AN ANOMALY BEHAVIOR ANALYSIS INTRUSION DETECTION SYSTEM FOR WIRELESS NETWORKS

By

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STATEMENT BY AUTHOR

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ABSTRACT

Wireless networks have become ubiquitous, where a wide range of mobile devices are connected to a larger network like the Internet via wireless communications. One widely used wireless communication standard is the IEEE 802.11 protocol, popularly called Wi-Fi. Over the years, the 802.11 has been upgraded to different versions. But most of these upgrades have been focused on the improvement of the throughput of the protocol and not enhancing the security of the protocol, thus leaving the protocol vulnerable to attacks. The goal of this research is to develop and implement an intrusion detection system based on anomaly behavior analysis that can detect accurately attacks on the Wi-Fi networks and track the location of the attacker.

As a part of this thesis we present two architectures to develop an anomaly based intrusion detection system for single access point and distributed Wi-Fi networks. These architectures can detect attacks on Wi-Fi networks, classify the attacks and track the location of the attacker once the attack has been detected. The system uses statistical and probability techniques associated with temporal wireless protocol transitions, that we refer to as Wireless Flows (Wflows). The Wflows are modeled and stored as a sequence of n-grams within a given period of analysis. We studied two approaches to track the location of the attacker. In the first approach, we use a clustering approach to generate power maps that can be used to track the location of the user accessing the Wi-Fi network. In the second approach, we use classification algorithms to track the location of the user from a Central Controller Unit. Experimental results show that the attack detection and classification algorithms generate no false positives and no false negatives even when the Wi-Fi network has high frame drop rates. The Clustering approach for location tracking was found to perform highly accurate in static environments (81% accuracy) but the

performance rapidly deteriorates with the changes in the environment. While the classification algorithm to track the location of the user at the Central Controller/RADIUS server was seen to perform with lesser accuracy then the clustering approach(76% accuracy) but the system's ability to track the location of the user deteriorated less rapidly with changes in the operating environment.

CHAPTER 1: INTRODUCTION

1.1 Introduction

Defense of computer networks has become an extremely important issue due to the exponential growth in attack's complexity, sophistication and speed. With the advent of Internet of Things(IoT)[9][10] [11] [12] [13] [14] and the Cloud Computing[15][16][17] [18] and mobile computing[2], gone are the days when the user would depend on an Ethernet connection to a computer network via a desktop computer. Most of current users access computer networks via wireless technologies that are ubiquitously available to their mobile devices (e.g., smart phones). Cisco predicts that mobile data traffic will increase 10- fold between 2014 and 2019 reaching 24.3 Exabytes per month by 2019[1]. According to a statistical analysis by Mike Roberts, Wi-Fi continues to be a critical network, wherein accounting for 70% of data usage of smart phones [2]. Infroma.com[3] predicts that the number of Wi-Fi hotspots will be hitting 5.8 million by the year 2015. Also there has been a growth in the number of public Wi-Fi hotspots deployed globally and Distributed Wi-Fi hotspots in various institutional campuses. This ever-growing size of the computer networks has also been companioned by an increase in attack's sophistication. This increase in network size and availability has also resulted in easy of availability of attack tools and knowledge to attackers. Thus an attacker with little or no technical knowledge can effectively execute sophisticated attacks with the help of tools obtained over the computer networks like the Internet[4].This trend has been highlighted by Figure 1.1 below,

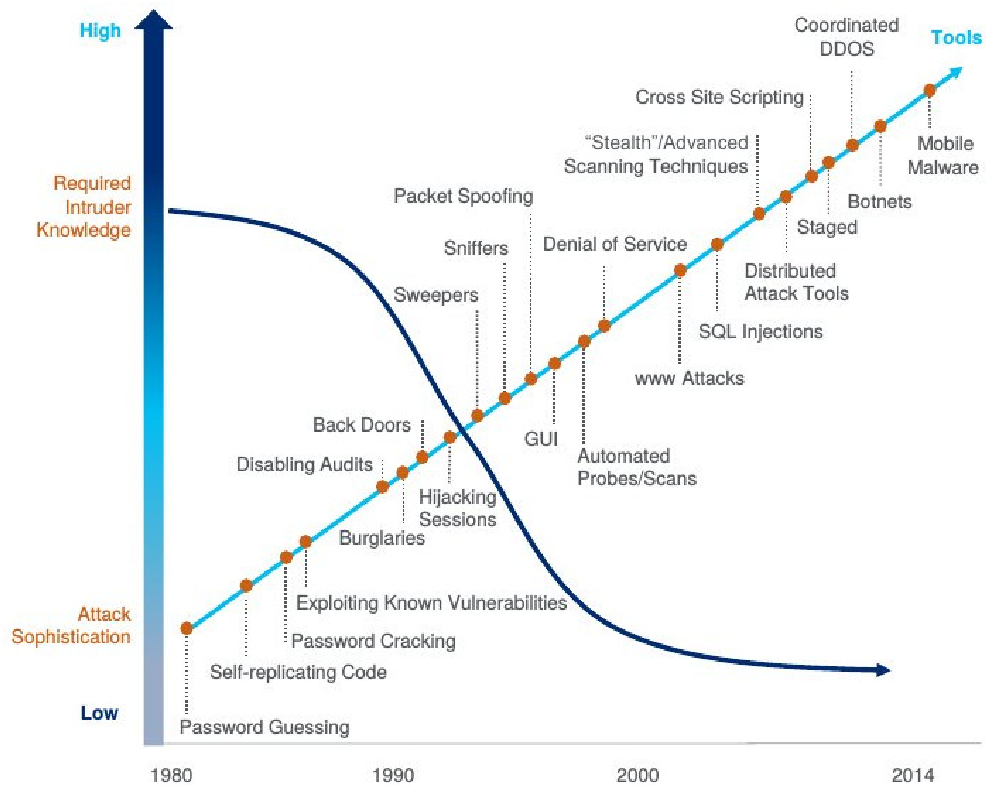


Figure 1.1: Attack Sophistication vs. Intruder Technical Knowledge

This ever-growing growth of Wi-Fi networks and ever increasing attack sophistication needs the development of an intrusion detection system that is able to detect attacks on the Wi-Fi networks.

1.2 Problem Statement

In this thesis we study the following problems:

"We pursue to build an intrusion detection system for distributed Wi-Fi networks that uses anomaly based detection approach which can detect accurately new and modified attacks with no false positives and no false negatives. Also, our approach can detect the location of the actual user who launched the detected attack on the distributed Wi-Fi network."

Hamid el at. [5] assumed that different protocols follow a stateful approach and that any unwarranted state transitions of the protocol could be classified as an attack. We use this approach for the Wi-Fi protocol, where in the Wi-Fi network follows a stateful approach and any unwarranted state transitions made by the protocol is classified as an attack. Hamid el at [1] implemented this approach on a Wi-Fi network with a single access point. As a part of this research, we have expanded this approach to a distributed Wi-Fi network. We have used machine-learning algorithms to analyze normal behaviors and generate rules to detect attacks on these networks. Moreover as a part of this research, we were able to expand this approach to detect the location of the actual user once the attack had been launched over the network.

1.3 Research Objectives

The main research objectives are twofold 1) Development of an anomaly based intrusion detection system for single access point and distributed Wi-Fi networks, that is highly accurate in detection, is able to detect new and zero day attacks and has low false positives and no false negatives; and 2) Development of a tracking system that is able to track the location of the actual user and is able to separate the location of the attacker from the normal users using machine learning approach.

The proposed approach will result in the development of online runtime monitoring modules that will monitor illegal exploitations of existing vulnerabilities in the IEEE 802.11 protocol and use the rules obtained during the machine learning stage to detect an attack, classify the attack and then detect the location of the attacker.

1.4 Dissertation Organization

The remaining chapters of the dissertation are as follows:

Chapter 2 describes the background and the related work to intrusion detection systems and data mining. In Chapter 3, we review the IEEE 802.11 (Wi-Fi protocol) in depth. In Chapter 3 we also discuss other intrusion detection systems for the Wi-Fi protocol. In Chapter 4, we discuss the architectures that were designed as a part of this research. In Chapter 5, we discuss experimental results pertaining to the presented architectures. In Chapter 6, we discuss conclusion and future work.

CHAPTER 2: BACKGROUND AND RELATED WORK

2.1 Introduction

In this dissertation we present two architectures for an anomaly based intrusion detection system for single access point and distributed Wi-Fi networks. In this chapter we present related work and background for these architectures. We review intrusion detection systems, various types of classification techniques, machine learning approaches and algorithms.

2.2 Overview of the Intrusion Detection System Taxonomies:

Axelsson, el at. [6] presented a completed taxonomy of intrusion detection systems. According to Axelsson, Intrusion Detection Systems are like 'Burglar Alarms', which are built with the aim of protecting the system against attacks by sounding a warning system on detection of an attack.
He suggested that intrusion detection systems can be of three major types.

2.2.1 Anomaly Based Intrusion Detection Systems:

In case of anomaly based intrusion detection systems [28][29][30][31], the intrusion detection system is designed such that it has an understanding of the normal behavior of the system. Such systems also make an inherent assumption that any abnormal behavior that is observed is a threat to the network. Designing and implementation of this kind of systems generally begins with collection of information on what constitutes normal behavior for the network and what constitutes abnormal behavior for the network. Anomaly based intrusion detection systems can be classified into two types depending on the method in which the previously mentioned behavior analysis takes place. The two types are discussed below.

2.2.1.1 Self Learning:

Self-learning systems as the name suggests perform the task of learning the normal behavior and the abnormal behavior on their own. They observe the network at the runtime and have the capabilities to judge the parameters that are characteristics of the network for normal behavior and abnormal behavior in accordance with the model on which the intrusion detection system has been designed. The systems that fall in this category may use different approaches to model the normal behavior and the abnormal behavior of the network. Some of the approaches involve the use of stochastic modeling, which may involve formulation of rules that are able to mark the conditions of normality of the systems or the use of distance vectors to measure the difference of certain traffic parameters that is measured at the runtime with the traffic parameters that are measured during the learning process. Some other approaches involve measuring the operation of the network keeping into account timed behavior of the network. This can be done modeling the network as an artificial neural network, which is able to learn the normal behavior of the system and the abnormal behavior of the system.

2.2.1.2 Programmed:

In case of a programmed intrusion detection system, a third party other than the original intrusion detection system itself, teaches the system by feeding it with information to detect abnormal events. This is generally done by feeding the system with different parameters that have statistical values that help deciding if the system is operating normally or not.

2.2.2 Signature Based Intrusion Detection Systems:

The signature based intrusion detection system [19][20][21][22][23][24][25][26][27]operate on the knowledge obtained from analyzing the behavior of known intrusions on the network. In such a system, the system checks for signs of previously known attacks or intrusions where their signatures are stored in its database. On a match, the intrusion detection system gives an alert. In a signature based intrusion detection system, the system does not have information regarding the normal and the abnormal behavior of the network. The Intrusion detection systems of this type are programmed intrusion detection systems, where in the intrusions are programmed as either state based models, or audit event (string matching models).

2.2.3 Compound Detection Systems:

Compound detectors are built of a composite of a signature based intrusion detection system and an anomaly based intrusion detection system. These systems generally use signature based detection on normal traffic.

2.3 System Characteristics of Intrusion detection Systems:

System characteristics of intrusion detection systems are independent of the type of detection the intrusion detection system performs. These characteristics are discussed below.

2.3.1 Time of detection:

Intrusion Detection Systems can be either Real Time(Near Real Time) Intrusion Detection Systems or Non Real Time Intrusion Detection Systems. The Real Time detection Systems are systems that check for Intrusions at runtime and thus respond to attacks in a timely manner. However, these systems must run their algorithms with low overhead to be deployed. Non Real Time Intrusion Detection Systems analyze network traffic offline and can run very sophisticated models to improve detection and accuracy.

2.3.2 Granularity of Detection:

Granularity of Detection is the smallest unit of Data that is processed by the Intrusion Detection System. The Intrusion Detection System can process data continuously or in small groups or batches.

2.3.3 Source of Audit Data:

Source of Audit Data is the data input source for the Intrusion Detection system. Source of Audit Data is either network packets tapped directly from the network interface or system logs like Kernel logs that are maintained by the operating system.

2.3.4 Response to detected intrusions:

Based on the Response to detected intrusions, Intrusion Detection Systems can be of two types: Passive and Active systems, which are discussed below.

2.3.4.1 Passive Response Systems:

Passive response systems are Intrusion Detection Systems that respond to detection of an Intrusion on the network by sending an Alarm. They warn the user of the attack but they do not take any preventive or countermeasures against the detected attacks.

2.3.4.2 Active Response Systems:

Active Response Systems are Intrusion Detection Systems that respond to detection of an Intrusion on the network by sending an alarm and then taking counter measures against the detected attack. The counter measures range from closing of the network connections, to even attacking the resources used by the attacker.

2.3.5 Locus of Data Processing:

The data processed in the Intrusion Detection System can be either performed at a central location or at distributed locations.

2.3.6 Security:

This is to measure the security of the Intrusion Detection System itself from attacks.

2.3.7 Degree of Inter-Operability:

This is a measure of the Intrusion Detection Systems ability to operate with other Intrusion Detection Systems.

2.4 Data Mining:

The amount of data that is collected in databases today is growing exponentially. This increase in the amount of data that is collected in databases can be attributed to many reasons, such as the increasing computing power, the increase in the channel capacity of computer networks, faster memory devices, to just mention a few. It has been observed that as the size of data increases, the ability of a human to make sense out of the data decreases rapidly. This brought about the need for means to process the data and obtain knowledge from mining and analyzing the collected data.

Data Mining is the process of finding patterns in data sets by the means of use of various data mining algorithms. The data mining process can be automatic or semi-automatic involving human interference. These algorithms are used to learn patterns from the data and thus learn conditions or patterns of behavior that help in prediction of a behavior of another data set having similar patterns.

The event space in data mining algorithms [32][33][34][35]represents the space or the set that holds all the events or the data points that are to be analyzed. Data mining could be viewed as a search to look for conditional statements that are able to group all the elements of the set with correct descriptions.

Machine learning algorithms are given inputs in the form of files that hold data in the form of rows and columns. The rows describe specific instances, while the columns describe different attributes. The attributes that are selected to represent the data set to be used by the data mining algorithm are typically defined by a process called Attribute Selection[36].

Once the processing of the data in the databases is completed by the use of data mining algorithms, the obtained results need to be represented in a readable format. There are a number of means by which the results of data mining on a particular data set can be represented. The methods in which these results can be represented are discussed below.

Decision tables are the easiest means to represent the output of the learning algorithms. It is a table with conditions in the first column and the result of the machine learning algorithm in the next. Decision Trees are tree like structures that represent the results of the machine learning algorithms. The nodes represent the conditions to be taken while the leaves represent the class of the result. Figure 2.1 below shows an example of a Decision Tree.

```
power2 < 55.5
|   power2 < 33.5 : 0
|   power2 >= 33.5
|   |   power2 < 51.5
|   |   |   power2 < 38.5
|   |   |   |   power1 < 38 : 0.2
|   |   |   |   power1 >= 38 : 1
|   |   |   power2 >= 38.5
|   |   |   |   power2 < 47.5 : 0.92
|   |   |   |   power2 >= 47.5
|   |   |   |   |   power2 < 48.5 : 0.56
|   |   |   |   |   power2 >= 48.5
|   |   |   |   |   |   power1 < 41.5 : 0.83
|   |   |   |   |   |   power1 >= 41.5 : 1
|   |   power2 >= 51.5
|   |   |   power1 < 39.5
|   |   |   |   power2 < 52.5 : 0.33
|   |   |   |   power2 >= 52.5 : 1
|   |   |   power1 >= 39.5 : 0.2
power2 >= 55.5 : 0.04

Size of the tree : 21
```

Figure 2.1: Decision Tree

Classification Rules are the simplest means to represent the results of machine learning algorithms. They provide the conditions in form of simple condition statements that can be used as test to classify the results. The conditional statements can also be ANDED together with other conditional statements to obtain longer rules. Example rules are shown in the Table 2.1 below

Table 2.1: Classification Rules

RULES: IF **FS1<97** AND **FS2> 279732** AND **FS3>1020** THEN TRAFFIC IS NORMAL;

Clusters are obtained as a result of machine learning when a clustering algorithm is used instead of a classification algorithm. The Clusters that are obtained help representing the distance of the instance from the center of the cluster. Clusters can be mapped in two dimensional space which is the simplest form to represent the cluster. The clusters could also be represented in multi dimensional space. Figure 2.2 below shows an example of a cluster representation.

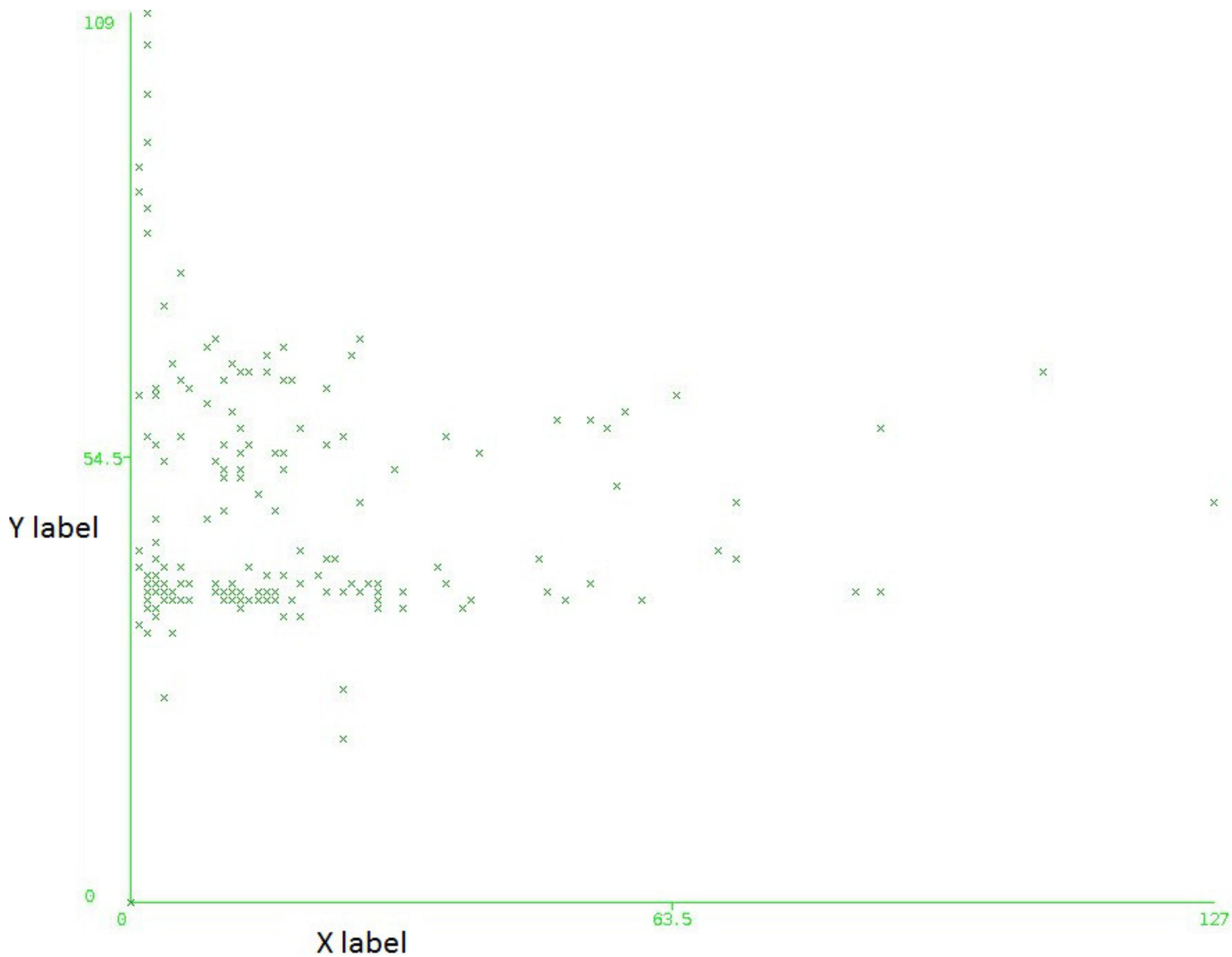


Figure 2.2: Clustering Example

Learning Types:

According to Witten and Frank el at[7] three different types machine learning approaches. The choice of the approach used depends on the type of data that is being processed and the application of the resulting conditions or rules from machine learning. These machine learning approaches are discussed below.

Classification Learning:

Classification learning involves using algorithms to understand the conditions which allow classification of unseen examples into predefined classes. Thus classification learning allows default classification of the unseen data into different classes.

Association Learning:

Association Learning allows the building of associations between different unseen examples by predicting attributes as well as classes. Association learning helps in learning strong rules of association between attributes and not just their classes. Association learning involves use of different algorithms like Apriori Algorithm[37], Eclat Algorithm[38], FP-growth Algorithm [39].

Clustering:

Clustering is the process of grouping together objects that are similar to each other more than other objects. Clustering is generally distance based, where in the clusters are judged depending on the center of the clusters. Clustering is generally Centroid based clustering, Distribution-based clustering or Density-based clustering. Some of the clustering methods include k-means clustering[40][41].

CHAPTER 3: WI-FI PROTOCOL

Wi-Fi protocol also known as the IEEE802.11[42] [43][44][45][46][47] is a wireless local area network protocol. It is the Ethernet's equivalent for wireless networks. The protocol was first formalized in the year 1997. This protocol over the years of its existence has been upgraded and has faced many changes. But most of these upgrades have been to enhance the data rate and the link quality of the network and little has been done to improve the security of the network.

3.1 The IEEE 802.11 Standard:

The Wi-Fi protocol[42] operates in the 2.4 GHz UHF and the 5 GHz SHF bands both of which fall under the category of ISM bands and hence have been sanctioned for unlicensed use. The original Wi-Fi protocol that was declared in the year 1997 specified bit rates of 1 or 2 Mbits/s while specifying 3 alternate physical layer configurations which were Diffuse infrared at 1Mbps, Frequency Hopping Spread Spectrum (FHSS) at 1 Mbps or 2 Mbps, Direct Sequence Spread Spectrum (DSSS) at 1 Mbps or 2 Mbps.

3.1.1 IEEE 802.11b:

This specification of the protocol [44] supports a maximum data rate of 11 Mbps using the same physical specifications as the original Wi-Fi protocol. This protocol supported the use of the DSSS in the 2.4 GHz UHF ISM band. Carrier Sense Multiple Access/ Collision Avoidance (CSMA/CA) is the protocol that is used to manage the media access.

3.1.2 IEEE 802.11a:

This standard was added to the original 802.11 protocol in the year 1999[43]. This standard specified the operations of the Wi-Fi in the 5 GHz SHF supporting 52 subcarrier Orthogonal Frequency Division Multiplexing supporting data rates upto 54Mbps.

3.1.3 IEEE 802.11g:

This standard was ratified to the original 802.11 protocol in the year 2003[45]. This standard increased the data rate in the 2.4GHz UHF ISM band to 54Mbps. This was done by the adoption of the use of Orthogonal Frequency Division Multiplexing (OFDM).

3.1.4 IEEE 802.11n:

This enhancement to the 802.11 protocol enhanced the data rates up to 600Mbps[46]. This increase in data rate is achieved by the use of multiple data streams with channels widths of 40MHz. It can operate in the 2.4GHz UHF ISM band and the 5 GHz SHF band. Moreover one of the enhancements that have been added includes the use of multiple antennas that allows seamless maintenance of simultaneous data streams.

3.1.5IEEE 802.11ac:

This standard was approved in the year 2014[47]. This protocol processes that each single link to have a throughput of 500 Mbps while overall throughput for a multi-station WLAN would be at least 1 Gbps. This increase in throughput is achieved by the use of wider channels, and up to 8 MIMO spatial streams and use of 256 QAM.

Table 3.1: IEEE 802.11 Physical Layer Standards

Release Date	Standard	Frequency Band	Bandwidth	Modulation	Data Rate
1997	802.11	2.4GHz	20 MHz	DSSS, FHSS	2 Mbps
1999	802.11b	2.4GHz	20 MHz	DSSS	11 Mbps
1999	802.11a	5GHz	20 MHz	OFDM	54 Mbps
2003	802.11g	2.4GHz	20MHz	DSSS, OFDM	542 Mbps
2009	802.11n	2.4GHz, 5Ghz	20MHz, 40MHz	OFDM	600Mbps
2013	802.11ac	5Ghz	40MHz, 80MHz,160MHz	OFDM	6.93Gbps

3.2 Architectural Overview:

The Wi-Fi protocol defines the Physical layer and the Datalink layer specifications to establish a wireless local area network. The architecture of the protocol is as in the Figure 3.1 below,

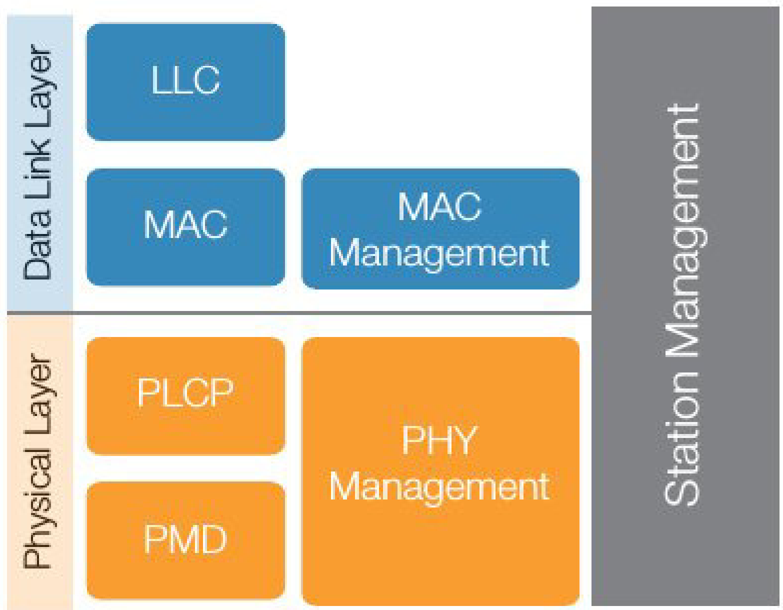


Figure 3.1: Wi-Fi Protocol Architecture

3.2.1 Physical Layer:

The Physical layer of the Wi-Fi protocol deals with the most important aspects of the communication link. The tasks of the physical layer include, establishment and termination of the link, make sure an effective policy is in place for the sharing of the link and handle signal modulation and demodulation. The physical layer of the Wi-Fi protocol is divided into 3 sub layers.

a. Physical layer Convergence Procedure (PLCP):

This is the layer that hides the lower physical layer activities like the modulation types and the channel data rates from the upper layer of the OSI model. It is also responsible to ensure proper channel sharing and packet building.

b. Physical Medium Dependent (PMD):

This is the layer that varies according to the IEEE 802.11 standard variation and is responsible for implementation of modulators, demodulators and the coding techniques.

c. The Physical Management layer:

The Physical Management Layer is involved in the task of link management. It ensures proper tuning of the modulators and the demodulators to the required frequencies.

d. Channel Allocation and Bandwidths:

The 802.11b, 802.11g, and the low frequency part of the 802.11n, use the 2.4GHz band located in the ISM spectrum, while 802.11a, 802.11ac, use the 5GHz band. The 2.4 GHz band is subdivided into 14 overlapping subbands each space 5MHz apart as shown in the Figure 3.2 below.

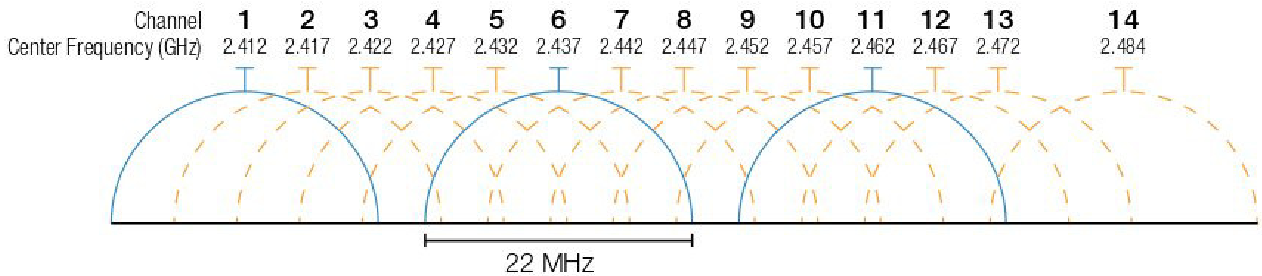
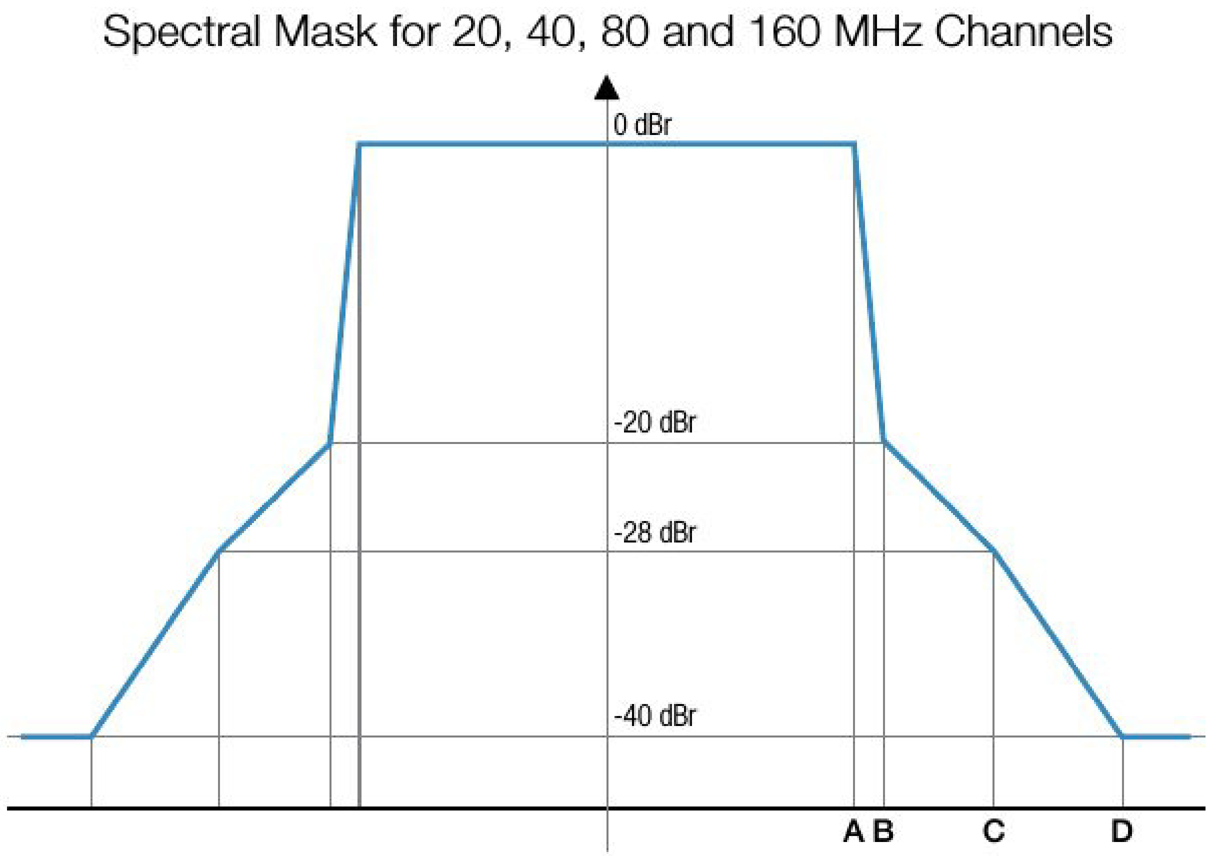


Figure 3.2: 2.4GHz band Channels.

The 5GHz band is split into different sub bands depending on the country of operation. The bandwidths of each of the channels is either 20MHz for the lower frequency band and 40 MHz for the higher frequency bands. In the case of the 802.11ac which supports 80MHz channels two adjacent 40MHz channels are used as a single channel.

e. Spectral Masks:

The 802.11 is a protocol that operates in unlicensed band of communication. Thus to ensure error free operation of multiple links in the same band, the protocol specifies a spectral mask which describes the manner in which the signal strength should attenuate with frequency offsets from the central frequency. The OFDM spectral mask used by 802.11 a/g/n/ac is specified in the Figure 3.3 below.



Channel Size	A	B	C	D
20 MHz	9 MHz	11 MHz	20 MHz	30 MHz
40 MHz	19 MHz	21 MHz	40 MHz	60 MHz
80 MHz	39 MHz	41 MHz	80 MHz	120 MHz
160 MHz	79 MHz	81 MHz	160 MHz	240 MHz

Figure 3.3:Wi-Fi Spectral Mask

3.2.2 Data Link Layer and Frame Structure:

The 802.11 protocol breaks the continuous stream of data into smaller data units and sends it over the network encoded as payload data in the frames. The protocol also defines other types of frames that are responsible for the maintenance of the link. The general structure of the frame is as shown in the Figure 3.4 below,

Figure 3.4: Wi-Fi Frame structure

a. Preamble:

The preamble is the first set of bit sequence that follows the actual header. The preamble marks the start of the frame. The preamble allows the receiver frequency synchronization and receiver time synchronization. This helps the receiver extract the header and the data from the modulated signals that are sent over the channel.

b. Header:

The Wi-Fi Header is made up of a 2 Byte frame control field, a 2 Byte Duration ID, 48 bit long address fields which include the source and the destination address fields. The structure of the Wi-Fi frame header is as shown in the Figure 3.5 below.

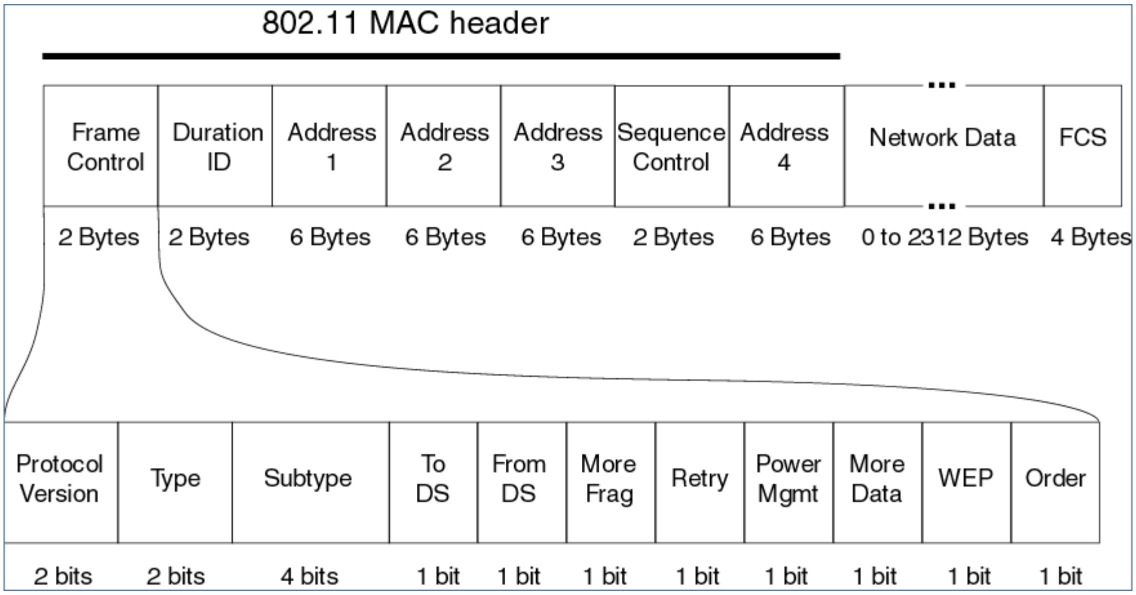


Figure 3.5: Wi-Fi Header

c. Frame Control:

The frame control field in the Wi-Fi header is a 2 Byte long field that acts as a control for the frame. This field is further sub divided into sub fields as shown in the Figure 3.5 above. The sub fields include various subfields like the Protocol Version, Type of the frame, Subtype of the Frame, the direction of the frame movement, power management specifics and many more. A Wi-Fi frame can be of three type namely Management frame, Control Frame and Data Frame.

d. Management Frames:

Management frames more specifically are the link management frames that help in the control of the link. These frames also setup the link and tear it down once the communication is complete. Management Frames are described below:

e. Authentication Frame:

An exchange of authentication frame takes place with an access point when the link setup between the access point and the user device takes place. It helps in establishment of the identity of the device connecting to the network.

f. Association Request Frame:

This Frame informs the access point that the device is ready to send data on the network and hence the access point allocates resources for the device.

g. Association Response Frame:

This frame is sent by the access point in response to the Association Request Frame. The response frame may be a positive response or a negative response to the device.

i. Beacon Frame:

This is the frame that is broadcast by the access point after a fixed interval of time. This frame informs the devices that are trying to connect to the access point of the various characteristics of the access point, like the name, the operating frequency, the transfer rates, Type of encryption scheme used and more.

j. De-Authentication Frame:

De-Authentication Frame is a complement of the Authentication frame. It is the frame that is sent over the network by the user device to the access point when the user device wants to disconnect from the network.

k. Disassociation Frame:

Disassociation Frame is a complement of the Association Frame. It informs the access point that it can de-allocate the resources that it had allocated for the device as the device no longer plans to use the network.

l. Probe Request Frame:

This frame is sent from a station to another station to get information of that station.

m. Probe Response Frame:

Probe response frame is the response sent by a station for the probe request.

n. Reassociation Request Frame:

Reassociation Request Frame is a frame that is sent when a device moves out of the range of one access point and moves into the range of another. The device sends a Reassociation request to another access point with signal strength more than the current access point.

o. Reassociation Response Frame:

This is the response frame that is sent in response to the Reassociation Request. The response may be a positive response or a negative response.

p. Control Frame:

The control frames are sent over the network and control the contention issues of the network.

q. Acknowledgement (ACK) Frame:

On the reception of a data frames the device sends an acknowledgement frame to the source.

r. Request to Send (RTS) Frame:

It is the request to send that acts as an optional contention control over the network.

s. Clear to Send (CTS) Frame:

It is the optional Clear to Send Frame that is sent in response to the Request to Send Frame.

t. Data Frame:

The Data frames are the frames that are used to move the data from the source to the destination.

They generally carry higher level protocols in their data sections.

Table 3.2: Wi-Fi Frame Types

Frame Name	**Frame Type/Subtype**
Association Request Frame	0
Association Response Frame	1
Reassociation Request Frame	2
Reassociation Response Frame	3
Probe Request Frame	4
Probe Response Frame	5
Beacon Frame	8
Announcement traffic indication map(ATIM) Frame	9
Disassociate Frame	10
Authentication Frame	11
Deauthentication Frame	12

Action Frame	13
Block ACK Request Frame	24
Block ACK Frame	25
Power Save Poll Frame	26
Request to Send Frame	27
Clear to Send Frame	28
ACK Frame	29
Contention Free Period End Frame	30
Contention Free Period End ACK Frame	31
Data + Contention Free ACK Frame	33
Data + Contention Free Poll Frame	34
Data + Contention Free ACK + Contention Free Poll Frame	35
NULL Data Frame	36
NULL Data + Contention Free ACK Frame	37
NULL Data + Contention Free Poll Frame	38
NULL Data + Contention Free ACK + Contention Free Poll Frame	39
QOS Data Frame	40
QOS Data + Contention Free ACK Frame	41
QOS Data + Contention Free Poll Frame	42
QOS Data + Contention Free ACK + Contention Free Poll Frame	43

NULL QOS Data Frame	44
NULL QOS Data + Contention Free Poll Frame	46
NULL QOS Data + Contention Free ACK + Contention Free Poll Frame	47

3.3 Wi-Fi State Machine:

The Wi-Fi protocols is a stateful protocol that is, each transition in the protocol follows state machine. The Wi-Fi state machine is as shown below.

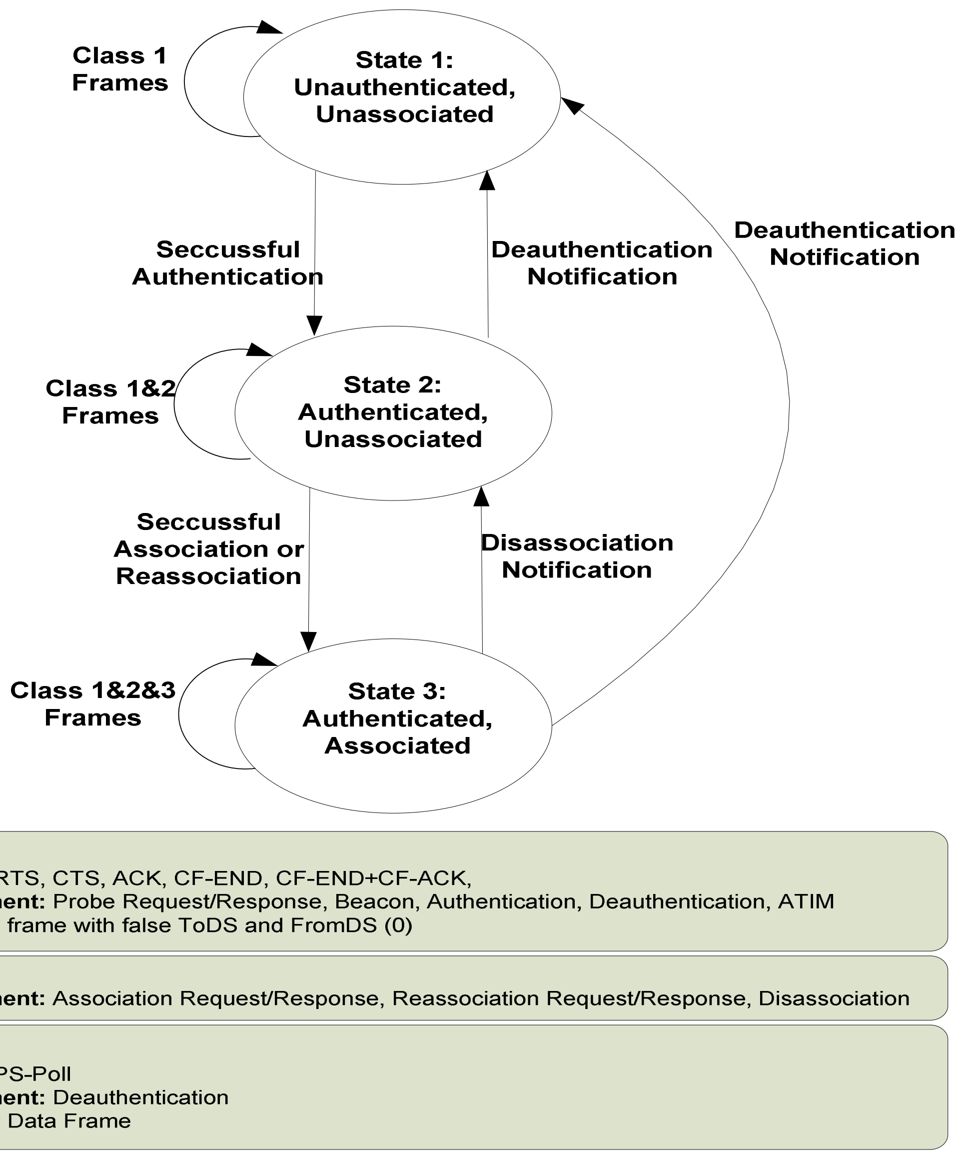


Figure 3.6: Wi-Fi State machine.

As seen in Figure 3.6 above the Wi-Fi state machine has 3 different states. State1 is the unauthenticated and unassociated state. In this state of operation of the Wi-Fi- device, it is not connected to the network. State2 is the Authenticated and Unassociated state. In this state of operation of the device is connected to the network but the access point has no resources allocated to for that device in the access point. In the state3 of operation, the device is Authenticated and is also Associated to the network. This allows the device to send the traffic over the network.

3.4 Related Wi-Fi work:

Depending on the layer on which the Intrusion Detection System (IDS) focuses on, we can classify them into 3 types: 1) physical layer based IDS[48][49][50][51][52], 2) MAC layer based IDS [53][54][55][56], and 3) physical layer and data link layer based IDS [57]. Most of the approaches to detect the physical layer attacks on the Wi-Fi network involve the use of signal strength or multiple antennas to detect the angle of the attack on the Wi-Fi network. This method can efficiently detect attacks on the physical layer of the Wi-Fi network such as network jamming or detect attacks on the data link layer as in MAC address spoofing. This approach is complex because it takes into account the effects of signal fading, noise, changes in the medium, and effects due to the movement of the target. This may negatively affect the performance of the intrusion detection system. The intrusion detection systems that operate on the data link layer use the data obtained from the Wi-Fi frame to detect attacks. Open source intrusion detection systems like Snort and most of the commercial Intrusion detection systems available like AirMagnet[58] and some detection engines in Air Defense[59] use the misuse detection approach to detect Wi-Fi attacks. But as this approach involves the use of attack signatures to detect attacks, modified attacks or zero day attacks cannot be detected by these methods. Alipour el at[60] proposed an anomaly based intrusion detection system to detect attacks on Wi-Fi networks with single access points. In this method, he uses the normal traffic of the network and machine learning to detect attacks on the system. In this paper we extend the work in [60] and present an anomaly based intrusion detection system that uses not only the normal traffic but also uses known attack traffic to detect attacks on distributed Wi-Fi networks. This approach achieves a high attack detection rate with low false positives against a wide range of Wi-Fi attacks. Also this extension contains an architecture that is able to track the location of the attacker and the actual user once the attack has been detected.

In [61] the authors focus on the use of the round trip time (RTT) of the signal to track down the location of the user from the access point. In [49] the authors use the signal strength of the received signal to track spoofing attacks. In their work, the authors profile the received signal using Gaussian Mixture models. Then the profiles that are generated by the use of these models for each transmitter used to detect spoofing attacks on the networks. In this paper we present a similar approach to track the location of the attacking device. The system uses the signal strength to track the location of the attacker once the attack on the network has been detected. In our method, we use machine learning algorithms to generate profiles for different access points.

CHAPTER 4: ARCHITECTURE

Below we present two anomaly based intrusion detection system for a Wi-Fi network. The intrusion detection systems uses machine learning to understand the behavior of the network. These two intrusion detection systems use two different architectures to track the location of the attacking device once the attack on the network has been detected. Each of the intrusion detection systems can operate in two modes. In the first mode the intrusion detection system is able to detect attacks and track the location of the attackers when the network in a non distributed Wi-Fi networks. In the second mode of operation the intrusion detection system is able to detect attacks on distributed Wi-Fi networks and track the location of the attacker. In the second mode of operation, the intrusion detection systems are deployed on each of the accesspoints that are deployed in the test environment.

4.1 Definitions:

Presented below are some common definitions of terms that are used in the architecture.

4.1.1 Ngram:

As stated in the section 3.3 the Wi-Fi protocol is a stateful protocol. Hence Wi-Fi follows a specific state machine and moves from the one state to another in a predictive manner. We use the **n-gram** concept [60] to model the temporal transitions of Wi-Fi frames among the finite state diagram shown in Figure 3.6.This modeling allows the Intrusion Detection System to track the transition of the protocol along the state machine, thus allowing the IDS to monitor the behavior of the state machine. Each n-gram has a predefined size where in the size of the n-gram gives the amount of previous transitions the n-gram tracks. For example, a 2-gram, represents two consecutive transitions of Wi-Fi frames.

For the Wi-Fi protocol the overall type of the frame is used to decide the state of the protocol. The overall type of a Wi-Fi frame is decided by the combination of frame type and the frame subtype field in the Wi-Fi protocol header. For example a De-Authentication frame is of type 8.
Each Wi-Fi frame has its type which is decided by combining the frame type and subtype fields in the Wi-Fi header.

Hence an **n-gram** of size ***n*** has n types of consecutive Wi-Fi frame types in it. For example 4 consecutive beacon frames will form a 4-gram with following sequence 8888. The concept of formation of an n-gram from a flow of Wi-Fi frames is as shown in the Figure 4.1 below.

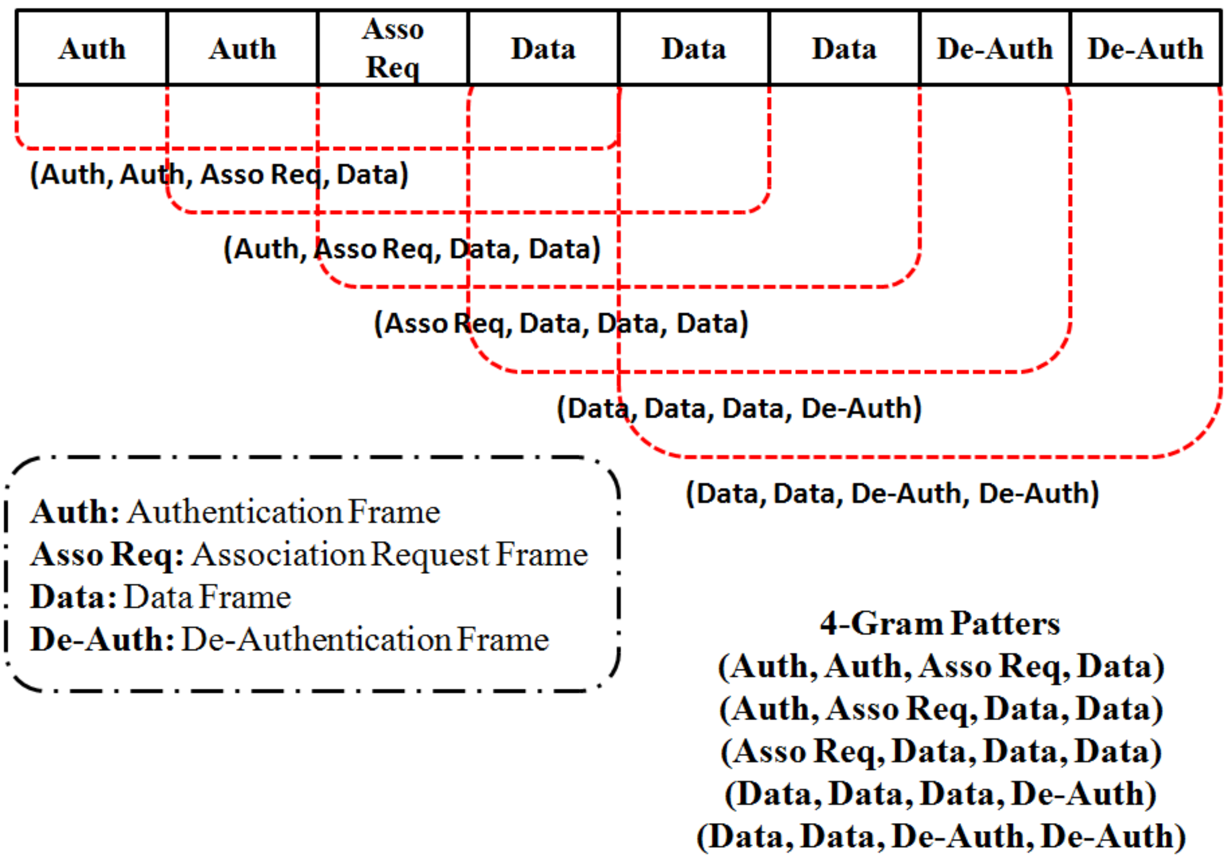


Figure 4.1: 4 n-gram extraction from the flow.

4.1.2 Wireless Flow:

There is a continuous flow of Wi-Fi frames in a Wi-Fi link between the access point and the network device. The frames that constitute this flow of traffic are of the three types of Wi-Fi frames. These flows of frames help track the state transition of the Wi-Fi state machine. This continuous flow of frames is sampled at a rate r is represented by a data structure called as the WirelessFlow(Wflow).

The sampling rate of the traffic affects the size of the WirelessFlow and sensitivity of the Intrusion Detection System(IDS) to attacks. A slower sampling rate increases the number of frames that constitute a flow thus increasing the size of the data structure Wflow but at the same time also increases the sensitivity of the Intrusion Detection System and helps it detect slow attacks. On the other hand a high sampling rate decreases the number of frames that constitute a flow and thus decrease the size of the data structure Wflow but at the same time it also makes the system less sensitive to slow attacks. More over a slower sampling rate also increases the response time of the Intrusion Detection System to the detected attacks as the IDS has to wait for the time period of the sample to complete before the detection of the attack takes place. The above mentioned issue of delayed detection can be circum-navigated by the use of multiple flows of different sizes in the system as proposed by Youssif, et al.[8]. In [8] the author proposed the use of flows with varying sampling rates and using multiple flows as a part of the Intrusion Detection System. The Figure 4.2 below shows Wflows with varying sampling rates and their effects on the ensuing flow analysis.

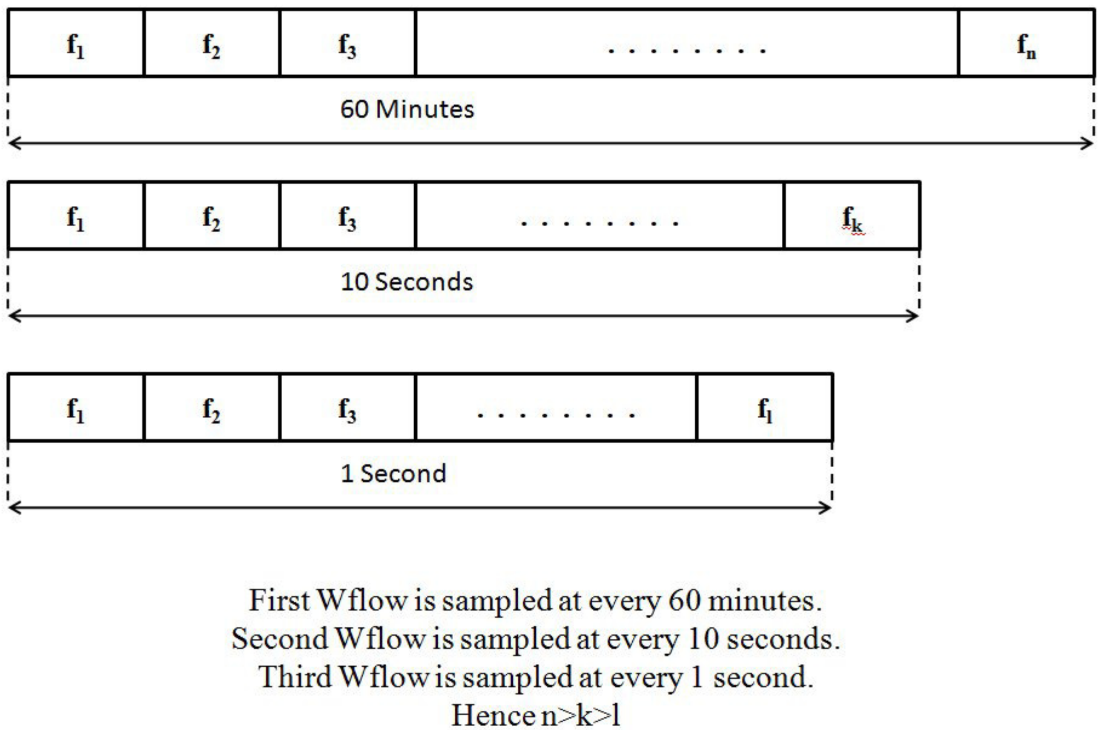


Figure 4.2: WFlows at different sampling rates

4.2 Intrusion Detection System with cluster tracking Architecture:

Below is the description of the Architecture of the Intrusion Detection System that is deployed on the distributed access points and the architecture of the system deployed on the Central Controller.

4.2.1 Architecture of the system deployed on the Access points:

The Figure 4.3 below shows the general architecture of the system that is deployed on each of the access points/IDS devices that make up the network. The three main modules of the system are discussed below

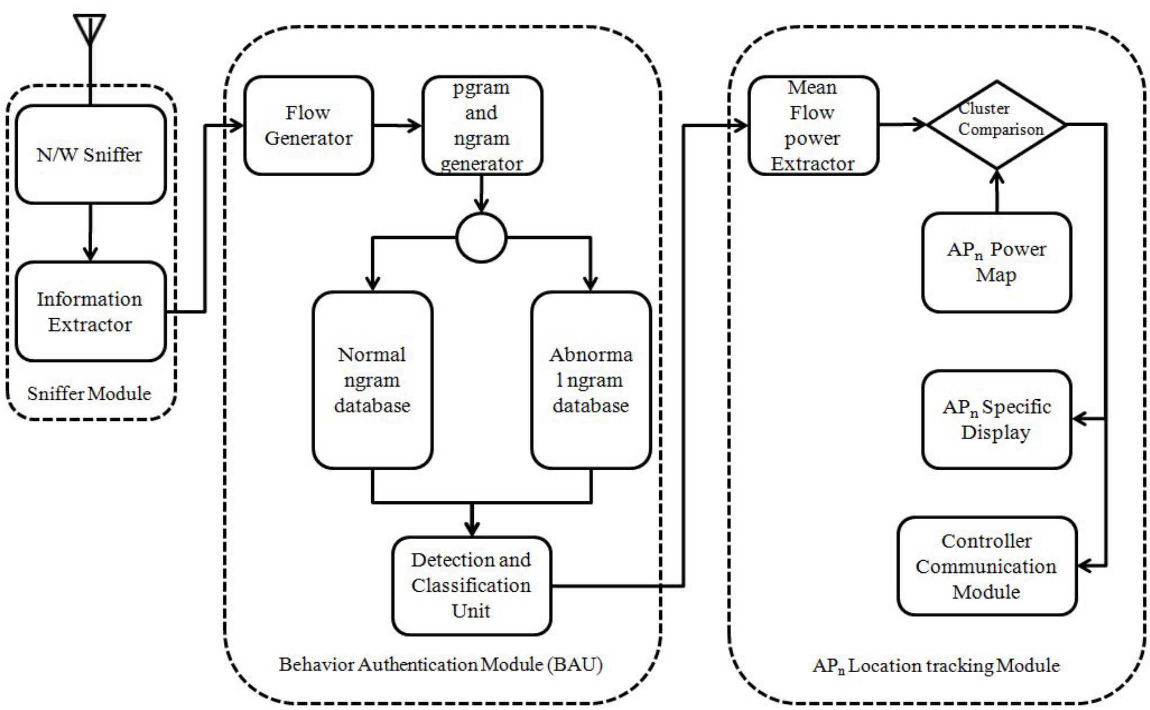


Figure 4.3: IDS and cluster tracking architecture

4.2.1.1 Sniffer Module:

The Sniffer Module is the module that does the task of collection of frames from the wireless medium. It collects the frames from the wireless medium and performs the task of information extraction from the collected frame. The information extraction sub module extracts the collected frame type and the received radiotap signal strength from the frame and passes the information to the Behavior Authentication Module.

4.2.1.2 Behavior Authentication module:

The Behavior Authentication Module is the module that performs the task of classifying if the traffic that is collected by the sniffer module is normal or abnormal. The Behavior Authentication Module receives the extracted information from the sniffer module and passes the frame parameters to the Flow Generator and the pgram and the ngram generator sub modules. The flow generator generates the Wflow for each connected device and the access point pair and passes the Wflow to the pgram and the ngram generator module. The pgram and the ngram generator module uses the Wflow to create the pgrams and the ngrams. The ngrams are then compared with the normal and the abnormal ngram traffic databases to score the amount of normality and abnormality of each ngram which is in turn used to judge the normality and the abnormality of the Wflow. This characteristic information is then forwarded to the detection and classification unit. The detection and the classification unit, compares the Wflow characteristics with the conditions presented but the machine learning algorithms to classify if the Wflow is normal or abnormal. On detection of an abnormal Wflow, the module also classifies the type of abnormality by using number of different frame types in the Wflow to classify the attack.

4.2.1.3 AP_n location tracking Module:

On detection of attack in the Behavior Authentication Unit the Wflow is passed to the APn location tracking Module which extracts the average power of the Wflow. This average power is then compared with the local power map of the AP_n. After the comparison of the average power of the flow to the power map, the average power is sent to the Central Controller for a centralized analysis of the power signal. While the local Ap_n logs the results of the local design process.

4.2.2 Architecture for the system on the Central Controller:

The Central Controller which also acts as the Radius Server for the distributed Wi-Fi network acts as the central control when the attack detection happens. On detection of attacks each of the access point's location tracking module sends the average power of the Wflow it detected to the Central Controller. The Central Controller then compares powers from all the access points with its power map to decide the location of the attack. The Architecture of the Central Controller is shown in the Figure 4.4 below.

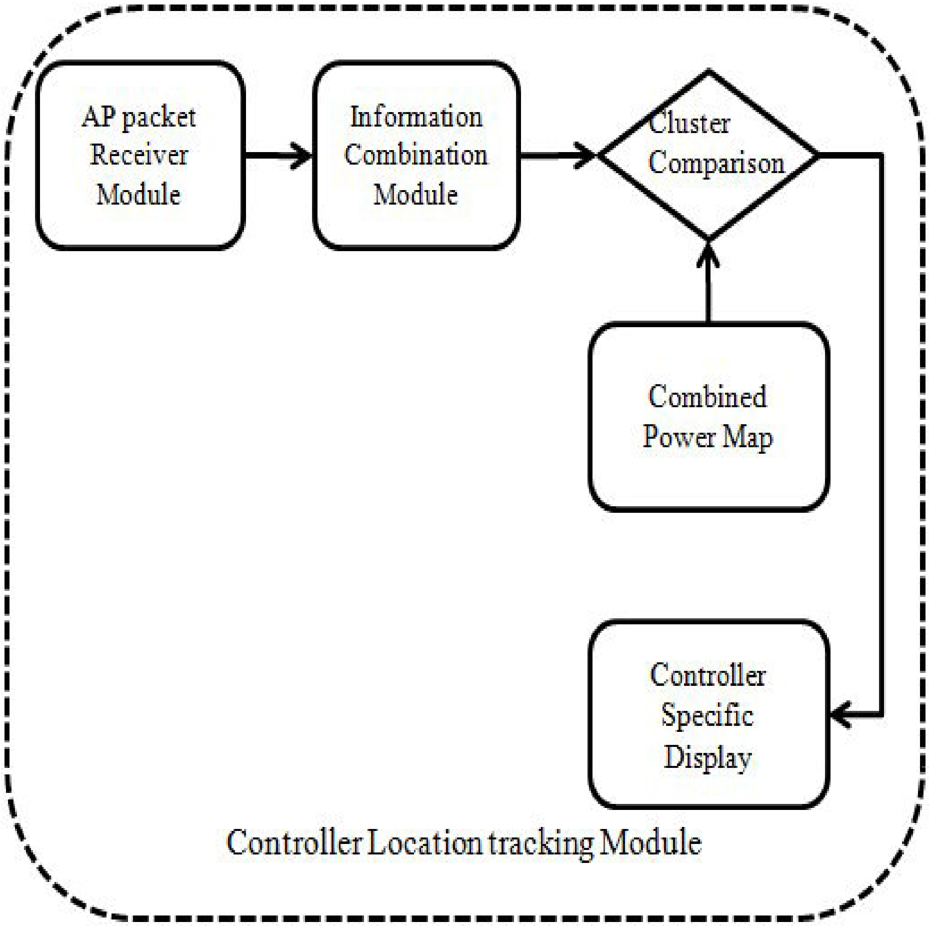


Figure 4.4: Central Controller Architecture

4.2.3Operation Phases of the System:

The System that has been developed is an anomaly based intrusion detection system, thus it operates in two phases. The two phases of operation are Training Phase and the Detection Phase. These phases are described below.

4.2.3.1Training Phase:

In the training phase, the system train's on the local Wi-Fi network and understands the normal behavior for the system. The training involves collection of the traffic that flows through the Wi-Fi network. Traffic is collected when the network is under normal operations and when the network is under some known attacks. The knowledge of the operations of the network when it is under known attacks, helps reduce the unknown event space and thus reduce the false positives during attack detection. This reduces the false positives that are generated by the system by reducing the amount of unknown event space. The training of the system happens in 3 stages.

a. Training Phase - Stage 1:

In this stage, we monitor the network to obtain all the possible ***n-grams*** in the Wi-Fi network. This stage is used to build two databases. The first database is for all the normal ***n-grams*** in the network. To ensure that attack traffic is not passed as normal traffic while building the database, the network is carefully monitored to filter out any known attack traffic.

The second database is for all the n-grams obtained from known attack libraries. This approach of having partial attack traffic helps us better shape the event space to differentiate between normal and abnormal traffic.

In addition to storing the n-grams that characterize the normal and abnormal behavior of the Wi-Fi frames, we also store information about:

1. Occurrence Rate (OR) – It measures the ratio of the number of occurrences of the ***n-gram*** during the training to the total number of ***n-grams*** obtained during the training,
2. Modulo of total N-grams (MG): It measures the modulo (remainder from division) of number of occurrences of the ***n-gram*** during the training with the total number of ***n-grams***.

The values of OR and MG for each of the ***n-gram*** in both the normal and the attack database can be used to accurately characterize the normal and abnormal traffic of Wi-Fi network.

Let us denote receiving an ***n-gram*** of Wi-Fi frames by an event $\boldsymbol{\varepsilon_i}$ where the ***n-gram*** is **the $\boldsymbol{i^{th}}$*n-gram***,

And the set of ***n-grams*** used during the training stage is denoted as **E**

Then, $\boldsymbol{\varepsilon_i \epsilon} \mathbf{E}$

$$OR_i = \frac{Number\ of\ times\ \boldsymbol{\varepsilon_i}\ occurs}{Size\ of\ \mathrm{E}}$$

$$MG_i = Number\ of\ times\ \boldsymbol{\varepsilon_i}\ occurs\ \%\ Size\ of\ \mathrm{E}$$

b. Training Phase - Stage 2:

In this stage of the training, the network is monitored first with normal traffic in the network and then with abnormal traffic in the network to calculate four metrics(Wflow$_1$, Wflow$_2$, Wflow$_3$, Wflow$_4$) for each of the wireless flows(***Wflows***) that are observed. The four wireless flow scores are computed as follows,

If we assume that a particular wireless flow has n ***n-grams***,

Then:

$$Wflow1 = (\sum_{i=1}^{i=n} OR_i)_{normal}$$

$$Wflow2 = (\sum_{i=1}^{i=n} MG_i)_{normal}$$

$$Wflow3 = (\sum_{i=1}^{i=n} OR_i)_{attack}$$

$$Wflow4 = (\sum_{i=1}^{i=n} MG_i)_{attack}$$

Where in values of the *OR* and MG for each ***n-gram*** are obtained from the normal and abnormal ***n-gram*** databases obtained in Stage 1.

This obtained set of 4 metrics for each of the ***Wflows*** is stored in a database called ***flow_score*** database with a binary entry added in front of each flow marking if the traffic that was observed was normal or abnormal. The abnormal traffic is generated as mentioned earlier by the use of known attack libraries.

Machine learning is performed in the ***flow_score*** database by the use of classification algorithms to obtain the conditions in which the 4 Wflow metric's represent normal and abnormal traffic. In the system that was developed as a proof of concept, a simple Conjunctive Rule algorithm was used to get the conditions of abnormal operation. This algorithm learns a single rule that predicts, nominal class value. In this algorithm, the uncovered test instances are assigned the default class, and the knowledge gain on occurrence of each of the antecedent is computed. The rule pruning is done by the use of reduced error pruning. The rules thus obtained are used in the Detection Phase of the system to detect attacks on the Network.

c. Training Phase - Stage 3:

During this stage of operation, a power map is created for each of the access points in its area of operation. This is done by monitoring the signals received at the access point when the source of the signal is placed at different locations. The power map for the Central Controller is obtained by combining the maps of each of the access points.

4.2.3. 2 Detection Phase:

The detection phase is the final operational phase of the system. In the detection phase, the rules that were learnt in Stage 2 of the training phase are used to detect the abnormal wireless traffic (wireless flows (Wflows)). In addition to detecting the abnormal Wflows, we also classify the type of attack and the location of the attacker.

For the attack location detection, each of the access points detects attacks independently. Each of the access points compares the values of the four metrics ($Wflow_1$, $Wflow_2$, $Wflow_3$, $Wflow_4$), with the ones that are obtained in the Stage 2 of the training to detect if an attack was performed on the network. Each access point then classifies the attacks that are happening over the network, by counting the different types of frames that are present in the anomalous wireless flow and associating the type of frame with the type of attack.

The access points that detect the attack activate their location tracking module, which compares the mean value of the power signal in the wireless flow with the power map for the access point. Thus enabling the access point to estimate the location of the actual user, assuming that the number of frames sent by the user is more than the number of frames sent by the attacker. Also the access points forward the mean power of the anomalous wireless flow to the Central Controller. The Central Controller then combines the mean power from the different access points and compares the power values to its power map to estimate the location of the user.

4.3 Intrusion Detection System with tracking using classification algorithm

Architecture:

Below we present, an architecture of an intrusion detection system for a distribute Wi-Fi network that uses classification based machine learning algorithms to classify the traffic flowing through the network as normal or abnormal. And in case of occurrence of abnormal traffic uses classification algorithms to classify the location of the abnormal traffic.

4.3.1 Architecture of the system deployed on the Access points:

The Figure 4.5 below shows the general architecture of the system that is deployed on each of the access points/IDS devices that make up the network. The three main modules of the system are discussed below

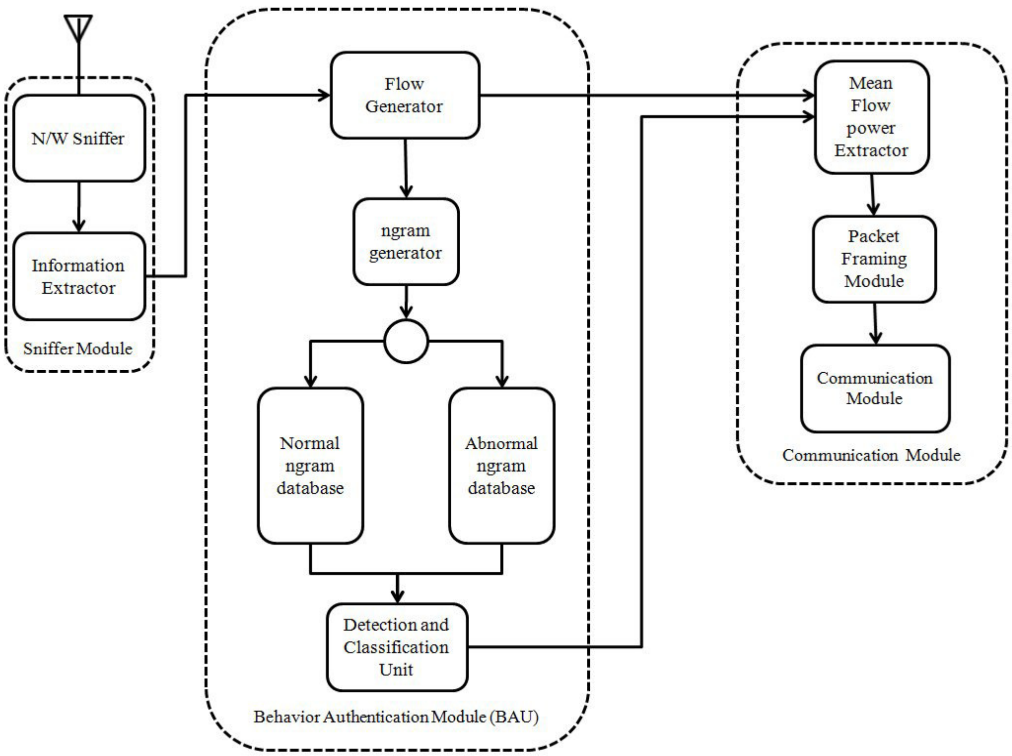


Figure 4.5: IDS and cluster tracking architecture

4.3.1.1 Sniffer Module:

The Sniffer Module collects the frames that flow over the Wi-Fi network. This module contains two sub modules. The N/W sniffer sub module sniffs the network for the frames. The second module that is the Information Extractor module extracts characteristic information from the frames sniffed by the N/W Sniffer sub module. The extractor module extracts the received signal strength from the Radiotap header, the frame type and the frame sub-type from the Wi-Fi frame. It passes this information on to the Behavior authentication Module.

4.3.1.2 Behavior Authentication module:

The Behavior Authentication Module is the module that classifies the normality and the abnormality of the traffic. It is made up of 4 sub modules. The Flow Generator receives the extracted data from the Sniffer Module. The data that is received from the sniffer module includes the power information of the received frame, the frame type and subtype of the received frame and a time stamp of the time of receiving of the frame.

The Flow Generator module uses the time stamp to group the received frames into Wflows. The information pertaining to the power of the received frames is passed on to the Mean flow power extractor sub module in the Communications module and the ngram generator sub module in the Behavior Authentication Unit. The ngram generator sub module converts the Wflow into a stream of ngrams which are compared with Normal ngram database and Abnormal ngram database. The results of the comparison are fed to the detection and the classification sub module. The Detection and the Classification sub module have the conditions that classify the traffic normal or abnormal. Also the Classification unit classifies the type of attack on the Wi-Fi network. On detection of anomalous activity by the Behavior Authentication Module(BAU) the Communication Module is activated.

4.3.1.3 Communication Module:

On detection of attack in the Behavior Authentication Module, the Communication module is activated. The communication module calculates the average signal strength in the Wflow and the size of the Wflow which are framed into a packet and sent to the Central Controller.

4.3.2 Architecture for the system on the Central Controller:

The Central Controller acts as the main control unit that performs the task of tracking the location of the attack in this architecture. The Central Controller receives average power for the Wflow and the Wflow size received by each of the access points in case of detection of an attack. The Central Controller combines the average power and the Wflow sizes received from each of the access points and then uses the conditional statements learnt by the use of classification machine learning algorithms to classify the location of the attacker.

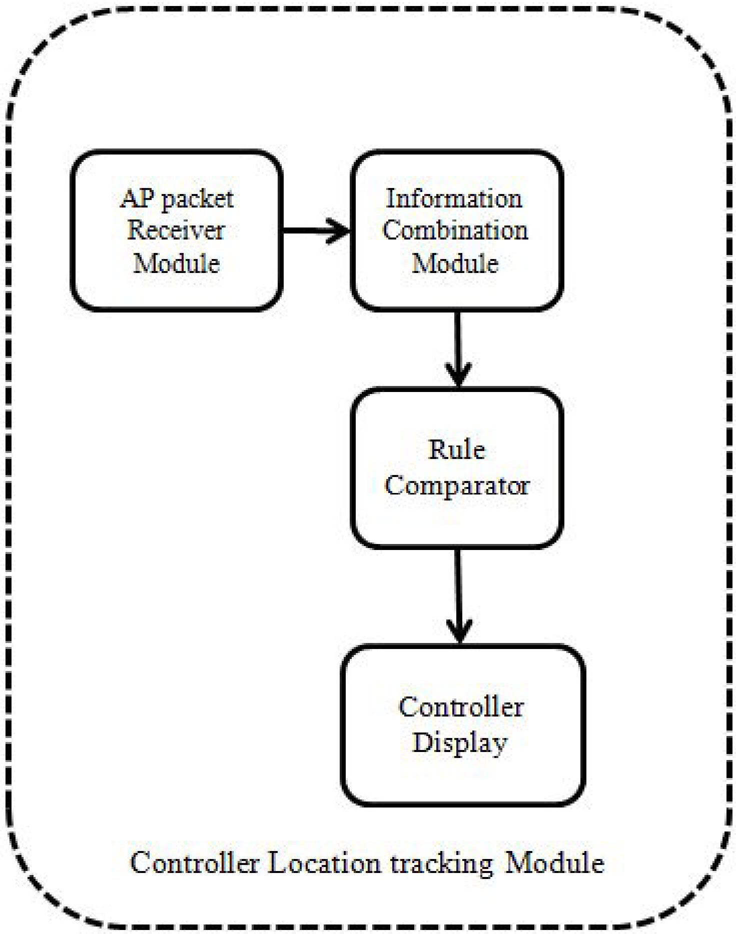


Figure 4.6: Central Controller Architecture

4.3.3Operation Phases of the System:

The System that has been developed is an anomaly based intrusion detection system, thus it operates in two phases. The two phases of operation are Training Phase and the Detection Phase. These phases are described below.

4.3.3.1 Training Phase:

The training phase of this architecture similar to the training of the previous architecture. The training happens in three stages. The first two stages of the system are the same. The training of the architecture varies in the third stage.

During the third stage of training, average Wflow signal strength and Wflow size is collected for each of the access points when the Wi-Fi device is operating at different locations in the network air space. This dataset is then used to train with the help of classification algorithms to obtain conditions that give location of the network device.

4.3.3. 2 Detection Phase:

The detection phase is the final operational phase of the system. In the detection phase, the rules that were learnt in Stage 2 of the training phase are used to detect the abnormal wireless traffic (wireless flows (Wflows)). In addition to detecting the abnormal Wflows, we also classify the type of attack and the location of the attacker.

For the attack location detection, each of the access points detects attacks independently. Each of the access points compares the values of the four metrics ($Wflow_1$, $Wflow_2$, $Wflow_3$, $Wflow_4$), with the ones that are obtained in the Stage 2 of the training to detect if an attack was performed on the network. Each access point then classifies the attacks that are happening over the network, by counting the different types of frames that are present in the anomalous wireless flow and associating the type of frame with the type of attack.

The access points that detect the attack activate their Communication Modules. In the Communication Module the average Wflow signal strength and the Wflow size is calculated and sent to the Central Controller. The Central Controller compares the received signal strength and

Wflow size from each of the access points with the conditional statements to track the location of the attackers.

4.4 Configurations of Operation of the proposed Architecture:

The proposed Architectures support 2 modes of operation. The system can operate with a single access point in the network(non distributed network) and with multiple access points in the network. The Figure 4.7 below describes these operational configurations.

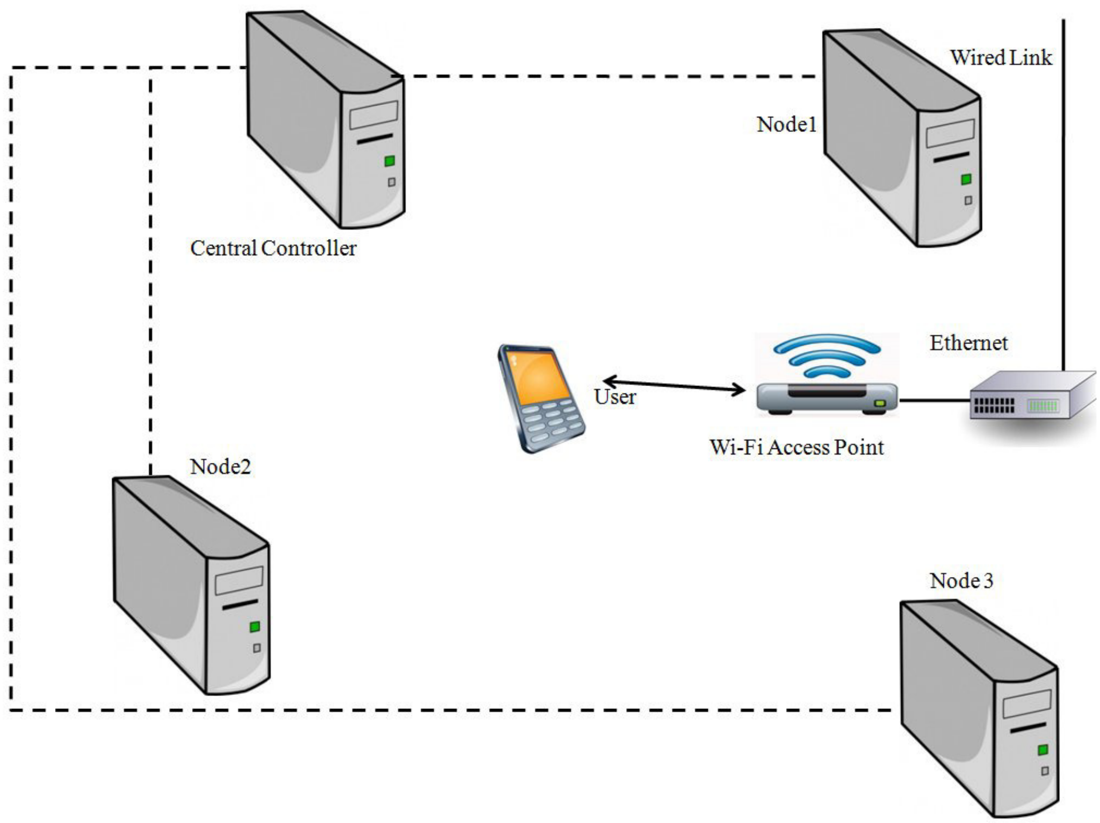


Figure 4.7: Mode1 Single Access Point

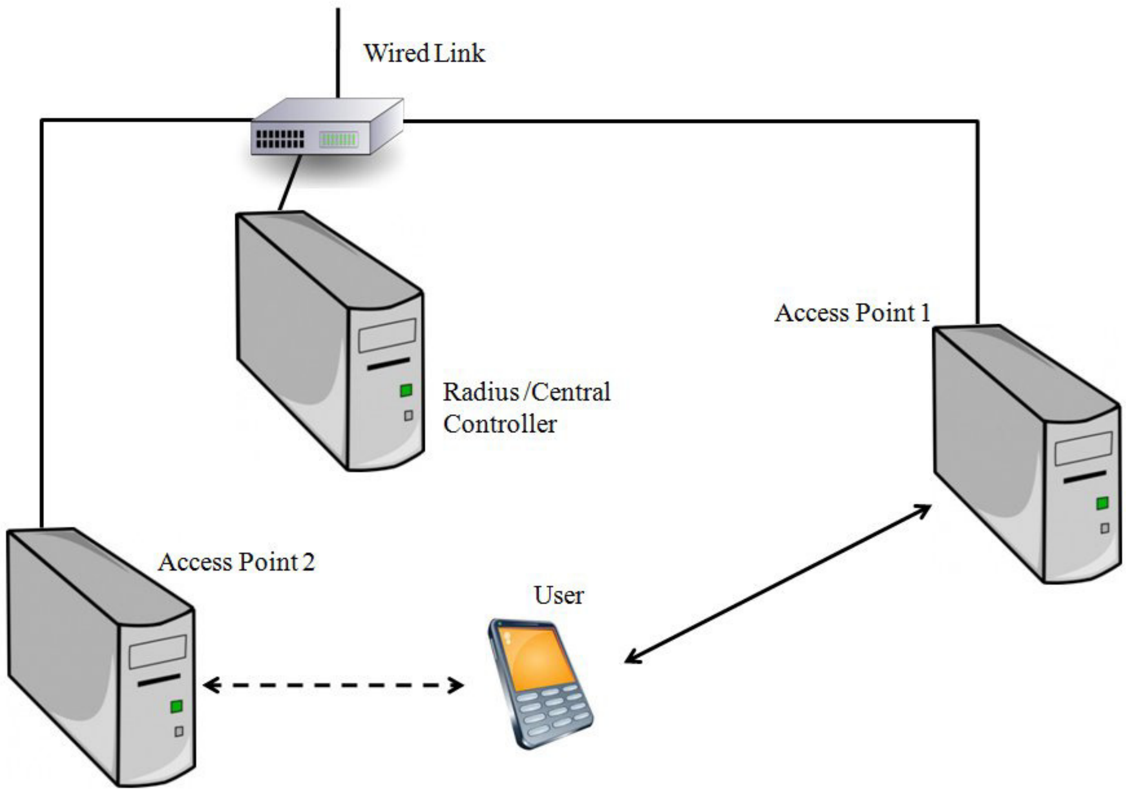


Figure 4.8: Mode 2 Distributed Wi-Fi Network.

CHAPTER 5: EXPERIMENTS AND RESULTS

5.1 Test Bed:

To test the performance of the above presented architectures a Wi-Fi test bed was built. The test bed that was thus built could operate as a single access point Wi-Fi network or a Distributed Wi-Fi Network. The general overview diagrams of the test bed are as shown below:

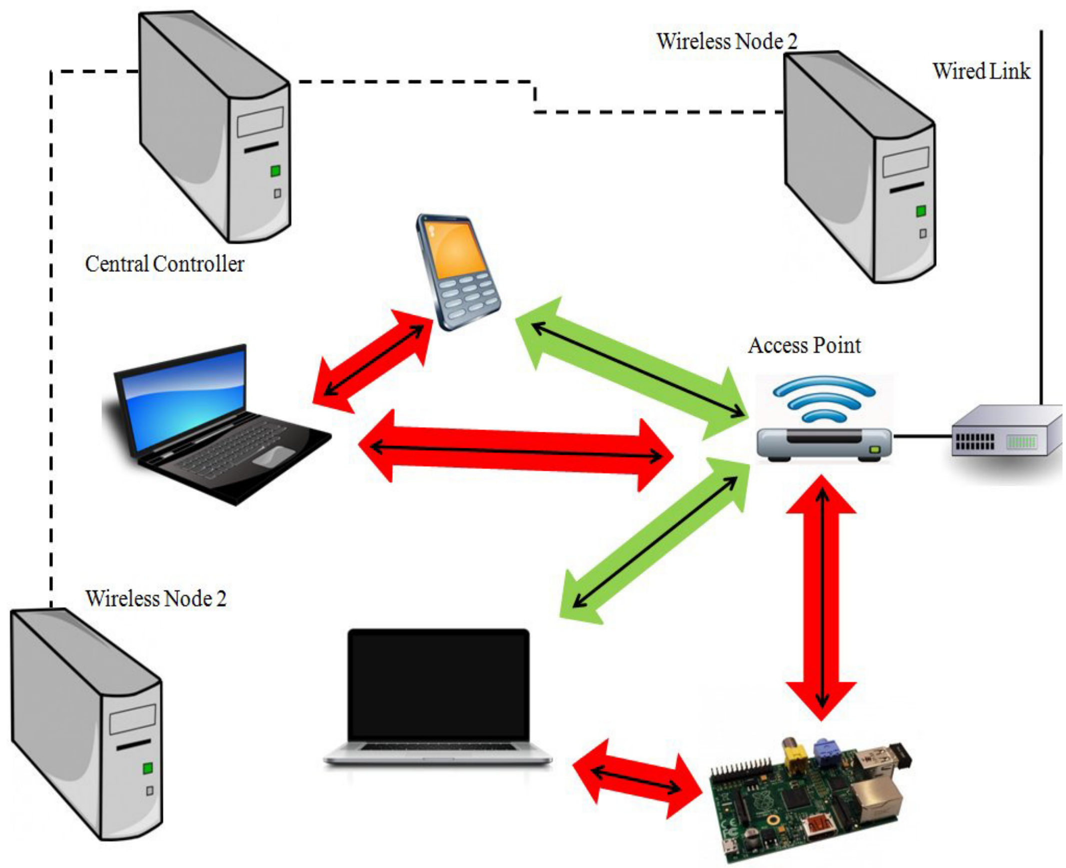


Figure 5.1: Test Bed(Single Access Point)

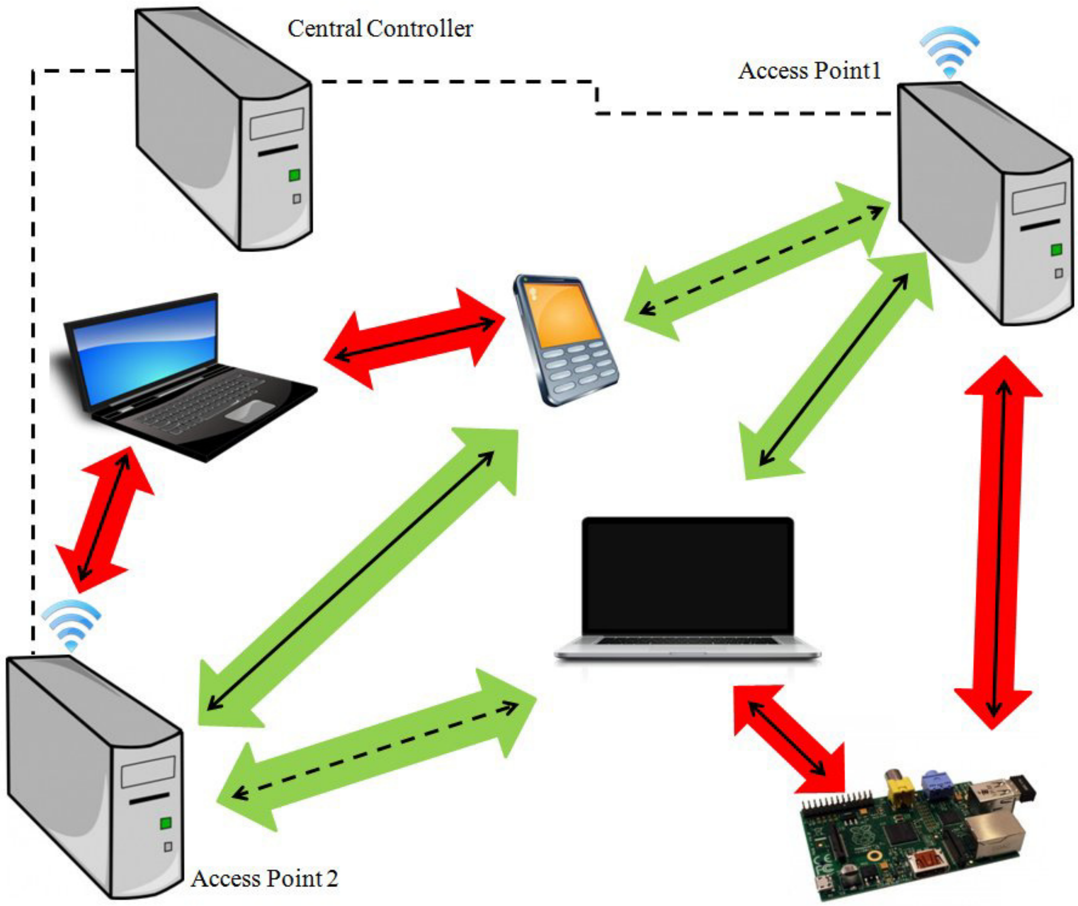


Figure 5.2: Test Bed (Distributed Access Point)

A Single access point test bed was built by the use of four Linux machine acting as the network infrastructure. The system was setup similar to the picture depicted in the Figure 5.1 above. The access point was built using hostapd[62]which is a user space daemon that allows setting up of Wi-Fi access points and radius servers. The access point was built using a Qualcomm Atheros AR5212/AR5213 Wireless Network Adapter. The Access point was configured to operate in the 6th Channel and supports 802.11b/g communication. The access point that was setup as a part of this test bed was an Open access Point. The Figure 5.3 of the NIC used is shown below,

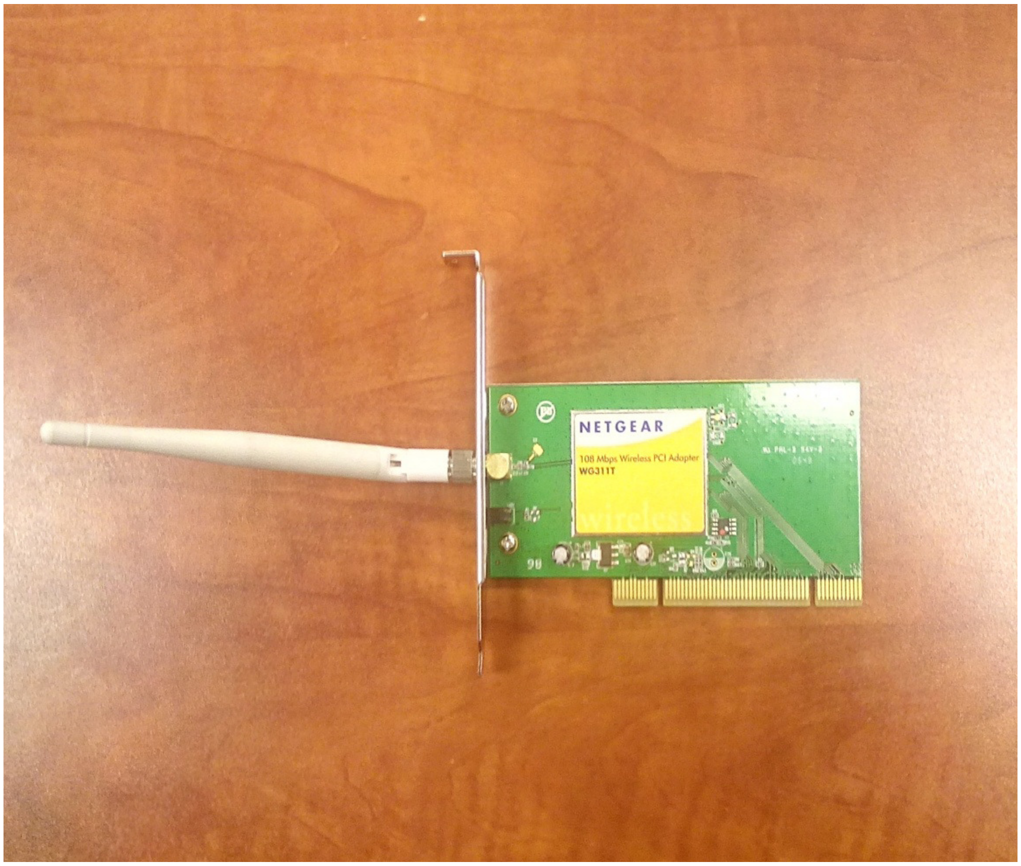


Figure 5.3: NIC

This testbed also contained two monitor nodes and a Central Controller. The monitor nodes were also built using Linux machines, with Qualcomm Atheros AR5212/AR5213 Wireless Network Adapters. Also each of the monitor nodes are connected to a wired network via an Ethernet Physical Interface. The Central Controller is also a Linux machine that is connect to the external network and the local wired network shared with the monitor nodes by the use of a TP-Link TLSG 1008D Giga bit switch as shown in the Figure 5.4 below.

Figure 5.4: TP Link TLSG 1008D Switch

5.1.2 Distributed Access Point Test Bed:

A Distributed Access Point Test bed was built to test the performance of the proposed architectures in the Distributed Environment. The Test bed consisted of 3 Linux machines of which two of the machines act as the access points. The access points were configured using the hostapd[62]. Each of the access points uses a Qualcomm Atheros AR5212/AR5213 Wireless Network Adapter for the Wi-Fi network. They use an Ethernet network to connect to the Radius Server/Central Controller. In each of the access points the Wi-Fi adapter and the Ethernet adapter are bridged together using a virtual bridge. Also each of the access points have the previously declared architectures running on the network using a virtual Wi-Fi interface. The access points that have thus been setup support 802.11 b/g communications over a WPA2-EnterpriseWi-Fi network. The Radius server that handles the authentication and pre authentication of the user devices to the network is connected to the local network by Ethernet by a TP Link TLSg 1008D Giga bit switch.

5.1.3 User Devices:

The Test bed has many user devices connected to it. The set of user devices connected to the network include a Samsung Galaxy SDuos2 Smart phone, multiple Linux based computers and a T61 Think pad using Ralink Tech Corp. RT-5370 Wi-Fi dongle. The Power tracking training for the above mentioned systems was done for this Lenovo T61 Think pad.

Figure 5.5: Devices using the network.

5.1.4 Attack Devices:

A multiple attack devices have been employed as a part of this test bed. This includes two Linux Desktop, T61 Think pad laptop and a Raspberry Pi. The Linux Desktops are equipped with Qualcomm Atheros AR5212/AR5213 Wireless Network Adapters, while the T61 is equipped with Intel PRO/Wireless 3945ABG Wireless Network card and the Raspberry Pi had Tp Link T WN-722N Wi-Fi dongle connected to it. The Raspberry Pi’s use the Raspbian which is a Debian Linux based operating system.

Figure 5.6: Attacking Device

5.1.5 RADIUS SERVER/CENTRAL CONTROLLER:

In the distributed Wi-Fi network a Linux machine acts as the RADIUS server. The RADIUS server uses FreeRADIUS to support authentication of the Wi-Fi users. The Radius Server is connected to the access points and the Internet through Ethernet. In case of the single access point network, the RADIUS server is present on the access point, while the Central Controller is a Linux desktop which is connected to the controller nodes and the internet through Ethernet.

5.2 Attacks:

The proposed architectures were tested against multiple attacks. Aircrack-ng was the know attack library that was used to test the system.

5.2.1 Aircrack-ng:

Aircrack-ng is an advanced Wi-Fi attack library that was used as a part of this testing process. The Aircrack-ng attack library can perform a number of attacks on the Wi-Fi network. Some of the attacks that can be performed include WEP and WPA-PSK key cracking. Some the other attacks that can be performed by the attack library include Caffe Latte attack, De-Authentication attack, Fake Authentication attack, Injection Flooding attack. The attack library can also be used to spoof handmade Wi-Fi frames over the network.

5.2.2 Modified Attack:

As a part of this test procedure to prove that our approach can detect modified and zero day attacks, we created a small Wi-Fi attack library that could perform a modified De-authentication attack which could be varied dynamically in the number of frames sent over the network, the rates at which frames are sent over the network. This attack was also modified a bit to allow the attackers to perform a Man in the Middle attack. The Library was built for Linux based operating system supporting Little Endean machines. The low level networking library Libpcap was used to develop this attack library.

5.3 Experimentation of the Attack detection and Classification System:

Both of the presented architectures have similar approach for attack detection and classification. Hence the experimentation and the training for the attack detection and classification systems was done together.

5.3.1 Single Access point Test Bed:

These experiments were performed with a single access point in the network. Hence the testbed looked similar to the diagram in Figure 5.1.These experiments were performed in this configuration as the aim was to test the performance of the detection and the classification system under worst conditions of operation.

5.3.1.1 Training:

The training of the system was done at the Autonomic Computing Lab(ACL) at the University of Arizona by monitoring the traffic on the channel 1. The traffic was supervised to ensure that no know attack would slip through the training traffic when the system was training for normal behavior of the network.

For sampling of the signal, we have experimented with two time windows: 10 and 2 seconds. During the tests it was observed that the system with a time window of 10 seconds performs better than the system that has a time window of 2 seconds. The reasons could be attributed to the fact that most of the processes that are a part of the Wi-Fi protocol occur in less than 10 seconds. Also the 10 second time window allows the system to detect attacks that are slow and affect over a period of time. The training to understand the normal behavior of the Wi-Fi protocol tool place for 1.5 weeks, in which the IDS was extensively trained to gain a complete understanding of the normal behavior of the protocol. The IDS was trained for 1 day on know attack traffic to gain partial knowledge of the attack traffic. Conjunctive Rule algorithm which is a classification based machine learning algorithm was used to obtain the conditional rules that classified the events in the protocol or the state changes of the Wi-Fi protocol as normal or abnormal. The rules obtained are presented in the Table 5.1 below.

TABLE 5.1: Intrusion Detection System Rules

Flowscore	Condition
1. Flowscore 1 (FS1)	Flowscore1 should be less than 97(**FS1<97**)
2.Flowscore 2 (FS2)	Flowscore2 should be greater than 279732 **(FS2 > 279732)**
3.Flowscore 3 (FS3)	Flowscore3 should be greater than 1020. **(FS3>1020)**
4. Flowscore 4 (FS4)	For the current environment, the abnormal condition is independent of flowscore4. **(FS4=NA)**

5.3.1.2 Detection Evaluation:

Multiple wireless attacks were performed on the distributed Wi-Fi network. Some of the attacks were performed using the aircrack-ng attack library. Some modified attacks were also performed on the network. The attacks in the aircrack-ng attack library include flooding attacks of management frames and denial of service attacks. The modified attacks developed include the modified de-authentication attacks. A complete list of the attacks that are used to evaluate our approach is shown in Table 5.2. We have evaluated our approach by conducting the following five experiments:

TABLE 5.2: Wireless Attacks

Attack Type	Description
1.De-Authentication Attack	This attack involves the flooding of the target with De-Authentication frames.
2.Fake Authentication	This attack involves fake authenticating to an access point.
3. Minimal De-Authentication	This attack is performed to De-Authenticate a user from a network with just 15 frames.
4. Disassociation Attack	This attack involves sending a Disassociation frame to both the access point and the target.
5. Man in the middle Attack	This attack results in a man in the middle on the Layer two of the network.

5.3.1.2.1 Experiment 1:

This experiment is designed to evaluate the percentage rise in the number of false positives given by the system due to the increase in the frame drop rate due to interference and wireless channel related issues when the network is not under attack.

To ensure frame dropping due to interference and wireless channel issues, small modules that enabled dropping of frames at random were inserted in the sniffer module. In these inserted modules the frame drop rate could be increased or decreased as per the users choice. During this experiment, the frame drop rate was increased from 1% frame drop rate to frame drop rates as high as 96%. At frame drop rates as high as 96% the Wi-Fi network is virtually non existent.

The result of this experiment was that no false positives were observed even at very high drop rates of 95-100%. Essentially at these high drop rates a network can be considered useless. But even at these high drop rates the percentage of false positives observed was 0%.

5.3.1.2.2 Experiment 2:

This experiment has been designed to detect the percentage rise in the number of false positives given by the system as the frame drop rate of the system increases when the system is under attack. The increase in the frame drop rate could be a result of interference and other channel noises. To simulate this interference, the received frames were randomly dropped by the packet sniffer unit. The percentage of the frames dropped was increased gradually over a period of time. It was observed that the intrusion detection system gives zero false positives till the frame drop percentage reaches 80%. Then there is a steady increase in the false positives till the system stops performing at 93% frame drop rate. The results of this experiment are presented as a graph in the Figure 5.7 below. Thus this experiment shows that the system performs exceptionally well even in an environment of high atmospheric and network interference.

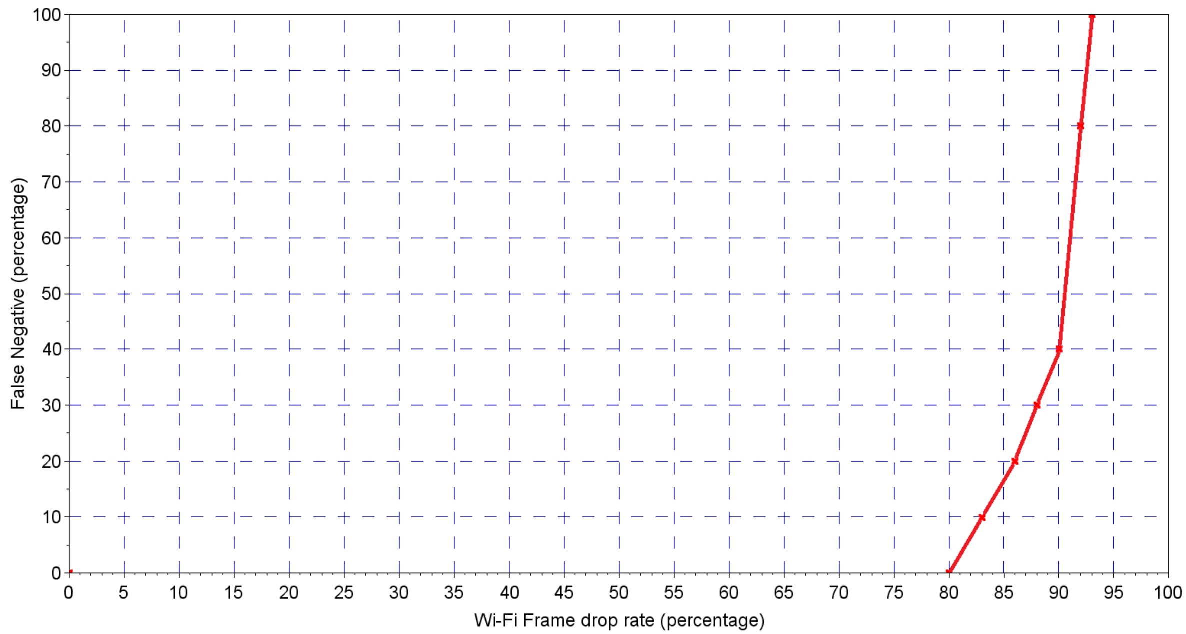


Figure 5.7. False Negative versus Frame drop rate.

5.3.1.2.3 Experiment 3:

This experiment has been designed to detect the ability of the system to detect new or modified attacks on the distributed Wi-Fi network. Modified De-Authentication attack and man-in-the-middle attack were launched several times against the network. Our detection algorithm was able to detect and classify both attacks successfully every time. The system was observed to classify two modified De-Authentication attacks on the access point and the same user, as one single attack if both the attacks were performed under 10 seconds (Wflow window size).

5.3.1.2.4Experiment 4:

It has been designed to demonstrate how each of the four Wireless flowscore values for the attacks listed in Table 5.2differ from the normal **WFlow** values (obtained during training) by a large margin. This large margin enables us to detect attacks accurately with low false alarms. Also this high sensitivity of our detection algorithm to the Wireless traffic can justify the results of Experiment 2 shown in Figure 5.7, where it is observed that the detection algorithm works even when the frame drop rate is as high as 80%.Table 5.3shows the rules used to detect anomalous behavior due to Wi-Fi network attacks.

TABLE 5.3: Intrusion Detection System Rules

Flowscore	Condition
1. Flowscore 1 (FS1)	Flowscore1 should be less than 97(**FS1<97**)
2.Flowscore 2 (FS2)	Flowscore2 should be greater than 279732 **(FS2 > 279732)**
3.Flowscore 3 (FS3)	Flowscore3 should be greater than 1020. **(FS3>1020)**
4. Flowscore 4 (FS4)	For the current environment, the abnormal condition is independent of flowscore4. **(FS4=NA)**

The results of the experiment are shown in Figure5.8. It also highlights the minimum difference between the condition for the anomalous behavior and the normal flowscore values.

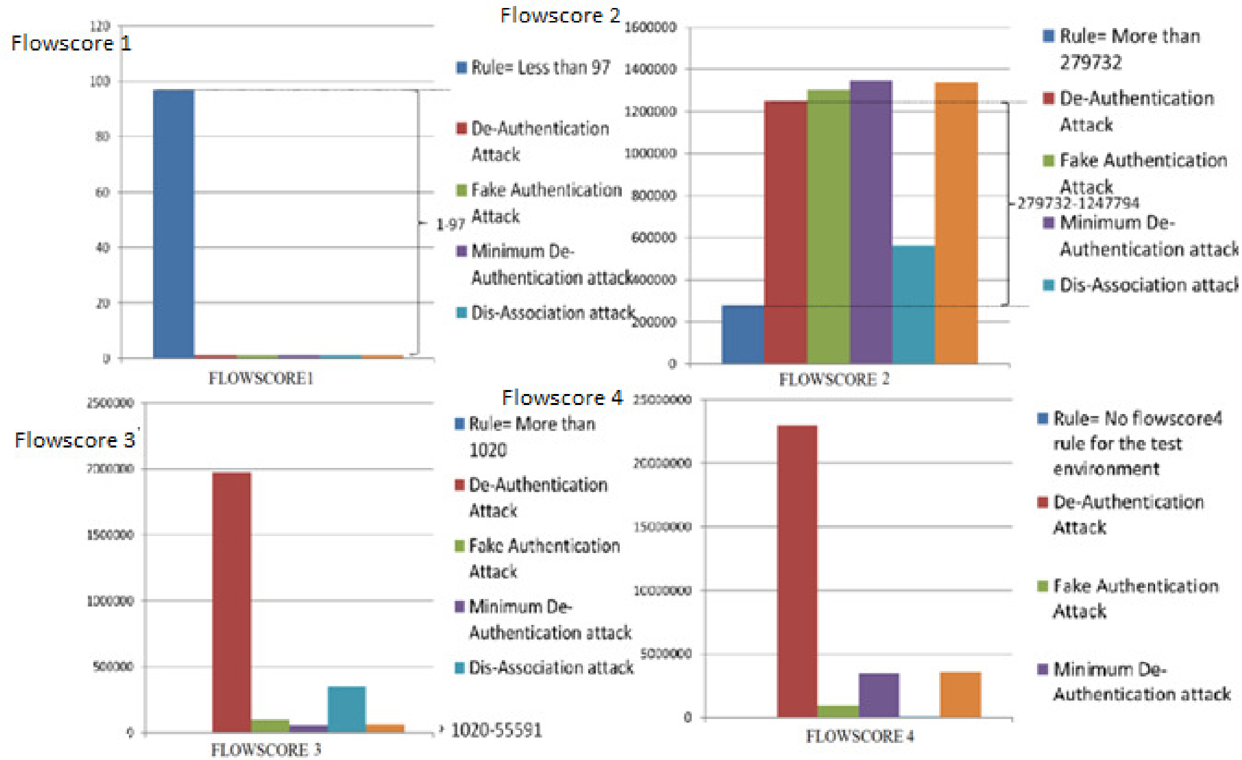


Figure 5.8. Flowscore value to rule comparison.

5.3.1.2.5 Experiment 5:

This experiment has been designed to evaluate the accuracy of attack classification algorithm as the frame drop rate increases. The increase in frame drop rate is due to the nature of the wireless physical layer being prone to error, interference and noise. Thus this experiment helps in identifying the maximum threshold beyond which the algorithm cannot effectively classify the attacks.

It is observed that the algorithm can classify all the attacks correctly at all times till the frame drop rate is as high as 66%. After that, we observe a steady decline in the algorithm ability to classify attack accurately as shown in Figure5.9.

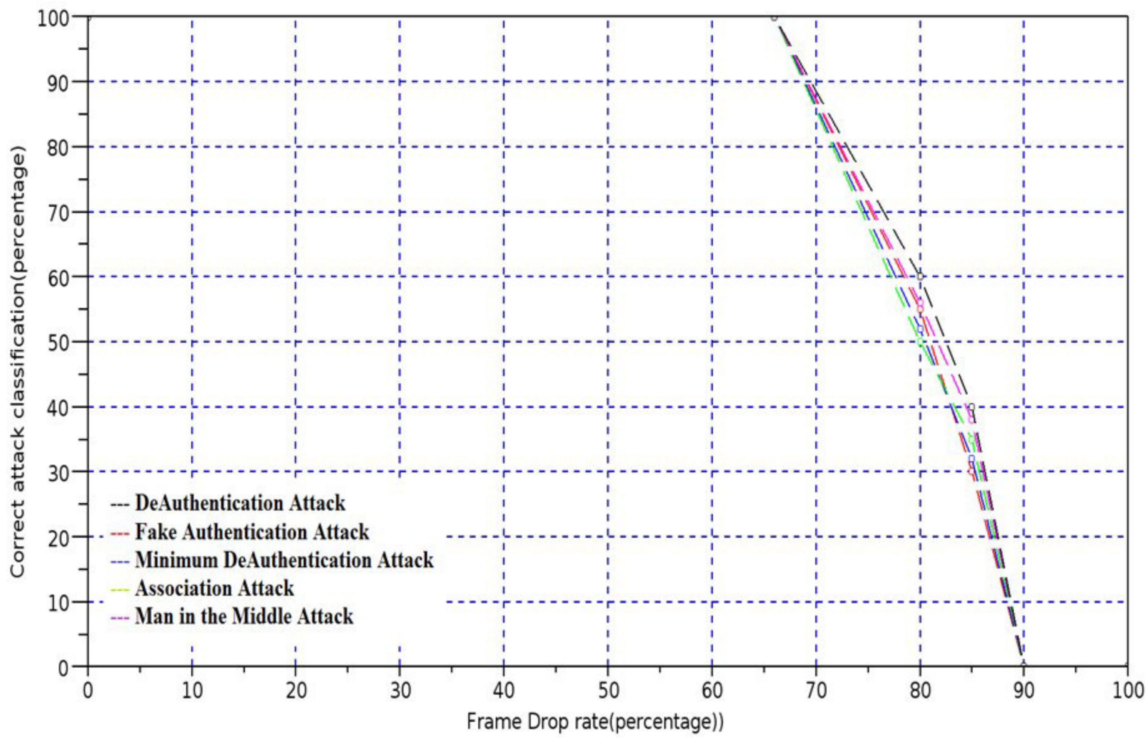


Figure 5.9: Correct Attack Classification(percentage) versus Frame drop rate.

5.3.2 Distributed Access point Test Bed:

The following experiments were performed on the Detection and the Classification Module in the Distributed Access point Test bed.

5.3.2.1 Training:

The Intrusion Detection System was trained in the Autonomic Computing Lab (ACL) at the University of Arizona. The system was trained on the first channel of the Wi-Fi network. In the previous experimentation for the Single access point testbed it was observed that a 10 second time window allowed the IDS to detect fast and slow moving attacks with high efficiency hence as a part of this training a 10 second time window was chosen depending on the previous experience.

The training to understand the normal behavior of the distributed Wi-Fi network lasted for 2 weeks. In this period of two weeks the IDS gained complete understanding of the normal behavior operation of the distributed Wi-Fi network. While the IDS was trained for 2 days to understand the behavior of the system when under attack. A Conjunctive Rule classification algorithm was used to train to for the conditions of normal and abnormal behavior of the Distributed Wi-Fi network. The rules thus obtained are in the Table 5.4 below.

TABLE 5.4: Intrusion Detection System Rules

Wireless Flowscore	Condition
1. Flowscore 1 (FS1)	Flowscore1 should be less than and equal to 1881**(FS1<1881)**
2.Flowscore 2 (FS2)	Flowscore2 should be greater than 591472**(FS2 >591472)**
3.Flowscore 3 (FS3)	For the current environment, the abnormal condition is independent**(FS3==NA)**
4. Flowscore 4 (FS4)	Flowscore4 should be greater than 505. **(FS4>505)**

5.3.2.2 Detection Evaluation:

The detection and the classification algorithm was tested on the Distributed Access point testbed. The Wireless flowscore values for the normal behavior of a distributed Wi-Fi network are presented in the Table 5.4.

The difference in the values of the normal wireless flowscore values and the attack flowscore values are shown in the Figure 5.9 below which shows that there is a huge margin between the wireless flowscore values of the rules and the values of the wireless flowscores observed when attacks are performed. Showing that the approach can easily detect attacks on a distributed Wi-Fi network.

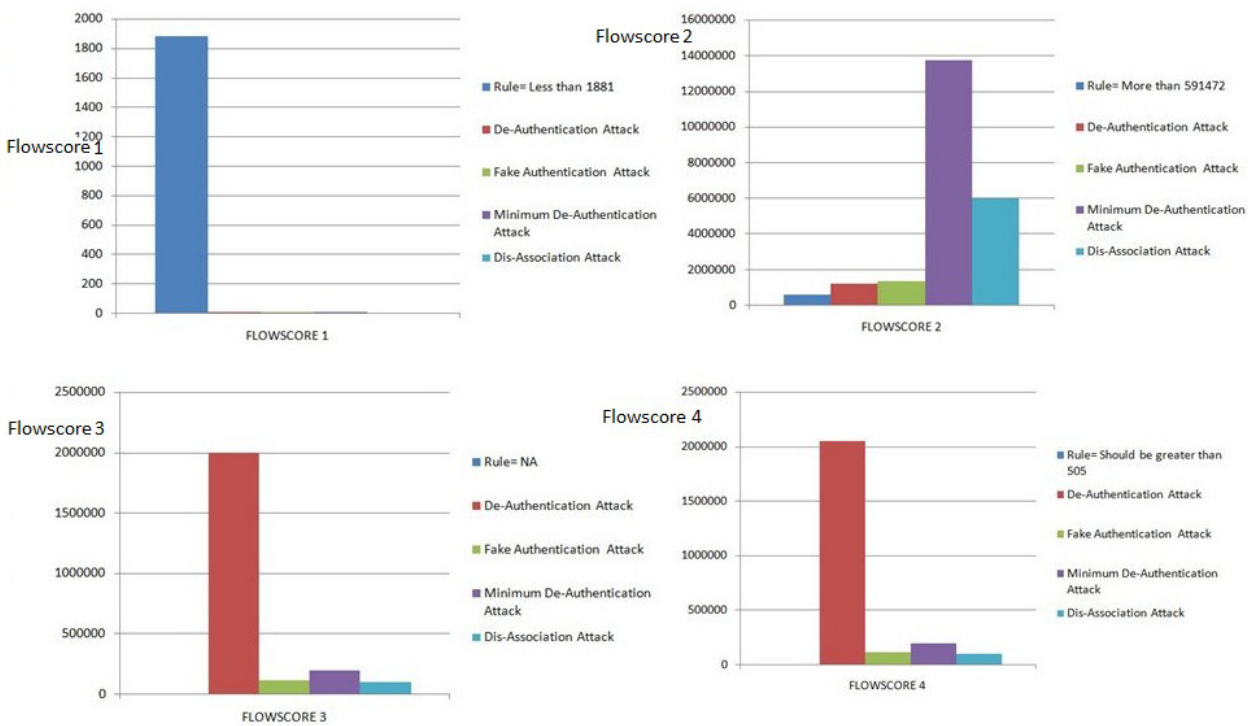


Figure 5.10: Flowscore value to rule comparison

5.4 Experimentation of the Power tracking System:

Two different approaches to track the locations were presented as two different architectures in this thesis. Both the architectures perform similarly on the Single access point testbed and the Distributed access point test bed respectively. That is, the first architecture has same results on the Single access point test bed and the Distributed access point test bed. Hence each of the architectures required only one training.

5.4.1 Power tracking Module of Architecture 1:

This Architecture as stated previously uses a clustering approach to track the location of the attack by the use of power maps. Where in each of the individual nodes/ access points provided with a location. Moreover the Central Controller also had a combined power map which was used by the Central Controller to give location of the attacker.

5.4.1.1 Training:

The training for the power tracking system for the Architecture 1 was performed in the Autonomic Computing Lab (ACL) at the University of Arizona. The power mapping was performed with the client device (T61 Think pad) using a Ralink Tech Corp RT-5370 wireless network card. The lab was divided into 8 small sectors and the signal strength for each of the sectors was measured by both the nodes/access points. The signal strengths were then used to create power maps that helped in clustering the location of the attacker. The combined power map that was obtained as a part of this training is shown in the Figure 5.10 below.

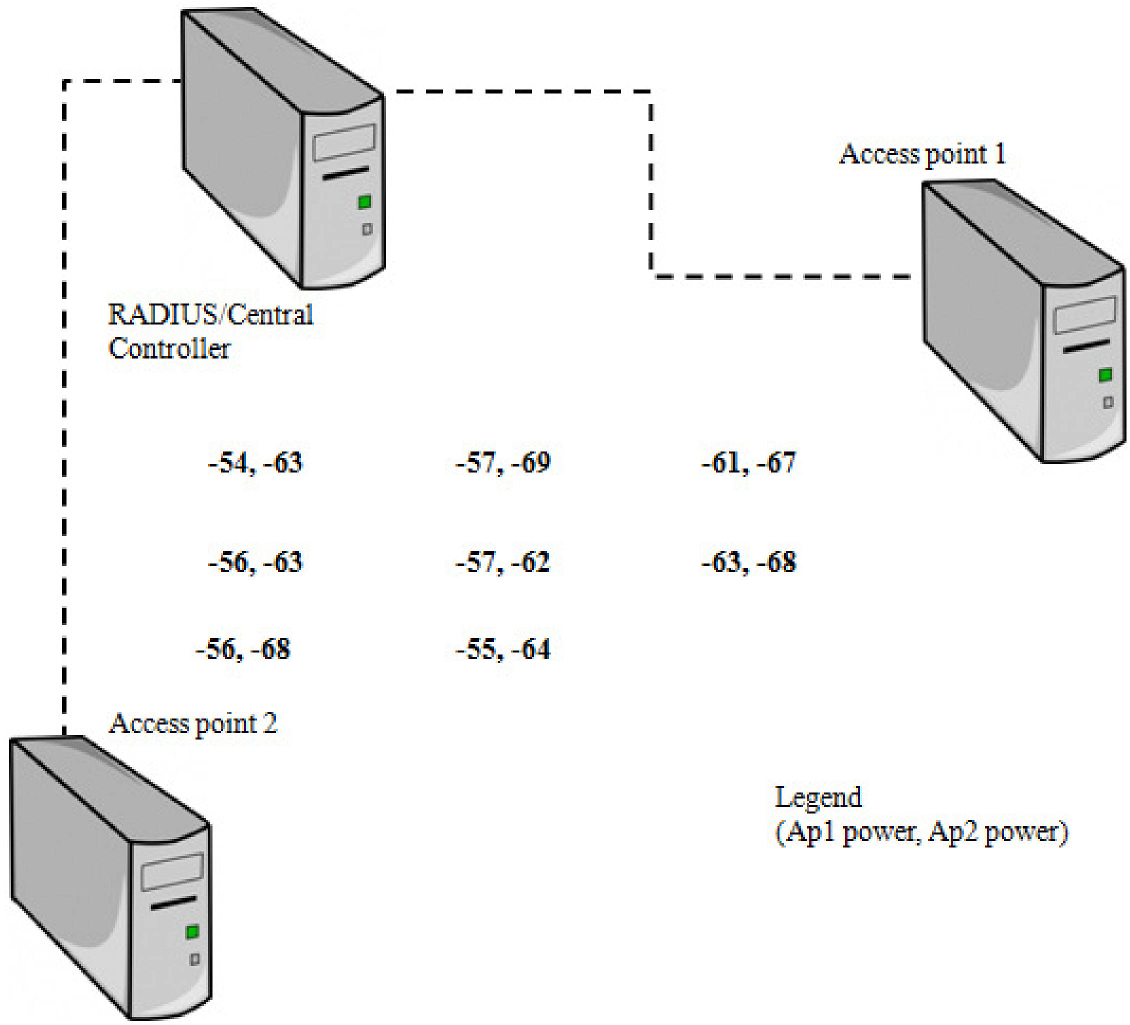


Figure 5.11: Central Controller Combined Power Map

5.4.1.2 Detection Evaluation:

The Power-tracking module for this architecture was evaluated by attacking the Wi-Fi network (on both the test beds) with multiple attacks. Then the locations provided by the architecture were observed. The attacks listed in Table 5.5 below were used as a part of this experiment. It was observed that the locations given by the individual access points were accurate 70% of the time while the locations given by the Central Controller were accurate 81% of the time. Also it was observed that this approach worked particularly well when the operating environment was static, and the performance degraded rapidly once the environment was changed.

TABLE 5.5: Wireless Attacks used for Power tracking module Evaluation

Attack Type	Description
1.De-Authentication Attack	This attack involves the flooding of the target with De-Authentication frames.
2. Minimal De-Authentication	This attack is performed to De-Authenticate a user from a network with just 15 frames.

5.4.2 Power tracking Module of Architecture 2:

This power tracking architecture as stated previously uses a classification algorithm. Wherein each of the access point/ node sends packets that contain wirelessflow average power and the Wflow size. The central Controllers compares the values received from each of the access points/nodes with the classification rules learnt in the training phase to conclude on the location of the attacker.

5.4.2.1 Training:

The training for this system was performed in the Autonomic Computing Lab(ACL lab). As part of this training, average power and wflow size was collected at various different locations in the lab. This training data was then trained on by the use of WEKA. Bagging algorithm which is a classification algorithm was used. The tree containing the rules of the algorithm is presented below.

```
power2 < 55.5
|   power2 < 33.5 : 0
|   power2 >= 33.5
|   |   power2 < 51.5
|   |   |   power2 < 38.5
|   |   |   |   power1 < 38 : 0.2
|   |   |   |   power1 >= 38 : 1
|   |   |   power2 >= 38.5
|   |   |   |   power2 < 47.5 : 0.92
|   |   |   |   power2 >= 47.5
|   |   |   |   |   power2 < 48.5 : 0.56
|   |   |   |   |   power2 >= 48.5
|   |   |   |   |   |   power1 < 41.5 : 0.83
|   |   |   |   |   |   power1 >= 41.5 : 1
|   |   power2 >= 51.5
|   |   |   power1 < 39.5
|   |   |   |   power2 < 52.5 : 0.33
|   |   |   |   power2 >= 52.5 : 1
|   |   |   power1 >= 39.5 : 0.2
power2 >= 55.5 : 0.04

Size of the tree : 21
```

Figure 5.12: Rules

5.4.2.2 Detection Evaluation:

The system was tested on both the testbeds. Multiple attacks were executed on the networks. The list of attacks that were used are listed below. The system was found to detect location of the attacks 76% of the time. But it was observed that the system was resilient to changes in the operating environment.

TABLE 5.5: Wireless Attacks used for Power tracking module Evaluation

Attack Type	Description
1.De-Authentication Attack	This attack involves the flooding of the target with De-Authentication frames.
2. Minimal De-Authentication	This attack is performed to De-Authenticate a user from a network with just 15 frames.

CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1 Conclusion:

In this thesis we reviewed the concepts of machine learning, Intrusion detection system Taxonomies and the IEEE 802.11 protocol. We discussed the protocol in depth and also discussed the security issues associated with the protocol. Moreover the thesis presented two architectures of Intrusion Detection Systems for Single access point Wi-Fi Networks as well as Distributed Wi-Fi Networks.

The proposed architectures use supervised learning to gain information of the normal operation of the system. They also train with some known attacks to get a better understanding of the event space. The presented approach detects attack with no false positives and no false negatives. The attack was tested to detect not only the known attacks but also modified and zero day attacks. The architectures use classification algorithms to classify if the attack is normal or abnormal.

The architectures also have location tracking modules that are able to track the location of the attacker, once the attack is executed. In case of the first architecture, the location tracking module uses a clustering approach to obtain the location of the attacker. This architecture is able to obtain the location at each of the access points / nodes in the network or at the Central Controller/Radius. In case of the second architecture, the location tracking module uses a classification algorithm to obtain the location of the attack at the Central Controller/ Radius Server. The differences between the approaches being that the 1starchitecture operates with 70% efficiency at each of the nodes/access points while the Central Controller/ Radius Server operates with 81% efficiency while the 2nd architecture has an efficiency of 76%. Moreover the first architecture is highly effective in a static environment, while the second architecture is effective in a changing environment. It was also observed that it is easier to add or remove access points/ nodes to the first architecture while the second architecture requires massive amount of retraining in case of modification to the number of nodes or access point in the network.

6.2 Future Work:

This work can be further expanded to include unsupervised machine learning making the system truly autonomous. Future work can address the following issues:

- Development of testing the approaches in different operating environments that cover large geographic areas and highly cluttered environments.
- Extend the research to cover outdoor Wi-Fi networks.
- Extend the existing architectures to allow their operations in dynamically changing environments.
- The current experimentation of the location tracking module was performed in a small room with little distance separating the multiple access points or wireless nodes. This results in not much variation in the signal strength as the user device moves around the operational cell. Hence experimentation needs to be performed with larger cell sizes. It is believed that a larger cell size will increase the signal strength variation as the user moves around the cell, thus increasing the accuracy of the location tracking algorithms.

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