connected to AP m in slice s

2.3 Optimization Model

We aim to maximize the total throughput of the network. Our IoT Slicing Optimization Problem (ISOP) can be written as:

$$\begin{aligned} \textbf{ISOP:} \max & \sum_{m \in M} \sum_{n \in N} \sum_{s \in S} \tau_{mn}^s x_{mn}^s \\ \text{s.t.:} \quad & (2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.7) \\ & x_{mn}^s \in \{0, 1\} \quad \forall m \in M, \forall n \in N, \forall s \in S. \end{aligned} \tag{2.8}$$

ISOP is computationally expensive and can be considered as an NP-hard problem, due to its binary and non-linear constraints. Therefore, it is difficult to find the optimal solution as the number of APs and corresponding consumers increases, and it would be impossible to solve this problem in a polynomial time. Thus, we design a polynomial-time algorithm to optimize the problem based on the stable matching approach.

2.4 Algorithmic Solution

To address the complexity of our optimization (ISOP), we model the association problem as a matching game in which we can consider consumers and access points as two sets of disjoint players in a bipartite graph presented in Figure 2.4. We map our problem to a game similar to the

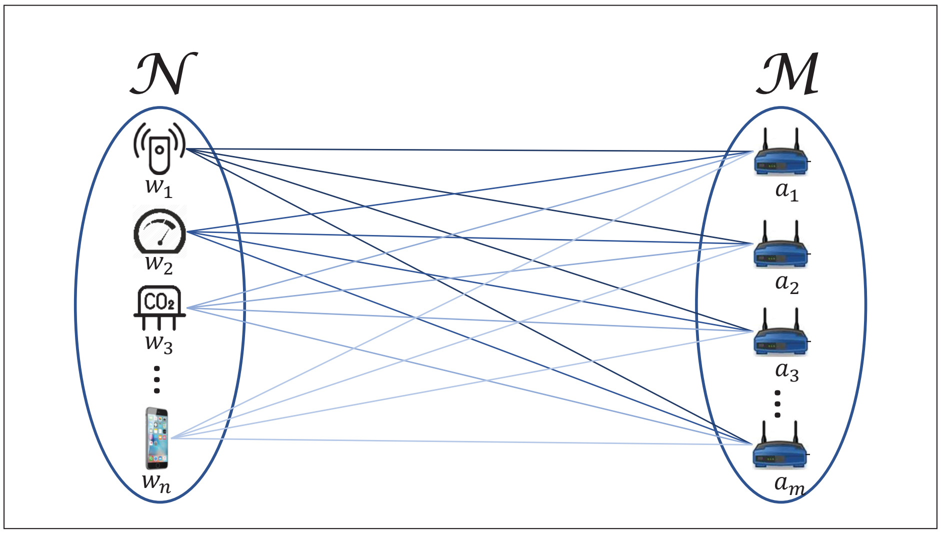


Figure 2.4 An example of a bipartite graph for user association

College Admissions Problem [Roth & Sotomayor (1989)] where access points are considered as collages and consumers as students. Let's denote the set of APs as $\mathcal{M} = \{a_1, a_2, \cdots, a_m\}$, and the set of consumers as $\mathcal{N} = \{w_1, w_2, \cdots, w_n\}$. In a matching game, individuals in each set have an ordered relations with members of the other set called preference, which indicates how an individual is willing to match with others. As an example, $w_2 \preceq_{a_1} [w_1, w_3] \preceq_{a_1} w_4$ illustrates that AP a_1 prefers to be associated to w_4 more that any other stations and it has similar interest in w_1 and w_3. We denote the preference list as $\mathbf{P} = (P_{w_1}, \cdots, P_{w_n}, P_{a_1}, \cdots, P_{w_n})$ (e.g $P(a_1) = \{w_1, w_2, \cdots, w_n\}$ depicts the preference list of a_1).

We can use the current mapping (many-to-one matching) due to the fact that each consumer can only connect to a single AP and an AP can be matched with a subset of consumers. Besides, with regards to equation (2.2) the consumer's preference is not only limited to the AP it is connected to, but also it relates to the other consumers connected to the same AP. On the AP side, the preference is twofold: the consumers that the AP is matched with, and how the subset of matched consumers contribute to the AP's residual capacity.

Definition 1 (Many-to-One Matching). Let $\mathcal{M}$ and $\mathcal{N}$ be sets. A many-to-one matching from $\mathcal{M}$ to $\mathcal{N}$ is a function $\mu : \mathcal{M} \mapsto 2^{\mathcal{N}}$ such that for any distinct a_1 and a_2 in $\mathcal{M}$, we have $\mu(a_1) \cap \mu(a_2) = \emptyset$. Furthermore, if $a_m \in \mathcal{M}$ has capacity q_m, then $|\mu(a_m)| \leq q_m$.

Therefore, to find a stable matching we need to define the preference lists for APs and the consumers and some quotas for access points (q_m). To recall, we already introduced a network-wide utilization constraint 2.7 which can be used to define the quotas for our matching problem. To use this constraint we map the network-wide quota to each access point, therefor access point has specific amount of airtime associated for each slice ($q_m = C_s$). We also consider the minimum amount of requirements for each consumer while performing the matching which we can considered as a relaxation step for our optimization problem. Next step is to define the preference lists for each set in the bipartite graph.

It is worth noting that the objective for each set ($\mathcal{M}$ and $\mathcal{N}$) while calculating the preference list, can be in contradiction with the other set. To show this contradiction, we present two separate optimization problems that correspond to each set. The first problem is as follows:

$$
\begin{aligned}
&\textbf{AP side:} && (2.9)\\
&\max \sum_{n\in\mathcal{N}}\sum_{s\in S}\tau^s_{mn}x^s_{mn} \quad \forall m\in\mathcal{M}\\
&s.t.: \sum_{n\in\mathcal{N}} w^s_{mn}x^s_{mn}\le C_s \quad \forall m\in\mathcal{M},\forall s\in S\\
&\sum_{m\in\mathcal{M}} x^s_{mn}\le 1 \quad \forall n\in\mathcal{N},\forall s\in S\\
&x^s_{mn}\in\{0,1\} \quad \forall m\in\mathcal{M},\forall n\in\mathcal{N},\forall s\in S
\end{aligned}
$$

where w^s_{mn} corresponds to the estimated airtime usage for each consumer. We calculate this value based on the assumption that the throughput demand of each consumer is known [Bayhan & Zubow (2017)]. In other words, all the consumers in the network belong to at least a slice in which the minimum throughput demands are already identified.

The second optimization corresponds to the consumer. Each consumer tries to gain higher throughput when connecting to an AP. Therefore, considering the consumer side, we can write:

$$
\begin{aligned}
&\textbf{Station side:} && (2.10)\\
&\max \sum_{m\in\mathcal{M}}\sum_{s\in S}\tau^s_{mn}x^s_{mn} \quad \forall n\in\mathcal{N}\\
&\text{s.t.: } dr^s_{mn} = \log_2(1+\gamma^s_{mn})\\
&\gamma_{mn} = \frac{p^s_{mn}x_{mn}}{N_0 + I^s_{mn}x_{mn}}, \quad \forall m\in\mathcal{M},\forall n\in\mathcal{N},\forall s\in S\\
&\sum_{n\in\mathcal{N}}\sum_{s\in S}x^s_{mn}\le 1, \qquad \forall m\in\mathcal{M}.\\
&x^s_{mn}\in\{0,1\} \quad \forall m\in\mathcal{M},\forall n\in\mathcal{N},\forall s\in S,
\end{aligned}
$$

where p^s_{mn} and I^s_{mn} define the signal power and the interference level of the consumer n while connecting to the AP m.

We use these two optimization problems to define our preference lists for the matching problem. The main incentive for APs to create their preference list ($p(a)$) is to choose a set of users that have the highest data rate which can lead to less airtime utilization. Users have a similar incentive for creating their preference list ($p(w)$). They try to match with APs that can provide higher SINR values. Aside from the aforementioned incentives, we consider the IoT devices with the highest priority on the AP preference lists.

Based on the requirements of the matching problem we chose DAA [Roth (2008)] which has been proven to provide a stable matching in the wireless domain [Gu, Saad, Bennis, Debbah & Han (2015)]. DAA is commonly used in distributed architectures but in this study, we modify this algorithm to be run on the controller to meet our design requirements. We name it Modified DAA (MDAA). Our proposed algorithm is presented in Algorithm 2.1.

Algorithm 2.1 Station association for EWLANS based on Modified Deferred Acceptance Algorithm (MDAA)

Input: User preference lists $p(w)$
Output: Association matrix (X_{mn})

Controller extracts AP proposals based on the $p(w)$;
Sort the proposals based on the SNR (γ);
Controller estimates the airtime (w) of the consumers in the AP proposal $p(a)$.
for *each slice s* **do**
    repeat
        User propose to its most favorite AP (a_{pref})
        and delete it from its list ($p(w) - a_{pref}$);
        Each AP accepts the user proposals based on its preference list $p(a)$ and its quota (C_s), and rejects the rest;
    until *All users are matched* ($\mu(w) \in \mathcal{M}, \forall\, w \in \mathcal{N}$) ***OR*** *all user preference lists are empty* ($p(w) = \emptyset\ \forall\, w \in \mathcal{N}$);
end for

The collected information from the consumers is used to create the APs' preference lists. The controller uses this information to find which consumers can connect to each AP. We adopt an algorithm based on the bubble sort algorithm [Bub (2022)] for creating the preference lists. Algorithm 2.2 depicts the procedure to create a preference list for each AP.

Algorithm 2.2 Find the AP's preference list $p(a)$

Input: List of stations in AP vicinity with SNR values from the controller
Output: Sorted list as an AP preference $p(a)$

for $i \leq |Input|$ **do**
    for $j \leq (|Input| - i - 1)$ **do**
        if $Input[j] \leq Input[j+1]$ **then**
            $temp \leftarrow Input[j]$
            ; $Input[j] \leftarrow Input[j+1]$
            ; $Input[j+1] \leftarrow temp$;
        end if
    end for
end for

2.5 Discussion

In the introduction chapter, we mentioned the main principles of network slicing: automation, isolation, customization, and elasticity. Here we explain how each of these principles has been addressed in our solution.

IoT broker, WiFi controller, and the APs are the components involved in automation which is achieved through scripts or applications running inside each component. A detailed description for each component is provided in 2.1. We consider isolation by guaranteeing some performance KPIs for the IoT devices in our problem formulation (2.2.2) and by imposing some constraints on our optimization model. Customization and elasticity are obtained through using different resource modelling and imposing proper constraints in the optimization model that affects the association scheme in the network.

Therefore, with regard to the potential that our research provides, we believe it can significantly impact how resources are provisioned in the network. Looking at the obtained results (demonstrated in the following chapter) and the interests that our research achieved from the industry (Ericsson research center in Montreal), we believe it can transform the way resources are provisioned in the EWLANs.

CHAPTER 3

NUMERICAL RESULTS

This section presents how we implement the simulation environment for the evaluations and the corresponding results from various tests performed during the simulations.

3.1 Simulation settings

The validation process includes two major steps. First, we need to create the network topology which defines the location of all APs and the consumers that are connected to these APs. The second step is to deploy different association schemes and compare the results. In the first step, we set the simulation area to be $100m \times 100m$ similar to the simulation area in [Oni & Blostein (2015)]. Also, We placed 16 (4×4) APs in a grid manner (based on the simulations in the literature [Amer *et al.* (2016)]) with a 20-meter distance from each other. This placement helps to provide a dense environment for the simulations. We designed the simulation environment in a way that consumers in each simulation scenario have a high probability of connecting to multiple APs in their vicinity that resembles a real-world environment such as universities, campuses, and enterprise workplaces.

Next, we use a function that assigns random locations to the consumers in the environment. Furthermore, we use the consumers' locations to calculate the RSSI value for each consumer. RSSI is a relative value and different vendors can have different representations for this value. However, based on the IEEE standard [IEEE (2016)] RSSI values are bounded between 0 to 255. In this research, we use the exact signal strength value (in dBm) which indicates the strength of the signal at the consumer's location. We obtain this value by finding the distance of each consumer to its neighboring APs and using the distance to calculate the amount of path loss. Several factors can affect the amount of path loss such as distance, absorption, and reflection. Here, we calculate the path loss based on the ITU indoor path loss model [ITU (2012)]. The final RSSI value is calculated based on the APs transmission power ($12dBm$ or $15.85wm$) and the calculated path loss [Oni & Blostein (2015)]. Figure 3.1 depicts how APs are placed in the simulation environment with random locations for consumers. It also presents how different sets of IoT devices can be assigned to different slices. We use different colors for separating slices. The dashed lines correspond to the station association to an AP.

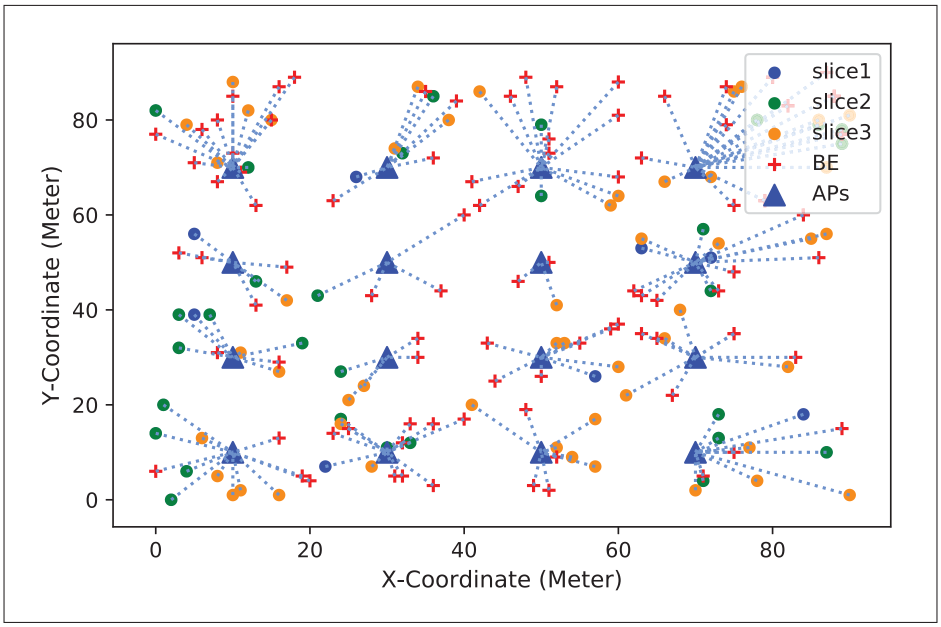


Figure 3.1 Network topology used for evaluation

To obtain the RSSI values, we assume all the APs are using orthogonal channels in the simulation environment which allows us to simplify the calculations by mitigating the interference. In a case that enough orthogonal channels are not available, different channel allocation schemes can be used to properly assign channels to overcome the CCI (e.g graph coloring). However, channel allocation is out of the scope of this thesis.

In the second step, using the predefined requirements of each slice, we calculate the IoT requirements defined by the broker. These values are utilized to form the constraints of our optimization problem (ISOP) and to create the preference lists in the matching problem (MDAA). In addition, we find the RSSI-based association using the obtained value in the first step prior to using the MDAA algorithm. MDAA uses the RSSI association as its initial step. We perform the simulations with the assumption that all devices are using the same transmitting power and all APs are running under the same power profile. Simulation settings are summarized in Table 3.1.

Table 3.1 Simulation Parameters

Parameter	Value	Parameter	Value
Network Area	100m×100m	Path loss Exponent	3.4 (ITU)
Transmission power	12 dBm	Background Noise	-90 dBm
Initial rate	54 Mbps	Rate control	Adaptive
DIFS	54 μs	SIFS	16 μs
RTS frame	20 byte	CTS frame	14 byte

3.2 Baselines

We use the following baselines to compare different metrics for validating our proposed solution.

- RSSI-based association approach (named RSSI): basic baseline for comparing different association approaches in the WiFi (e.g [Gómez *et al.* (2020)]).
- Optimal association approach (named ISOP): results obtained from the solver. We use this baseline to validate the results obtained from our heuristic (MDAA).
- Hardware virtualization approach (named HVA): This baseline is used for comparing our solution with existing work using the hardware virtualization for slicing (e.g [Aleixendri *et al.* (2019)]).
- MDAA: Our proposed solution which is a many-to-one matching-based association.

The metrics used to compare these baselines are as follow:

- Throughput: We compare the total throughput obtained by all users in the network when RSSI, ISOP, and MDAA are applied in different scenarios and settings.
- Satisfaction rate: similar to throughput, we compare the percentage of user requests that cannot be afforded by the system when RSSI, ISOP, and MDAA baselines are applied.

- Utilized airtime: we use this metric in two different comparisons. First, we use it to compare RSSI, ISOP, and MDAA baselines. Second, we use it to compare MDAA with HVA for a specific test designed for this comparison.

3.3 Results

Simulations have been carried out with different settings to verify the proposed algorithm in different scenarios. The main purpose of the simulations is to verify the integrity of our proposed solution by considering the essential aspect of network slicing which is maximizing the infrastructure utilization. We consider APs as the existing infrastructure and try to maximize their utilization while considering different and diverse service requirements. Therefore, in each scenario, we vary the number of IoT devices and mobile users. We use a fixed location for the APs, while the location of the consumers is randomly chosen which results in a random distribution of consumers around the APs. We use different requirements for IoT devices in different simulations to capture the effect of these changes on the overall outcome of our solution. It is worth noting that we keep the number of slices fixed in all the simulations (except for one comparison). We use the total throughput of the system as the main metric to compare the different approaches because this metric has been used as the objective of our optimization problem.

Figure 3.2 presents the overall achievable throughput of the network using different approaches. As can be seen, MDAA outperforms the conventional RSSI method in terms of total achievable throughput. We can see that MDAA is a bit drifted apart from the optimum results of ISOP (obtained from Gurobi solver [Gurobi (2021)]) which is an expected phenomenon since we used the minimum requirements of the slices to perform the matching. We consider the obtained results sufficiently good, considering the solving time and scalability of MDAA compared to ISOP. To recall, the time to solve the ISOP can grow exponentially according to the increasing number of APs and consumers (Table 3.2) while the complexity of the matching approach only depends on the algorithms creating the preference lists. For AP's preference list, we use Algorithm 2.2 with the complexity similar to a bubble sort that in the best case has $O(n)$

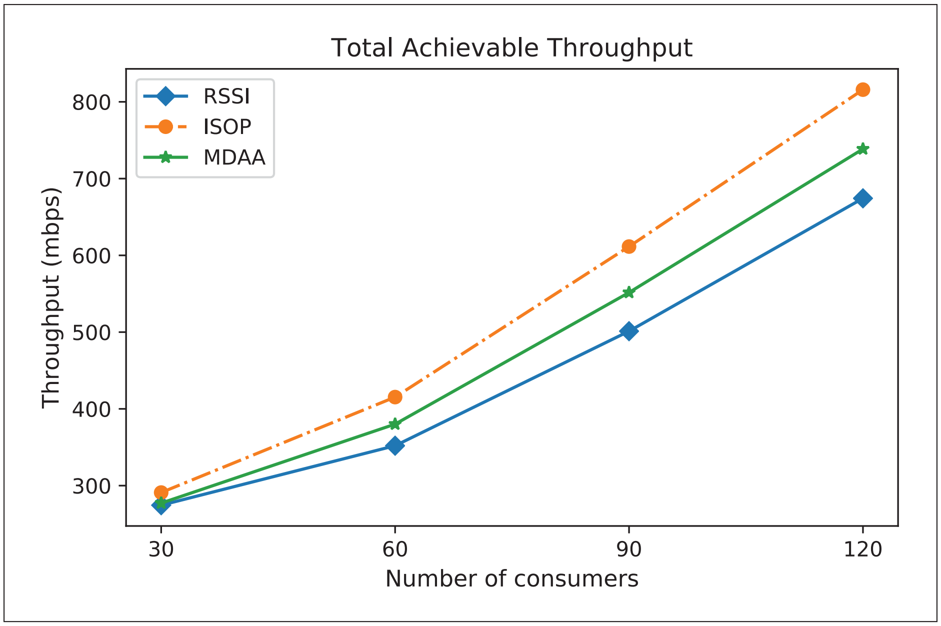


Figure 3.2 Comparison of overall achievable throughput of the network for different approaches

Table 3.2 Average solving time for optimization

No. Consumers	30	60	90	120	180
Average solving time (s)	12.5	48	116	220	614

complexity and has $O(n^2)$ in its worst-case scenario. Therefore, the complexity to create the AP's preference lists is $O(|\mathcal{M}|n^2)$ for the set $\mathcal{M}$ of APs. Similar complexity applies to the algorithm that creates the consumers' preference list. Consequently, the time complexity of the algorithm is $O(|\mathcal{N}|n^2) + O(|\mathcal{M}|n^2)$.

In addition, the results show that with an increase in the number of consumers, the difference between the MDAA and RSSI approaches slightly increases which can be considered as the vantage point for our proposed algorithm, especially in the context of EWLANs where the number of stations is relatively high.

Next, we use two different network-wide slicing schemes (Table 3.3) that can be enforced by the network administrator to observe the differences in the network achievable throughput.

Table 3.3 Different slicing schemes for simulations

	Slice1 (%)	Slice2 (%)	Slice3 (%)	BE (%)
First setting	50	20	10	20
Second setting	40	10	10	40

Total system throughput obtained from the simulation is depicted in Figure 3.3.

We observe that with different schemes the total network throughput varies which corresponds to different constraints applied to each slice for the amount of airtime it can consume. We also notice that the maximum achievable throughput for the Best Effort (BE) slice has a huge impact on the obtained throughput since we let the BE consumers reach higher throughput values. Figure 3.4 illustrates this difference between the two settings. In both settings, we set the maximum throughput of the BE slice to be 8 Mbps. As expected, we see that with more resources for the BE slice comes higher throughput (second setting), and therefore, the total network throughput increases (Figure 3.3b).

In the meantime, we checked the airtime utilization of each slice in the simulation (Figure 3.5) and the obtained results certify that the proposed algorithm enforces the administrative policies on the amount of airtime utilized for each slice. It must be noted that, although the main objective of using slicing is to maximize the hardware utilization, the extra utilization in the RSSI approach is emanated by an improper association of consumers that causes extra re-transmission and higher utilization with lower yielded throughput.

We use a similar metric to compare our solution with HVA baseline (i.e. [Aleixendri *et al.* (2019)]) For this test we consider two slices with 60% and 30% utilization similar to the HVA reference. The share of airtime distributed among different slices corresponds to the values enforced by the schedule controlling mechanisms. We define these airtime shares per slice (per virtual AP in the reference) and observe whether our proposed solution can perform similar to the HVA baseline in terms of satisfying per slice (per virtual AP) utilization. We present the amount of airtime utilized by each slice in Figure 3.6 where we tried to fully utilize the amount of accessible airtime for each slice (similar to [Aleixendri *et al.* (2019)] where the constant load

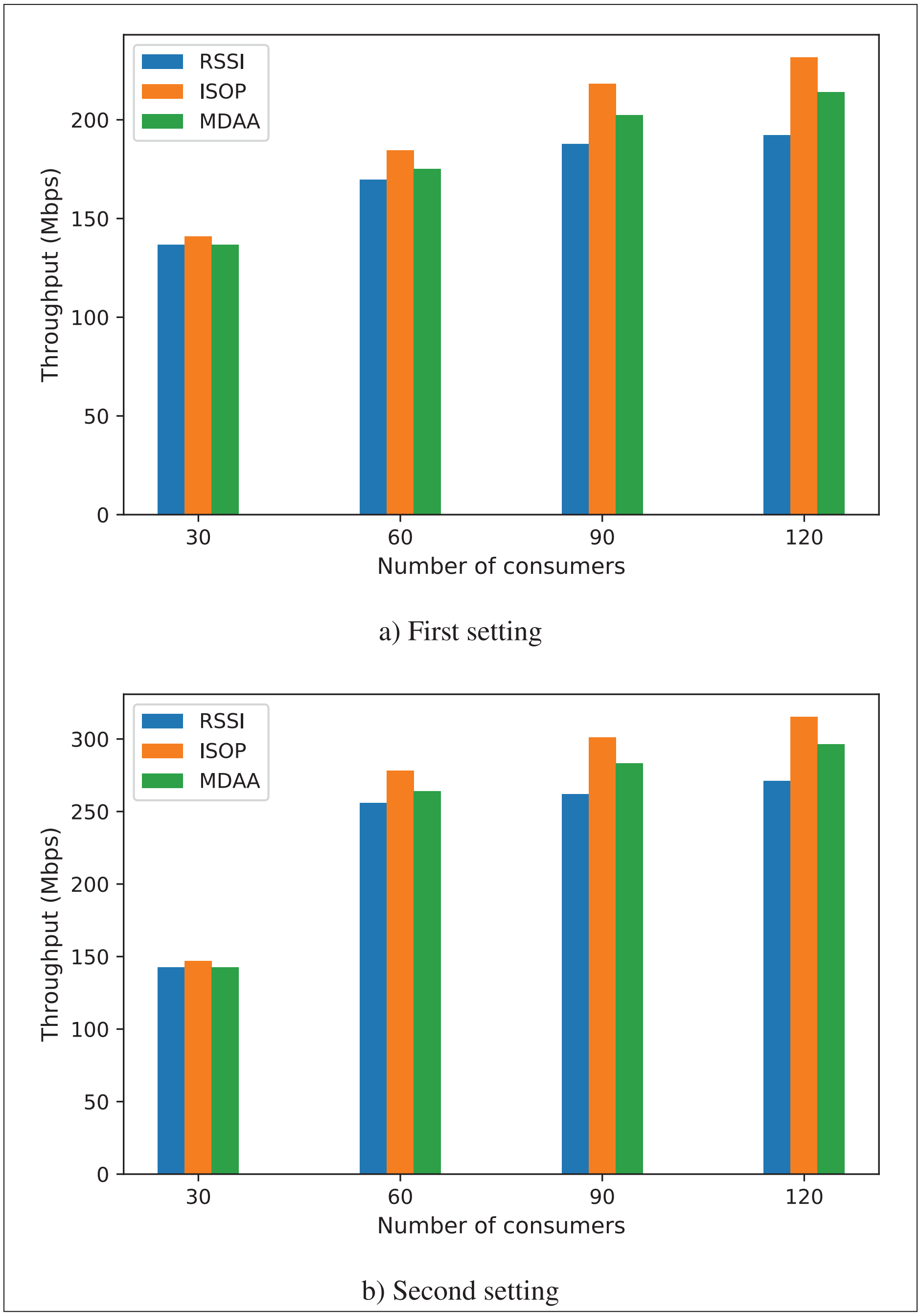
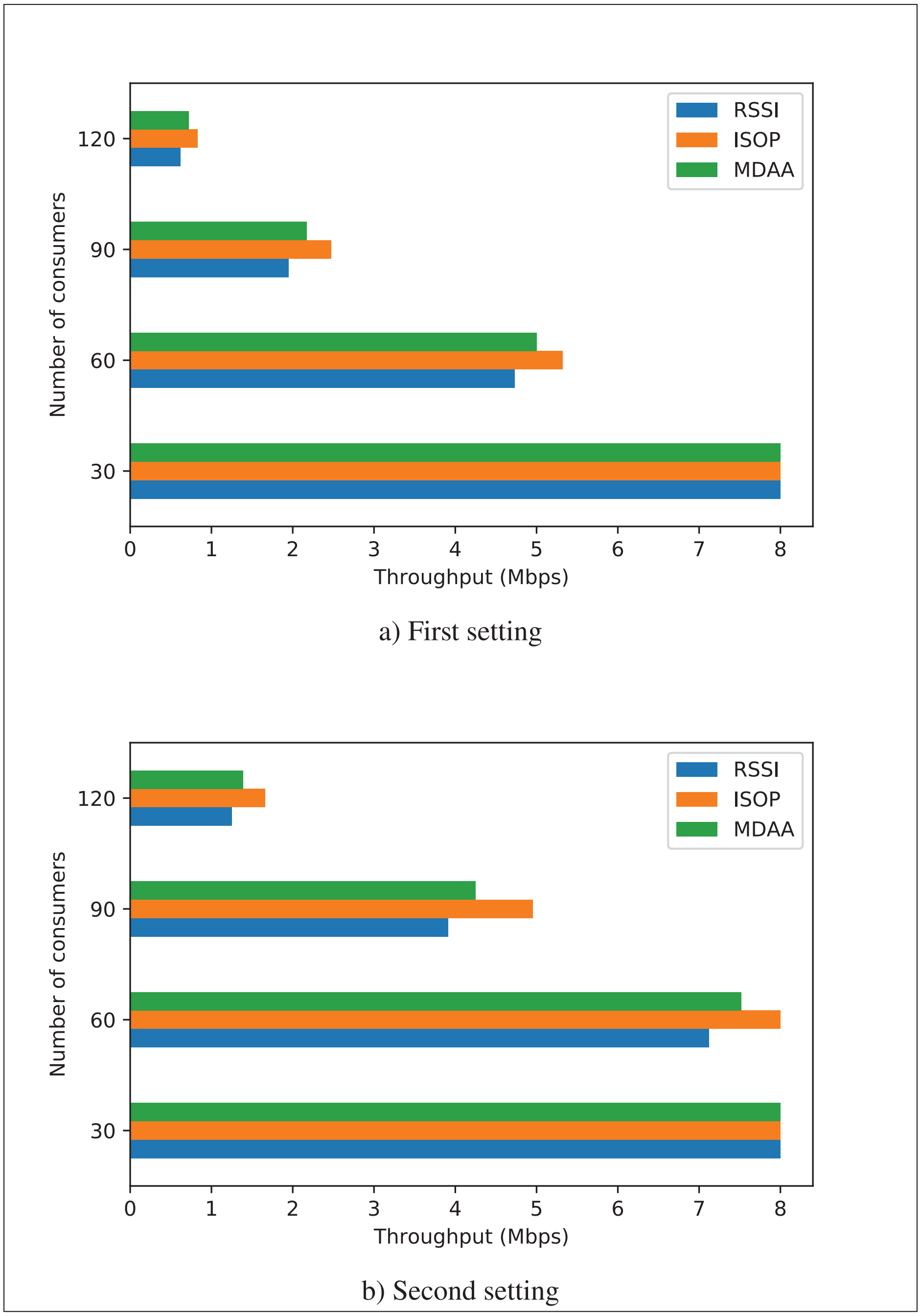


Figure 3.3 Comparison of overall system throughput of the network for different slice schemes

is used) by running the simulations with the highest number of consumers using video and BE slices. Results show that although our proposed solution has more variance, in general, it performs almost similar to HVA, and it can obtain the predefined amount of airtime per slice.

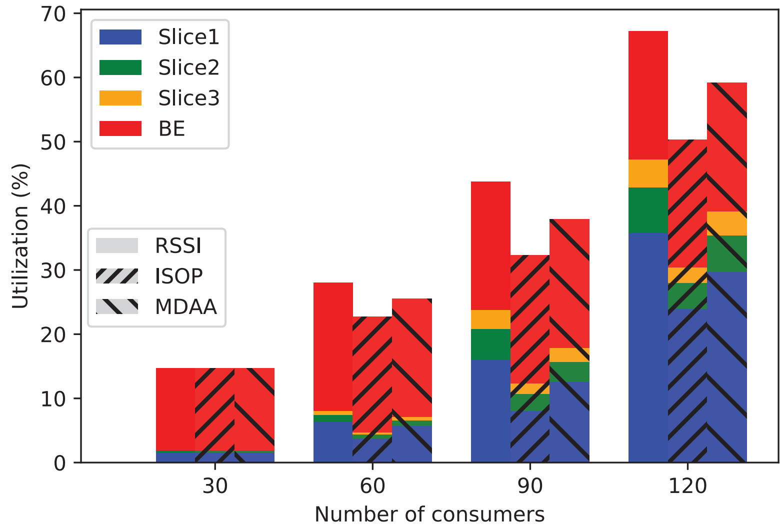


a) First setting

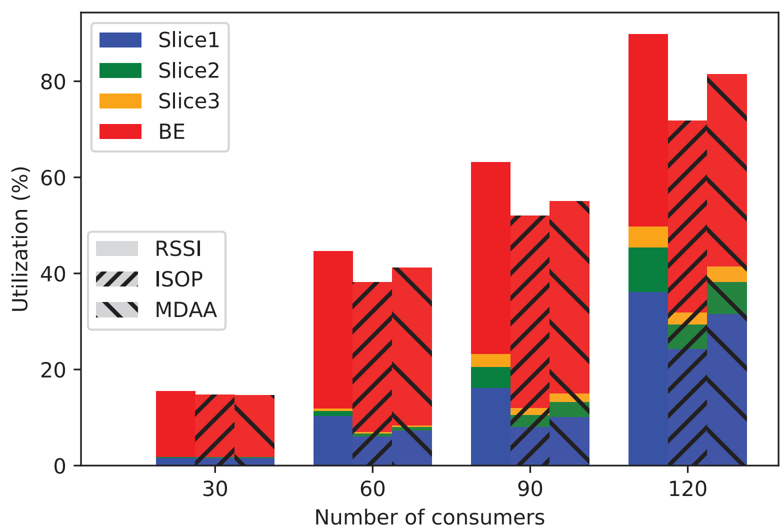
b) Second setting

Figure 3.4 Comparison of maximum achievable throughput for best effort consumers in different slice schemes

The other important metric that we focused on is the acceptance or satisfaction rate. This metric shows how our algorithm performs in terms of rejecting those connections whose throughput requirements are not going to be satisfied in the current state of the network. Since there is no



a) First setting



b) Second setting

Figure 3.5 Overall Slice airtime utilization

rejection for the RSSI approach, we use the term satisfaction rate. A similar metric is used in hardware virtualization approaches for slicing (i.e. [D'Oro *et al.* (2020)]) where the authors emphasize the number of admitted slices. In this thesis, we calculate an average satisfaction rate

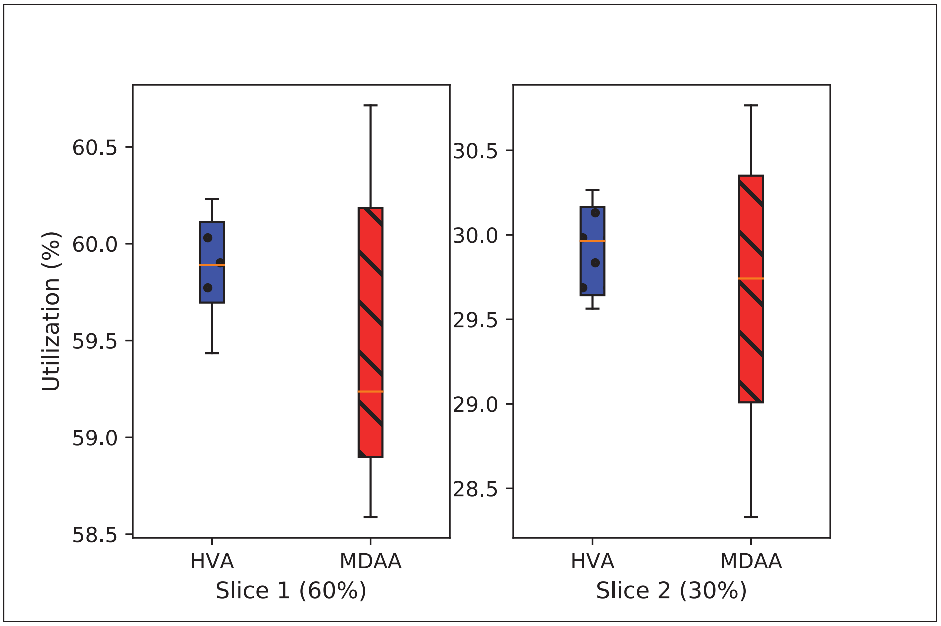


Figure 3.6 Comparison of HVA utilized airtime for each slice with MDAA

for each algorithm based on the number of consumers in the simulation. Table 3.4) illustrates our findings. The results are presented in percentages

Table 3.4 Satisfaction rate comparison

	30	60	90	120	180
RSSI	100	100	99.12	97.13	91.1
ISOP	100	100	100	100	99.33
MDAA	100	100	100	99.12	97.89

We can see that increasing the number of consumers, lowers the satisfaction rate. However, our algorithm performs much better compared to the RSSI and it almost approximates the optimized results.

We extend the simulations by testing two different slice requirements (Table 3.5) on the second setting where we allocate more resources to BE slice and allow consumers in different slices reach to higher throughput values.

Table 3.5 Different slice requirements for simulations

	Slice1	Slice2	Slice3	BE
Set 1	1 to 3 Mbps	300 to 500 Kbps	100 to 300 Kbps	0 to 8 Mbps
Set 2	1 to 5 Mbps	300 Kbps to 2 Mbps	100 Kbps to 1 Mbps	0 to 15 Mbps

The main idea behind these tests is to observe how these requirements contribute to the total throughput of the network. Results show that using a wider range for acceptable throughput in each slice highly impacts the total network throughput (Figure 3.7). It also can be compared with hardware virtualization approaches (i.e. [Aleixendri *et al.* (2019)]). We can see that similar to those approaches, our solution reacts to different airtime distributions and also different requirements enforced by the IoT broker. We observed that BE consumers have a huge contribution to the increased throughput amount. Figure 3.8 depicts the max achievable throughput for each set in the simulations.

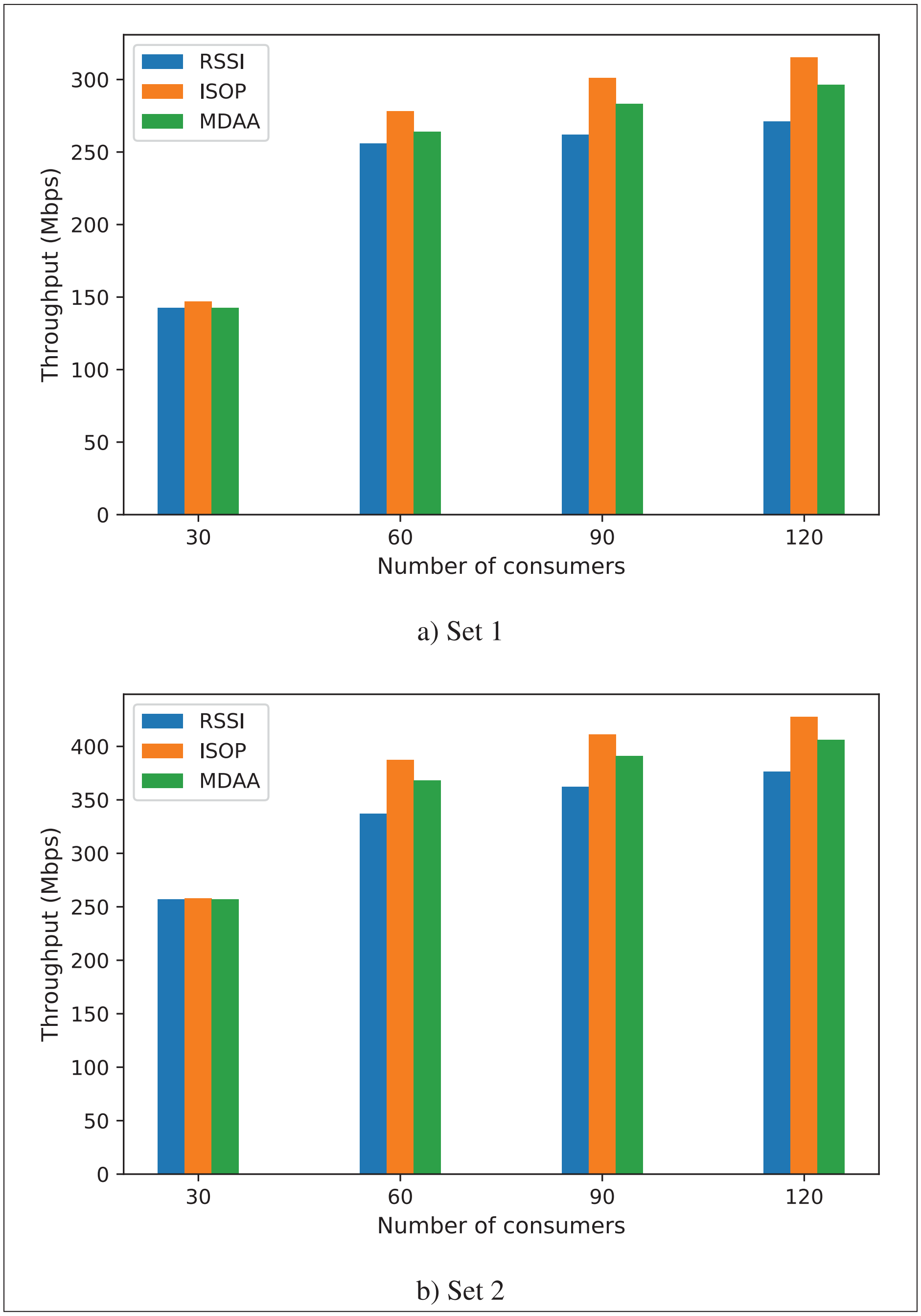
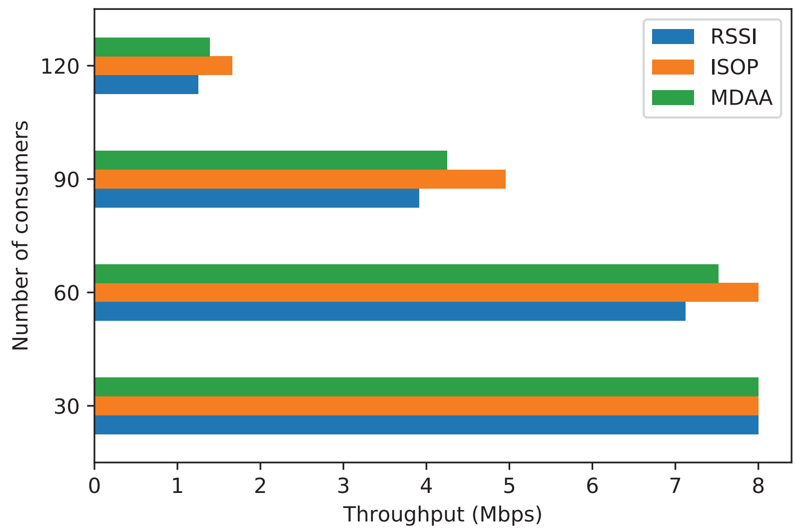
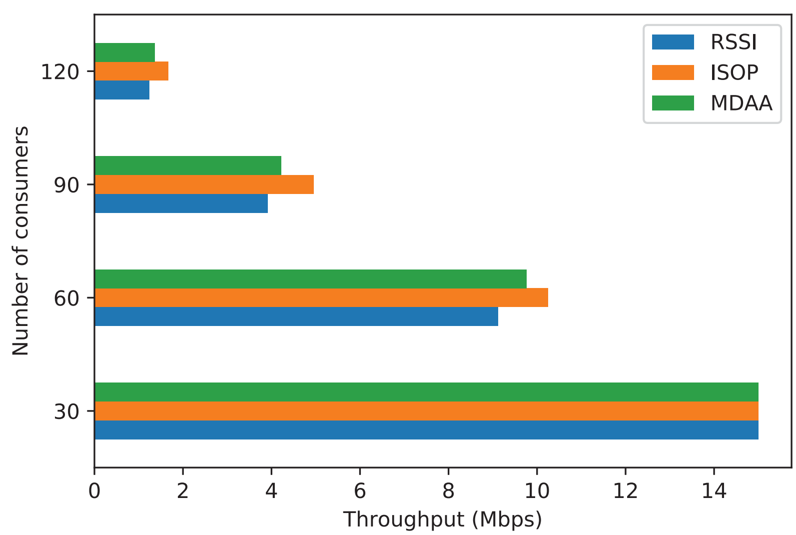


Figure 3.7 Comparison of total system throughput of the network for different slice requirements



a) Set 1



b) Set 2

Figure 3.8 Comparison of maximum achievable throughput for best effort consumers with different slice requirements

CONCLUSION AND RECOMMENDATIONS

We can conclude the thesis by stating that we managed to achieve all our research objectives indicated in the introduction of the thesis. We aim to implement a slicing solution that requires no modification on AP hardware that can perform similar to hardware virtualization solutions. Our proposed solution relies on the dynamic association of consumers in EWLANs that requires no modification on AP hardware. Meanwhile, we observe the performance of our solution. The obtained results obviously present that our solution performs better than the conventional approaches (RSSI-base) and also can be compared to similar solutions using hardware virtualization.

In terms of achieving the sub-objectives, we can say that we managed to obtain all the sub-objectives that we mentioned earlier. To brief that, we can say that:

- We propose a new slicing solution based on the dynamic association of user equipment which requires no modification in the APs' hardware. Our approach deals with the massive and diverse requirements of the IoT devices in the EWLANs where 802.11 has been adopted as the preferred technology for wireless communications (SO1).
- We model the system and formulate it as a MILP optimization problem that aims to maximize the total throughput of the network while preserving the requirements of the IoT slices in the network (SO2).
- To deal with the complexity of the optimization problem, we proposed a many-to-one matching heuristics which takes into account RSSI level and AP utilization to match the consumers to the APs. The proposed matching-base algorithm has the complexity of $O(|\mathcal{W}|n^2) + O(|\mathcal{M}|n^2)$ and can be solved in the near real-time to meet our objectives. Simulation results show that the proposed solution outperforms the conventional RSSI-based association while meeting the slice requirements (SO3).

This study can be extended by relaxing some existing assumptions in the formulation and the simulation. It must be noted that this research was done during a productive internship at Ericsson's second largest research facility in Montreal, where it has gained extensive interest. Aside from the academic interests and achievements acquired from this research (three published papers in well-known conferences [Appendix1]), this study can highly affect the business sector, especially with a high tendency for wireless access for network consumers. It also can bring tremendous added value to the existing WiFi networks. With the exceptional potential of current work, such an approach can revolutionize the existing EWLANs both economically and technologically.

APPENDIX I

ARTICLES PUBLISHED IN CONFERENCES

We have presented the main content of this thesis in three conference papers.

- "Towards IoT Slicing for Centralized WLANs in Enterprise Networks" which has been published in International Symposium on Networks, Computers and Communications 2020 [Fami, Pham & Nguyen (2020)].
- "Slicing WiFi Networks for Differentiated IoT Service Provisioning" has been published in IEEE Wireless Communications and Networking Conference 2022 [Fami, Hammami, Pham & Nguyen (2022b)].
- "Optimization of IoT Slices in WiFi Enterprise Networks" has been published at The 37th ACM/SIGAPP Symposium On Applied Computing [Fami, Hammami, Pham & Nguyen (2022a)].

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