A Network Security Solution to Manage and Increase Effectiveness of Servers

by

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Abstract

In today's digital landscape, the proliferation of cyber threats, particularly Denial-of-Service (DoS) attacks, underscores the critical need for advanced server monitoring systems. Traditional monitoring tools, while prevalent, often lack the adaptability and proactive capabilities required to address these evolving threats effectively. This thesis introduces the Adaptive Monitoring System (AMS), an innovative solution designed to enhance network security and operational efficiency. Developed using Python and API scripting, AMS integrates with existing protocols such as Simple Network Management Protocol (SNMP), SSH, and Syslog to offer comprehensive real-time monitoring and automatic system adjustments.

The primary goal of the AMS is to improve network monitoring through the automation of server configuration changes in response to detected anomalies. The system's effectiveness is demonstrated across various attack scenarios, including TCP SYN flood, UDP, ICMP, and HTTP attacks. The results indicate that the AMS not only effectively identifies and mitigates DoS attacks but also exhibits significant scalability and robustness as the attack intensity increases. One of the system’s standout features is its automatic reconfiguration capability, which allows it to restore normal operations autonomously, reducing the administrative burden and enhancing network reliability.

Additionally, the AMS is equipped to generate timely alerts and notifications, enabling system administrators to take pre-emptive actions to mitigate potential impacts to system performance. This thesis details how the AMS addresses the challenges of contemporary server monitoring and provides a robust defence against network intrusions, thereby contributing to the field of cybersecurity.

KEY WORDS: Adaptive Monitoring System (AMS), Simple Network Management Protocol (SNMP), DoS Attacks, Key Performance Indicators, TCP SYN Flood, UDP Attack, ICMP Attack, HTTP Attacks.

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Glossary

API Application Programming Interface

AMS Adaptive Monitoring System

CPU Central Processing Unit

DoS Denial-of-Service

HTTP Hypertext Transfer Protocol

ICMP Internet Control Message Protocol

SDN Software-Defined Networking

SNMP Simple Network Management Protocol

TCP Transmission Control Protocol

UDP User Datagram Protocol

1 INTRODUCTION

1.1 Introduction to the monitoring system

Nowadays, nearly all networks are potentially vulnerable to network intrusions or interruptions despite security measures. In practice, it is impractical to build a completely secure system [1]. Various factors can cause damage to a network system but a significant factor is a system attack. It is undeniable that the most challenging defence is protection from a Denial-of-Service attack (DoS) [2]. A Denial-of-Service attack is a cyberattack that disrupts the service of the host connected to a network, making it unavailable to the users for a temporary period or indefinitely [3]. This type of attack attempts to make computer resources or network systems unable to serve users. The attack is accomplished by flooding it with traffic or triggering a crash with a target to attack legitimate users or high-profile organisations such as banking, government, or trade organisations. Though the attack might not result in the loss of significant information or assets, it still costs time and money to handle. Therefore, it is necessary to have a variety of devices and software on the market to monitor network systems so then they can work properly.

Network monitoring is used as a logging and analysis tool to determine the traffic, utilisation, and indication of the network, which helps users know precisely what is happening, where is it happening, and any adjustments that might be needed to the system. Therefore, the tool has enormous importance as it is used as a health check-up for the network to diagnose and troubleshoot any problems that may occur. Network monitoring is an important task for a system or network administrator to continuously observe the process of a server and network's topology and to avoid critical consequences such as network downtime, system failure, data loss, etc [4]. In the case of a system malfunction, the network monitoring immediately notifies via email, SMS, or other notifications the network or system administrator when problems occur. Examining network monitoring includes parameters such as network traffic, processor, memory usage, and application performance. Server monitoring consists of monitoring the operating system, CPU, memory, disk, power utilisation, etc [5]. Network monitoring systems generally work with the protocol ICMP. These systems regularly monitor the state of an element. The systems can regularly check the status of network devices and check whether the system is available or unavailable. Moreover, monitoring systems typically work with more protocols like the Simple Network Management Protocol (SNMP), SSH, and Syslog. They are

generally supported by many network devices and get information from network devices on the state of services, disk, memory utilisation, and so on [6]. To overcome problems, there have been several suggestions for a new, secure, and possibly closed system using encryption techniques but in terms of feasibility, this system might not work depending on the investment and existing infrastructure of an open data network [7,8,9]. Nowadays, many proposed network monitoring products are available on the market, both open-source tools and commercial software. Open-source tools include many options like Zabbix, Nagios, Cacti, etc while commercial products typically offer comprehensive features but require the paying of licenses every year. More often than not, the open-source software license costs are zero. Zabbix is the most common tool for monitoring and is designed to support almost all distributions of Linux. Without the installation of agents, it can monitor standard SMTP, HTTP, ICMP services, and Syslog. It is a lightweight program that offers an excellent method to monitor and analyse patterns using real-time graphics. Many other plugins can be used along with the tool and API scripts. Since the study of network monitoring is important and rapidly growing as an area of interest, this study aimed to enhance the network monitoring system with the development of new algorithms specifically. In particular, a new algorithm that will analyse traffic and combine events in order to detect anomalies within a network system. That is, to detect unusual patterns within the system and network utilisation. To address this issue, the research proposes a new algorithm that is developed from the Python Programming Language and API script that can be dynamically customised and sent back to change or reconfigure the device parameters in the network system automatically to recover to a normal state. Besides, this research's challenge is to monitor and detect attacks characterised by an indeterminate attack, rapidly increasing traffic volume. Typically, it’s always too late to know that the system has been attacked and the system could not provide any service. A suitable detection system can distinguish between normal and attack traffic and improve the speed of detecting attacks for a while.

1.1.1 Network and Server Monitoring

In a modern business world environment that relies on technological tools, it is important to have good, reliable, and competent networks for all business owners. Network monitoring is a method used to monitor the state of the computer network and security system, alerting the network administrators in case of any interruptions. Diagnosing and reporting any problems that would lead to a malfunction or irregularity in the network system is critical. It is also possible to monitor the performance and utilisation of a network [4]. A Network

Monitoring System is an essential tool with a critical function that offers benefits for network and system administrators at all times [10]. It is used for observing, monitoring problems, reporting problems, and improving the network performance of network and security systems. The process of monitoring the server's system resources like CPU usage, bandwidth consumption, network, disk, memory utilisation, power consumption, SNMP and Syslog etc. is known as server monitoring.

1.1.2 Simple Network Management Protocol (SNMP)

Networks consist of many different types of device that allow them to operate smoothly but sometimes they do not run as they should. There are protocols that existed to support network management. One of them is the Simple Network Management Protocol (SNMP). It's easy, simple, and is used as a standard protocol for collecting and creating information about managed network devices on IP networks and modifying that information to change device management [11]. Devices that typically support SNMP include switches, routers, firewalls, servers, workstations, and more [12]. SNMP is regularly used for network monitoring and network management. In general, SNMP is used to manage a large number of computer systems, which can monitor or manage groups of hosts and devices in the network [13]. The components consist of the SNMP manager who manages it from a remote place and they are often the one who installed the software on the server, therefore when a problem arises, they will be automatically informed. SNMP agents are the software that is installed and are able to communicate with the SNMP manager [11,14]. The Management Information Base (MIB) is the last component to hold information about all network devices, allowing administrators to identify and isolate any fault that occurs and monitor the operations. When the network monitoring system has finished collecting the SNMP and other values, the Network Monitor System will take responsibility by alerting the network or system administrators through email and SMS, or whatever is commonly used as a notification method [11,13].

1.1.3 Open-source and commercial software

The SNMP protocol is used by most network and server monitoring tools. The network monitoring open-source and commercial software on the market is comprised of many alternatives such as Zabbix, Nagios, Hyperic, Cacti, Zenoss, WhatsUp gold, etc. Open-source software is a computer software developed either by an individual, group, or organisation to meet requirements and it is available based on its body's interest. Open-source software is published for the public and the source code is open for all. Users do not need to spend any

money since it is available under free licensing. Commercial software is created by a person, team, or organisation, and only they have an exclusive right over the software. Anyone who needs to use it will have to pay for a valid and authorised license with the source code protected [15,17]. Both open-source software and commercial solutions have always been contentious but many companies have tended to get open-source resources because they are free of charge. Several parameters have been checked based on deployment, reporting, warnings, resource usage, API scripts, etc. [5,16].

1.1.4 Zabbix

Zabbix Network Monitoring software is an open-source tool and one of the best-known software options that monitors many network parameters, including the integrity and availability of a server. Zabbix has the capability of a flexible notification mechanism that can be alerted and allows users to find and respond to problems under a controlled amount of time [18]. Zabbix has useful data visualisation features and is able to provide statistical reports for all parameters, including Zabbix Network Monitoring, accessible via GUI, allowing access to the network and server status from anywhere. It is one of the most useful software options used to monitor networks such as applications, services, databases, and more. As mentioned in its flexible notification mechanism, the alert can be via a number of platforms such as email, slack, jira, etc. [18]. As Zabbix is an open-source tool, the main benefit is that it is free of charge and the software can be installed freely without limitation. Zabbix has features for monitoring the network for data collection, availability, and performance monitoring. There are many monitoring forms, such as SNMP, IPMI, JMX, VMware, Zabbix agents used to gather the required information. The Zabbix Network Monitoring software supports SNMP v1, 2 available on almost all network devices such as switches, routers, IDS, firewalls, network appliances, power systems on the UPS, and many others. Zabbix Network Monitoring can monitor the network, CPU, memory utilisation, port status, etc. The Zabbix server works by collecting data from its agents, analysing them and properly giving a representation. Moreover, in Zabbix, the API can be configured. Zabbix API allows for the programmatic retrieval and adjustment of the configuration of Zabbix and provides access to historical data. It is generally used to create new applications to work with Zabbix and to combine Zabbix with third-party software [18].

1.1.5 API

Zabbix API supports programmatically retrieving and changing the configuration of Zabbix and provides access to historical data. Zabbix API uses the JSON-RPC 2.0 protocol, which can consist of a separate method of sets where each of them function in different tasks. It is usually used to create new applications to work with Zabbix. The API consists of several methods that are grouped into separate APIs [19].

1.2 Research Background

In recent years, the digital transformation of services has significantly increased the reliance on web servers, making them essential components of business operations, and information dissemination. This reliance has, in turn, made web servers prime targets for various cyber threats, notably Denial-of-Service (DoS) attacks, which aim to overwhelm server resources, rendering services unavailable to legitimate users [20]. The implications of such attacks are far-reaching, affecting not only the immediate availability of services but also causing financial losses, eroding customer trust, and damaging the reputations of organisations [21]. The frequency and sophistication of these attacks has underscored the critical need for robust, effective monitoring systems capable of detecting and mitigating such threats promptly.

Previous research has focused on efforts to safeguard web servers from DoS attacks and on analysing patterns in network traffic, scrutinising system resource utilisation, and evaluating application-level metrics to identify anomalies indicative of malicious activities [22]. Such analyses have become increasingly sophisticated, employing advanced statistical methods, machine learning algorithms, and anomaly detection techniques designed to accurately differentiate between legitimate and malicious traffic [23]. These approaches are pivotal in developing proactive defence mechanisms, enabling the identification and mitigation of potential threats before they can cause significant damage. Moreover, the evolution of DoS attack methodologies has necessitated the development of real-time response mechanisms. These mechanisms include traffic filtering, which seeks to block malicious data packets while allowing legitimate traffic, and resource allocation optimisation, designed to ensure that critical services remain available even under attack [24]. These strategies are part of a broader arsenal of defensive measures aimed at maintaining service continuity and safeguarding the integrity and availability of web servers.

This research aims to contribute to this evolving field by proposing an innovative server monitoring system that leverages the latest advances in data analysis techniques and integrates real-time response mechanisms to detect and effectively mitigate DoS attacks. By focusing on the development of an adaptive intelligent monitoring system, this study seeks to enhance the resilience of web servers against a wide range of DoS attack vectors, thereby ensuring the uninterrupted delivery of online services and protecting critical internet infrastructure. The findings of this research will significantly contribute to the body of knowledge on cybersecurity, offering actionable insights and practical solutions to enhance the security and resilience of web servers against the ever-present threat of DoS attacks.

1.3 Aims and Objectives

The primary aim of this research is to develop a novel design methodology that significantly enhances network monitoring capabilities. This will be achieved through the implementation of the Adaptive Monitoring System (AMS) utilising the Python programming language and innovative algorithmic approaches. The following specific objectives have been set to fulfil the aim of this research:

1. Develop a new method for enhanced network monitoring that surpasses existing systems, distinguishing from complex solutions like SDN which are costly and challenging to implement [25].
2. Automate server configuration adjustments using API scripts to reduce manual intervention by network administrators.
3. Create the AMS to improve network monitoring automation and performance using Python and new algorithms.
4. Advance network security techniques to meet future demands in network security.

These objectives are designed to collectively forge a robust foundation for the proposed AMS, ultimately facilitating superior network management without the continuous need for direct intervention by network personnel. The outcomes of this research are expected to contribute substantially to the field of network systems management, presenting both practical implementations and theoretical advancements.

1.4 Research question

"What are the most effective and efficient methods and algorithms for developing a real time server monitoring system to detect and mitigate Denial-of-Service (DoS) attacks, ensuring optimal server performance and uninterrupted service delivery?"

1.5 Thesis Roadmap

This thesis is structured to provide a comprehensive exploration of network monitoring and its efficacy in mitigating Denial-of-Service (DoS) attacks. Chapter 1 introduces the essentials of network and server monitoring, including protocols such as SNMP, as well as contrasting open-source and commercial software with a focus on the Zabbix monitoring tool and its API. Chapter 2 delves into the literature review, discussing the evolution of network monitoring, the need for and challenges of Software-Defined Networking (SDN), advanced monitoring systems, and the characteristics and common types of DoS attack. Chapter 3 outlines the methodology, detailing the data collection techniques, system design, threshold settings, and the reconfiguration processes used in experimental setups. Chapter 4 presents the experiments and results, examining the setup and outcomes of various simulated DoS attacks. Chapter 5 discusses these results, interpreting their implications for network security. The conclusion in Chapter 6 synthesises the findings, offering conclusions and recommendations for future research. The references and appendices follow, providing supplemental material and sources cited throughout the research. This structured approach ensures a thorough analysis and presentation of the research conducted, guiding the reader through each critical phase of the study.

2 LITERATURE REVIEW

This chapter consists of scholarly sources on information related to the topic of this study. The literature review provides an overview of network monitoring, its methods, and detailed studies done to enhance monitoring systems.

2.1 Network Monitoring

Network monitoring and its measurement have become crucial in modern complicated networks. It was clearly seen that in the past, administrators only had to monitor systems with a few computers. However, now administrators must deal with both high-speed networks and wireless networks [26,27]. In addition, they have been striving to keep the network operations running smoothly. Network monitoring is an essential tool for them to constantly monitor complex networks [28].

Networks today connect millions of users throughout the entire world, with their role being the main infrastructure for many applications. Therefore, network monitoring is a tool to maintain its smooth operation, stability, and the availability to fix any problem that may arise [28]. It is undeniable that monitoring the network is a difficult job because if the system were to go down even for the shortest period of time, it could cost a lot of assets. In general, when a network fails, a monitoring agent will detect, isolate, and correct the malfunctions and try to recover. Monitoring involves many methods, depending on their purpose. Implementing a good monitoring system for a given network requires the following characteristics [29]:

1. To justify the network budget and resources, to make sure that the monitoring tools are suitable and able to handle the requirements of all users.
2. Make sure that intruders are detected and filtered to prevent access by an attacker to internal servers and services.
3. To be alerted to the presence of network viruses and to take action before they destabilise the network.
4. To simplify the troubleshooting of network problems specifically, allowing them to be repaired automatically.
5. Highly optimised network performance to achieve the best possible performance as part of the effective monitoring.

Fortunately, achieving the characteristics of having an effective monitoring system network monitoring itself does not need to be expensive as they are many free options available as tools to consider (as previously stated in Chapter 1). The parameters of monitoring for each network are slightly different, and the table below illustrates the different parameters for monitoring. Free available tools also can show as much detail as indicated in Table 2.1 [30,31].

Table 2.1 Parameters of each network

Wireless statistics	Switch statistics	Internet statistics	System health statistics
- Received signal and noise - Number of associated - Detected adjoining networks - Excessive re-transmission - Radio data rate	- Bandwidth usage per switch port, broken down by protocol, by MAC address - Broadcasts as a percentage - Packet loss and error rate	- Internet bandwidth use by host and protocol - Proxy server cache - Top 100 sites accessed - DNS requests - Inbound emails, spam emails, email bounces - Email queue size - Availability - Ping times and packet loss rate - Status of backups	- Memory usage - Swap file usage - Process count/zombie process - System load - USP voltages and load - Temperature, fan speed, system voltages - Disk SMART status - RAID array status

In today's world, this tool is desirable as it enables finding out when intruders are trying to break into the network or when part of the network has failed. According to the tool used in this study, the parameters that will be used are involved in resource utilisation, which consists of CPU utilisation, memory, and network bandwidth.

1. CPU utilisation [30,32]

This parameter indicates the computer's usage of processing resources and the load of work that is handled by a CPU. It is said to be ideal for a CPU to be utilised at an average of 50%. However, even when the percentage is at 100%, it can still be tolerated.

2. Memory utilisation [33]

The second parameter detected from the server in this study is memory usage, which is used to know its performance. The higher the memory used, the lower the performance is for the associated processes.

3. Network bandwidth [31]

Network bandwidth is another crucial parameter to consistently monitor in order to maintain stability and solve any problems that may arise. This parameter allows for the observation of the network's capacity in transmitting data between devices. The higher the bandwidth is, the faster the rate of data transfer.

Authors in [31] found that a network monitoring system ensures that the network infrastructure is secure and robust by closely monitoring a number of important parameters. This system evaluates CPU utilisation. Memory utilisation was also examined, with the data revealing that a higher memory usage may affect process performance, emphasising the importance of closely monitoring this parameter. Furthermore, network bandwidth monitoring is described as critical to ensure that any data is carried efficiently throughout the network. This section of the literature review emphasises the critical relevance of these characteristics in detecting network anomalies that could indicate potential security breaches or failures. Additionally, the literature review delves into the design and methodology of Denial-of-Service (DoS) attacks, including TCP SYN flood, UDP flood, ICMP flood, and HTTP attack, each characterised by its unique method of exploiting network vulnerabilities to overwhelm systems. To analyse these attacks, this study references specific tools like LOIC (Low Orbit Ion Cannon) for simulating TCP, UDP, and HTTP flood attacks, Net Tools 5 for executing UDP flood attacks through its "UDP Flooder" tool, and NetScanTools for conducting ICMP operations that could lead to flood attacks. This dual-focused approach in the literature review not only highlights the significance of a robust network monitoring system but also emphasises the importance of understanding and preparing for potential DoS attacks to maintain network integrity and security.

2.2 Software-Defined Networking (SDN)

The authors in [34] defined Software-Defined Networking (SDN) as "as a revolutionary new idea in computer networking, is the new approach that promises to dramatically simplify network-control and the management plane." It is implemented with cutting-edge network programming. Controlling network operators and the services people access, maintaining the equipment, and meeting requests all become challenging tasks in a Cloud-based environment.

In this case, other command and information transfer operations are combined on networking devices [34]. However, this approach is distinct from conventional systems, which manage network traffic using specialised hardware (such as routing devices and switches). With programming, SDN can build and manage virtualisation or manage conventional equipment.

2.2.1 Need for Software-Defined Networks

The rising internet usage and advanced technology have made it more demanding for a new system to operate, such as SDN. Firstly, high bandwidth is one of the key drivers of SDN networks [35]. The fixed design of network equipment in conventional networks makes it often impossible to fulfil consumers' rising bandwidth demands. In these circumstances, SDNs that have the ability to adjust flexibly to large bandwidth needs are more advantageous for users. The authors in [35] also mentioned that Dynamic Traffic Pattern is another factor that has influenced the development in and growth of SDN. Customers can now connect various databases, computers, and business systems using a variety of gadgets from any location at any moment. So, it is impossible to expect a continuous flow of traffic over a system because traffic frequently has a chaotic nature. [30] also demonstrates that scalability is also a driving factor for SDN research because conventional systems with fixed designs find it challenging to grow flexibly as the bandwidth requirements grow.

2.2.2 Challenges of using Software-Defined Networks

SDNs may seem like a solution to a number of network routing and control issues, such as dynamic traffic, flexible scalability, high bandwidth, etc., but realistically, deploying a comprehensive SDN presents a number of difficulties and dangers that must be avoided [36]. The following is a description of a few of the major difficulties encountered when adopting SDNs. The primary issue with SDNs is reliability. This is crucial in the design of any program since, in the scenario where the network fails, customers must be notified and a fix must be automated [37]. The likelihood that the program will operate correctly in a given setting and for a given period of time is known as its reliability. For the system to be more adaptive, available and allow for the handling of failures, the SDN operator's setup must be sophisticated and verify the network services. Another concern with the SDN's system is security-related [38]. While the deployment and interoperability of SDNs with current systems has received a lot of interest, there has only been a small amount of academic and industrial support for study into the safety elements of SDNs. SDNs cannot be properly deployed without adequate protection and breach monitoring systems.

2.3 Advanced Monitoring System

It is suggested that due to the complications above, there is a need to make the current monitoring system adaptive to enhance the best performance in network monitoring. Advanced monitoring is a new method introduced to a changing condition that has been useful in many applications from the monitoring system to customisation in other applications. In today's application of monitoring, the control system is the start from where to gather and collect information that will be used later on by other software systems to analyse. The results of an analysis can indicate the system's state and whether or not any action must be required. The adaptation of the monitoring system will allow them to manage and control their monitoring themselves [39]. Moui and Desprats [40,41] described a monitoring strategy by answering the questions of why, how, what, and when. The term "adaptive" has a wide range of definitions that can be implemented all the way from the customisation of the monitoring process to the reconfiguration of a monitoring system's components [42,43,44].

Past research related to this study has found that studies have covered a broad range of network monitoring systems, such as where authors Renita and Elizabeth [5] and Hernantes et al. [45] reviewed, in overview, a network's server monitoring and analysis. Moreover, Renita and Elizabeth [5] and later on Silver [46] developed a network's server monitoring using Nagios and found that the monitoring of networks and servers is essential, and can be by measuring server measurements such as processor state, memory utilisation, etc. that have been monitored continuously as well as their status, which is reviewed periodically. In the tool created, it was designed to alert through email the network administrator when there is a device malfunction. In addition, performance and utilisation can also be recorded. However, Hernantes et al. [45] argued that when selecting appropriate monitoring software, there is a need to take into account the many factors involved to find the best suitable match for the business. For example, selecting a tool or software first would be based on the required functionalities of the business. Then there is the evaluation of the deployment and maintenance factors to match the tool with the network and administrator team's resources and capabilities. Last, with a proper understanding of how the tool will affect an organisation, there is an estimation of the total cost needed. Roohi et al., [47] proposed a server monitoring tool based on the SNMP protocol. The researchers developed a network server intelligence monitoring system via the SNMP protocol, MIB-II and host resources MIB. They also measured significant parameters such as server connectivity, server CPU load and memory anomaly, and server disk anomaly to guarantee the normal network system. On the other hand, Renita and Elizabeth [5],

Hernantez et al. [40], and Silver [41] monitored a computer network system using the upper bound usage to set the maximum threshold value. If the usage reaches the threshold value, the system will operate abnormally [47,48,49,50]. Similarly to Roohi et al., [47] Detken et al., [4] and Petruti et al. [48], they have also used SNMP to monitor the system by implementing an intelligent monitoring system running advanced mechanisms for correlating events from the different sensors.

A number of sensors and collectors support the intelligent monitoring system, including new sensors that can be easily mapped to the system. The researchers also presented a web-based application for an automated private Cloud management system using the NtopNG and Zabbix monitoring tools [48]. Petruti et al. took advantage of the detailed configuration capabilities of NtopNG and the graphical features of Zabbix and expanded the applicability of the management solution to devices installed in vehicles acting as Cloud computing nodes. Zhang [49] did another work with a network intelligent monitoring system based on SNMP and it has been emphasised that during the real-time monitoring process, this program can identify the current problems in the network and provide a decision guideline for network administrators to perform troubleshooting and network maintenance through the expert database. In general, techniques of monitoring server and network devices in computer networks are based on SNMP which is used to monitor other systems as well [50]. This technique has been adopted by Xiaojun for remote monitoring TV transmitting stations, presenting a web-based centralised monitoring solution [51] which is considered to be a replacement for the traditional monitoring system connected via serial ports (RS232 or RS485) to collect the information on the various devices' status together. Grover and Nail recommended the use of SNMP in monitoring android devices [52], which has been used to monitor various features of the mobile phone's health, such as uptime, memory usage, ping latency, several processes, and watching for real-time updates. Later on, Jiangyu and Yan [53] developed a multifunction probe based on SNMP with SNMP managers and agents installed on a computer device to collect data such as the Cisco router switch. This data consisted of the source IP address, the purpose of all IP addresses, the packet, and the number of bytes. The flow and bandwidth usage rate was then measured and shown on the graph output to a network administrator. Affandi et al. [54] researched a network monitoring system and found that the network monitoring system (NMS) and a warning system are sent to the administrator when devices are down. They concluded that the network monitoring system has to warn as well. The network monitoring system will notify network administrators when abnormal usage

happens. Whether it is an abnormal server or network usage, the notification will be through email or SMS, and sent to the administrator when problems occur. A notification system was also developed to inform the user via the website, sending push notifications to their mobile phone together with the real-time monitoring of the network system [55].

Yayah et al. [56] used the prototype of a lightweight monitoring system based on the agent-manager model for IoT devices with limited resources. They made a comparison with SNMP. The input data was CPU, memory, swap usage, network usage, and disk usage. The team discussed how a lightweight monitoring system developed generates smaller packet sizes on the same function as the SNMP-based monitoring system, and also generates smaller packet sizes based on the same function as the SNMP-based monitoring system. They also presented low CPU and memory usage for monitoring thousands of devices, which is really suitable for IoT devices. Other researchers have monitored the network system using other methods. Roesch [57] used snort to monitor the network system, which is a tool for small, light-utilised networks and is free for use in any environment. It can be used to monitor and identify a wide range of abnormal network traffic as well as noticeable attacks on small TCP/IP networks. Khan et al. [58] and Otoum et al. [59] reviewed machine learning (ML) techniques and deep learning (DL) solutions for monitoring critical infrastructure through sensor networks. To support Roesch [57], Shen [60] discussed an Efficient Network Monitor for SDN networks by proposing an SDN-monitor that carefully selects switches to monitor in order to reduce the consumption of resources. [53,54,55,61] have monitored computer and network systems by setting traffic upper bound thresholds to find abnormalities in the network system, while [57,58] monitored and detected network performance by configuring a signature in the database. If the traffic through the network matches the specified signature value, anomalies in the system can be identified.

2.4 Denial-of-Service Attack

A denial-of-service (DoS) attack is an old but effective type of cyberattack that is still in use and that people need to be aware of. DoS attacks function by overwhelming or flooding a targeted machine until normal traffic is unable to be processed, resulting in a denial of service to users [62]. The most common denial-of-service attacks include TCP attacks, UDP attacks and HTTP attacks. Bergamini de Neira et al. [63] demonstrated that the threat of cyberattacks has greatly grown with the internet's rapid expansion in connectivity and society's emphasis on digital infrastructure. DoS attacks are one of many risks that network managers, companies,

and people all share a common worry about. Through overflowing a system that is being attacked with a large amount of traffic or by taking advantage of holes in the system's facilities, DoS attacks seek to interfere with the accessibility of essential services or supplies. Gu and Liu [64] also mentioned that DoS attacks are significant because of the harm they may be able to do to individuals and companies. DoS attacks can have serious effects on enterprises by making their systems or networks inaccessible, resulting in economic losses, reputational harm, and interruptions in crucial activities. The consumers' utilisation of internet tools and resources might also have an impact. In addition to this, these assaults are directed at particular industries and may have been driven by various motives. In particular, a sizable amount of DDoS attacks, or 76.92% of all assaults throughout the 3rd quarter of 2020, were aimed at gaming companies and the gambling market [63]. Ndichu found that the year 2020 saw attackers broaden their scope and target industries like online shopping, healthcare, and education [64]. Due to the area's expansion, there were many teachers and students in the UK who experienced serious interruptions, particularly outages of online learning environments. The majority of this expansion was caused by assaults on educational resources. When compared to the same period in 2019, there was a spike of no less than 350% in the amount of DDoS attacks that targeted educational materials between January and June 2020 [65].

2.5 Characteristics of Denial-of-Service Attacks

According to research conducted by [66], it has been determined that there are two basic categories of denial-of-service (DoS) assault: flooding attacks and logic attacks. Logic attacks take advantage of flaws in programs, including web servers and operating systems, to slow down the system's functionality or even bring it to a complete stop. These assaults profit from software flaws and security gaps that have not been addressed. In order to increase the security of the system and stop the exploitation of vulnerabilities, neutralising logic attacks requires putting countermeasures in place such as software upgrades and filtering particular traffic sequences. In this case, implementing preventative steps enables enterprises to strengthen their defences against logic-based DoS assaults and reduce the potential damage to their operations and networks. Apart from this, research by Kaur et al. [67] determined that Denial-of-Service (DoS) assaults are distinguished from other cyberattacks by a number of essential characteristics. For this reason, designing successful preventive, identification, and mitigation measures requires an in-depth knowledge of these features. Some crucial aspects of DoS attacks include the following:

Bonguet and Bellaiche [68] stated that one main characteristic of DOS is attributed to its feature to overload system resources. For instance, attacks such as Distributed Denial-of-Service (DDoS) have been demonstrated to overload system resources and prevent a target system from operating normally. These assaults make use of gaps in networking, navigation, and internet protocol systems. Attacks like the SYN flood, which sends a lot of SYN messages before recognising the SYN ACK packets stop new users from creating TCP connections, are one such attack. By permitting more concurrent TCP connections and lessening the server's storage load, proxy-based apps might assist in counteracting attacks like this. Another characteristic of DOS is its ability to overwhelm the target system's bandwidth [69]. Under this characteristic, attackers overwhelm the system with too much traffic, using up all of the bandwidth and preventing authorised individuals from using Cloud infrastructures. In this situation, even reliable packets are lost. Identifying the Cloud topology, particularly weak links and bottlenecks uplinks, is essential to carrying out this kind of attack effectively. Attackers must seize ownership of a sufficient number of hosts in the intended network and produce a sizable volume of UDP traffic across the exposed uplink. According to research [70], it can be determined that the characteristics of DOS are foremost its stealth and variability. Attackers frequently use methods that render their attacks challenging to stop and mitigate. It might be difficult to discern between harmful and lawful traffic because they may employ tactics like IP spoofing to conceal their identities or methods to imitate regular user activity. Furthermore, attackers could frequently change their assault strategies and tactics, making it more difficult for defences to keep up with developing dangers.

It is essential to comprehend these traits in order to create DoS attack defensive strategies that work [71]. To quickly recognise and stop such assaults, organisations must put in place the effective monitoring of networks, traffic evaluation, and methods for detecting anomalies. Furthermore, it is essential for businesses and internet service suppliers to work together to identify and block out malicious traffic at network borders. Companies can lessen the effects of DoS assaults and guarantee the dependability and predictability of their network operations by exercising vigilance and being proactive [71].

2.6 Common denial-of-service attacks

As previously mentioned, the goal of a Denial-of-Service (DoS) assault is to overload the targeted server or network using a variety of tactics. A technique that is frequently used involves overloading the server's memory with traffic, which renders it incapable. In a DoS

attack of this kind, the attacker deliberately sends a flood of service requests to the target server, overwhelming its ability to manage the inbound traffic. In SYN floods, this is a sort of Denial-of-Service (DoS) attack aimed at the three-way handshake procedure in the Transmission Control Protocol (TCP), which is the protocol in charge of forming links with the equipment over a network [72]. To overrun the target server, an attacker using a SYN flood attack takes advantage of the manner in which the TCP three-way handshake protocol is designed. Attackers purposefully mimic the original IP addresses of an extensive amount of SYN packets sent to the server, making it impossible for the server to distinguish genuine and unwanted requests [73]. In a Smurf Attack, the attacker broadcasts Internet Control Message Protocol messages to a variety of sites using a source IP address that is fake and corresponds to the target system. These faked packets will subsequently elicit answers from their intended receivers, which will eventually overwhelm the targeted host with information [74]. An attack on the network known as an ICMP flood seeks to overload a target network or device by overwhelming it with a large number of ICMP messages. A protocol called ICMP is employed for network administration and testing, including features like logging errors and congestion mitigation [75]. In contrast, an ICMP flood attack uses the protocol to purposefully disturb the target's operations. In this case, an ICMP flood attack involves an excessive amount of ICMP echo demand packets, sometimes referred to as "ping" packets, being sent to the target system by the attacker. Since the source IP address in these messages might be spoofed, it is challenging to determine where the attack originated [76].

However, it should be further elaborated that Ping floods and Smurf attacks all involve delivering a large number of ICMP Echo request packets of data, which is how both are conducted. Smurf is an amplification attack route that increases its harm capability by taking advantage of the features of broadcast systems, in contrast to the standard ping flood [77].

2.7 Challenges in detecting and mitigating DoS attacks

Computer network security is greatly hindered by denial-of-service (DoS) attacks. This section examines the unique strategies put forth in recent research and highlights the main difficulties in identifying and preventing DoS assaults.

The primary goal of current detection techniques is to locate incidences of Distributed Denial-of-Service (DDoS) assaults. According to Kentik [78], “DDoS detection is the technique of separating distributed denial-of-service (DDoS) assaults from regular network traffic in order to carry out efficient attack mitigation.” However, pinpointing the precise route

the attack flow took through the network is still difficult to do. In this case, this restriction makes it more difficult to successfully counteract DDoS attacks. Thus, conventional detection techniques find it difficult to offer information about the network path the attack flow takes, which hinders the installation of customised remedies [79]. One of the main drawbacks is the emphasis on only identifying DDoS attacks without offering thorough information on the route the malicious activity flow takes throughout the entire network [79]. To find possible attacks, conventional techniques frequently analyse network traffic trends, packet headers, or unusual activity. Although these methods can sound a warning when unusual activity is found, they are unable to identify the precise network route that the attack takes, which hinders attempts at focused prevention [80].

Secondly, traditional detection techniques also have trouble distinguishing between safe and harmful traffic, which increases the possibility of inaccurate results. This may lead to the interruption of required mitigation efforts and legal network functions, which would be inconvenient for users and could harm the computer infrastructure's credibility [81].

Thirdly, the flexibility of conventional detection techniques is another issue. The sheer amount of data that needs to be examined is a major challenge due to the rapid increase of network activity and the advanced nature of DDoS attacks. Traditional techniques frequently have trouble managing the heavy traffic and may experience efficiency problems, which causes difficulties in quickly identifying and retaliating to attacks [82].

Furthermore, the unpredictable character of DDoS attacks also makes it more difficult to identify them [83]. Attackers frequently alter their strategies utilising a variety of evasive methods to get past detection mechanisms. It may be challenging to properly detect and prevent these developing tactics of assault using conventional techniques because they lack the versatility and quickness needed.

Last but not least, traditional detection techniques frequently are not able to offer immediate tracking and evaluation, which hinders their capacity to act quickly in the face of new risks. In this case, prolonged periods of network unavailability and greater attack damage are both possible outcomes of slow investigation and reaction periods [84].

For this reason, various scholars have been investigating novel strategies that use modern methods like deep learning, machine learning, and graph-based models to overcome these restrictions. These tactics seek to address the drawbacks of conventional techniques by

offering more precise and effective detection capabilities, allowing the recognition of attack pathways and the application of focused mitigation measures.

2.8 Current Methods in DOS detection

An innovative detection method that uses a Spatial-Temporal Graph Convolutional Network (ST-GCN) across a data plane programmable SDN has been developed to overcome this. The router's data is captured using In-band Network Telemetry (INT) with sampling, and the ST-GCN detection model is used to identify the switches that the DDoS assault flows pass through [85]. In this case, DDoS assaults can be efficiently mitigated while having the least possible impact on genuine network traffic by employing a system of defence that incorporates an improved whitelist and targeted dropping tactics. The research outcomes in [80] show how much the identification approach has improved over traditional ones, and how accurately it recognises attack flow channels. Lastly, in agreement with the research above, the authors in [86] also demonstrated that this modern approach shows less CPU overhead and southbound interface stress than more conventional methods. Moreover, the use of an autonomous SDN data plane in IoT settings to identify and mitigate DoS and DDoS attacks has been suggested by [87] as a different approach. Real-world IoT data traffic analysis is used in the assessment to show, for the first time, how well this technique targets IoT traffic in real-world settings. The method precisely identifies and reduces attacks, boosting IoT network security by tracking entropy, as well as spotting trends and abnormalities. The review emphasises the significance of autonomous SDN data planes for repelling attacks by preserving contextual awareness. With this method, managers are given the ability to vigorously protect IoT systems, which advances the IoT settings' protection tactics [88].

2.9 Measurement of Parameters in Network Monitoring

2.9.1 Importance of measuring network parameters for effective monitoring

The precise measurement of numerous network metrics is essential for efficient network monitoring. Network managers are able to effectively control and maximise network resources as a result of these metrics, which offer useful insights on the habits, achievements, and usage of the network. Several crucial aspects play a role in the significance of assessing network characteristics in network monitoring.

First of all, measuring network parameters makes it possible to identify movements and trends in the network [89]. Network administrators can develop a thorough awareness of how

the network is being used and detect any unexpected or irregular actions by keeping an eye on factors like traffic on the network, capacity utilisation, and packet loss. This data is essential for identifying possible threats to security, performance obstacles, or traffic problems that could reduce network efficiency.

Secondly, measuring network parameters enables the creation of performance measures for the baseline [90]. Network managers are able to define the network's baseline level of efficiency by regularly monitoring variables including delay, productivity, and the number of errors. These baselines act as a point of comparison to evaluate departures from typical behaviour. Notifications can be set off if the network performance deviates from the predetermined levels, allowing administrators to swiftly look into and resolve any root causes before they worsen and affect the overall user experience [91].

Thirdly, measuring network metrics enables resource optimisation as well as capacity management [92]. Network administrators may recognise periods of high use and manage the network assets appropriately by examining characteristics like bandwidth usage. This preventative approach guarantees that network resources are deployed as efficiently as possible, reducing the likelihood of congestion, and guaranteeing a seamless and undisturbed user experience. Furthermore, precise network parameter evaluation helps managers discover unused resources and move them to regions with greater usage, leading to lower expenses and increased network effectiveness.

In addition, measuring network metrics is essential for problem-solving and maintenance [93]. Administrators can use the measured parameters to identify the underlying reasons for problem networks when they occur. Administrators can detect sections of the network or equipment that are suffering from significant levels of traffic or package decreases, for instance, by examining traffic trends and loss of packet rates. This knowledge enables managers to concentrate their troubleshooting work and deploy focused remedies, limiting downtime and the effect on those using the network.

Lastly, network parameter measurement is also necessary for safety and regulatory reasons. Addressing network performance, safety, and information confidentiality, several sectors have special requirements. Companies can verify that they meet their procedures and any industry requirements by routinely measuring factors including network security incidents, transmission of data speeds, and user records. This not only assists in fulfilling all legal duties but also raises the general level of confidence in and respect for the network infrastructure [94].

Therefore, assessing network metrics is crucial for efficient network monitoring. It offers useful information on network behaviour, efficiency, and usage, allowing administrators to spot deviations, improve the distribution of resources, resolve problems, and guarantee compliance with laws and regulations.

2.9.2 Key parameters to monitor in network monitoring systems

Most of the time, network monitoring systems concentrate on tracking a few crucial metrics that reveal important details about the network's performance. These variables consist of:

Traffic: Tracking network traffic entails examining the quantity and distribution of data packets sent over the network. Monitoring bandwidth utilisation, discovering unusual traffic patterns that can point to criminal activity, and conserving network capacity are all made easier with its aid [95].

Utilisation: Assessing network utilisation entails calculating how well different network resources—like bandwidth, CPU, and memory—are being used. It aids in locating resource obstacles, improving resource distribution, and making sure the network runs within the allowable speed limits [96].

Performance: Measuring variables like latency, packet loss, and jitter is a part of monitoring network performance. These give information about the standard of service that network users are receiving, aids in detecting service decline, and streamlines attempts at improvement and maintenance [97].

2.9.3 Techniques and tools for measuring network parameters

Network monitoring systems can measure network metrics using a variety of methodologies and technologies. Among the strategies frequently utilised are:

Packet Sniffing: To learn more about network activity, the process of packet sniffing entails collecting and studying packets sent over a network. Network administrators can investigate packet headers and payloads, examine protocols, and retrieve useful information for network maintenance as well as conduct performance analysis using programs such as Wireshark and tcpdump [98].

Flow Monitoring: Flow records typically describe network traffic patterns according to crucial fields including both origin and destination IP addresses, ports, and protocols kinds,

which are collected and analysed during flow tracking [99]. Technologies like NetFlow, sFlow, and IPFIX offer perspectives on network traffic flows, aiding the analysis of traffic, capacity scheduling, and anomaly detection [100].

Performance Monitoring: Solutions that track and evaluate network efficiency indicators including delay, loss of packets, and jitter are known as performance monitoring tools. In this case, Ping, traceroute, and SNMP-based monitoring techniques are tools that aid in immediate time network utilisation tracking, the detection of operational obstacles, and preventive maintenance [101].

2.10 Resource Utilisation Monitoring

2.10.1 Definition and significance of resource utilisation monitoring in network systems

Colantonio [102] defined resource utilisation monitoring as the practice of monitoring and evaluating how different assets are being used inside a network system. The Central Processing Unit (CPU), memory, disk storage, electricity, and other pieces of software and computer equipment are among these resources [103]. In this case, resource utilisation monitoring is important because it can give useful information on the effectiveness, capability, and overall efficiency of network resources. Network managers may recognise obstacles, improve the distribution of resources, and guarantee the network's maximum capacity and resilience by keeping a check on resource usage.

2.10.2 Types of resource to monitor

Chekkilla [104] demonstrated that multiple types of resource throughout a network system are covered by resource consumption monitoring. First, CPU utilisation monitoring entails keeping a record of how much the CPU is used, which reveals the amount of traffic and the processing power of the network devices. Additionally, RAM (Random Access Memory) monitoring maintains a close watch on how RAM is being used to make sure that there is enough memory accessible to run programs and applications without having to frequently switch to the disk. In order to ensure efficient information retention and search, disk utilisation monitoring also includes assessing storage device performance and consumption [105].

2.10.3 Techniques and tools for monitoring resource utilisation

Resource usage in network systems can be tracked using several methods and technologies. Firstly, SNMP (Simple Network Management Protocol) is a popular protocol

that gives network managers the ability to keep surveillance on and control network resources and equipment [106]. For gathering and arranging information regarding resource consumption, it offers a uniform structure. The operating systems and network hardware have counters for performance that provide specific data on the utilisation of resources, including memory, processor, and disk I/O statistics. These counters can be monitored manually or through software that monitors the collection of the current data for the study. On the other hand, extensive resource utilisation monitoring features with custom visualisations, alerting systems, and analysis abilities are provided by monitoring systems like PRTG Network Monitor [107].

2.10.4 Challenges in resource utilisation monitoring and analysis

Network administrators must overcome various obstacles while monitoring and analysing resource usage. One difficulty is the enormous amount of data that network systems and devices produce [108]. An enormous volume of data must be analysed when several devices track a large-scale system. To properly manage this data, appropriate procedures for gathering information, preservation, and utilisation are required. Another difficulty is the variety of tracking instruments and information formats utilised by the various network devices and manufacturers. To maintain an identical perspective in the utilisation of resources throughout the entire network, network managers may need to combine several instruments for monitoring and establishing information types.

2.11 Chapter conclusion

Chapter 2 of this thesis provides a comprehensive review of the current literature surrounding network monitoring and its critical importance in managing complex modern networks. The literature review outlines the evolution of network monitoring from simple setups to today's high-demand environments, where monitoring must account for both high-speed and wireless networks. The chapter discusses the essential characteristics of an effective monitoring system, which includes the ability to justify network resources, detect intruders, simplify troubleshooting, and optimise network performance. A significant portion of the chapter is dedicated to exploring specific monitoring parameters like CPU, memory utilisation, and network bandwidth, which are pivotal for maintaining network stability and performance. The review also touches upon the evolution of network types, such as Software Defined Networking (SDN), highlighting its benefits and challenges in contemporary network management. Lastly, the chapter examines the types of Denial-of-Service (DoS) attack and the

challenges in detecting and mitigating these attacks, which are crucial for maintaining network integrity and security.

The findings from this literature review set the stage for Chapter 3, which will delve into the methodologies employed in this study to explore network monitoring further. Chapter 3 will outline the methodology employed for monitoring and detecting DoS attacks on a web server, bridging the gap between theoretical knowledge and practical application. This approach aims to substantiate the literature review's findings with empirical evidence and provide a solid foundation for the subsequent analysis and conclusions of the study.

3 METHODOLOGY

This chapter outlines the methodology employed for monitoring and detecting DoS attacks on a web server. The main focus is on establishing baseline values for the server-side parameters and comparing them to the current values to detect potential attacks. This methodology is designed to be adaptable to different server environments and traffic patterns, providing a versatile and effective monitoring system. This chapter is organised into the following sections: data collection, establishing baseline values, monitoring system design, setting thresholds, reconfiguration, and validation.

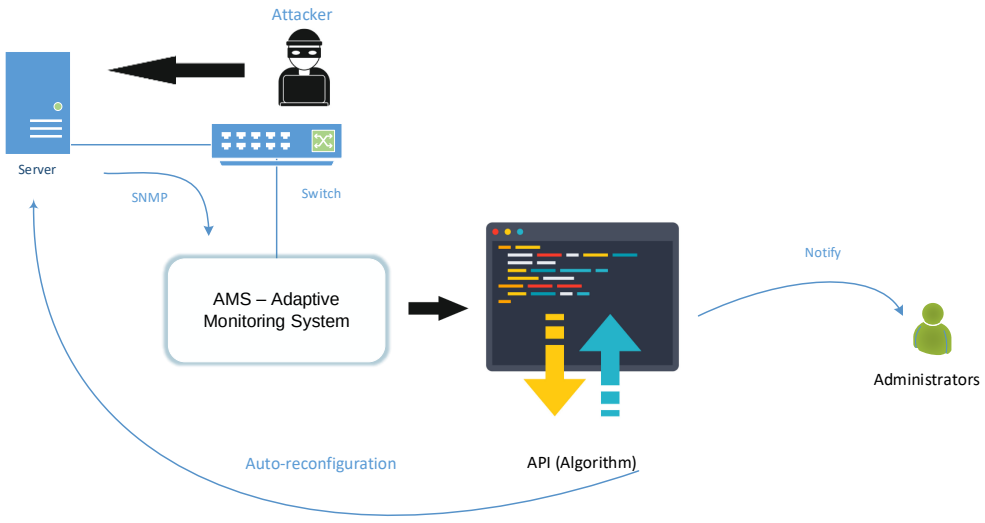

Figure 3.1 AMS: Adaptive monitoring system.

3.1 Data Collection

The first step in developing an adaptive monitoring system is collecting historical data on the server's performance and resource utilisation. This data serves as the foundation for establishing the baseline values for the server-side parameters and detecting unusual patterns that may indicate a DoS attack.

The main aim of DoS attacks is to disrupt service and network availability by attempting to reduce a legitimate user’s bandwidth or preventing access to a service or server system.

To obtain a comprehensive understanding of normal server behaviour, the data should cover various time periods, including peak and off-peak hours, weekdays, and weekends. This ensures that the baseline values account for different traffic patterns, seasonal variations, and other fluctuations in server performance.

The following server-side parameters can be monitored and logged:

3.1.1 CPU Utilisation:

The percentage of the server's processing power being used. High CPU utilisation can cause delays in processing requests and decrease server performance.

3.1.2 Memory Utilisation:

The percentage of the server's memory being used. Excessive memory usage can lead to performance degradation, as the server may need to swap data between memory and disk, slowing down response times.

3.1.3 Network bandwidth usage:

The amount of data being transferred over the server's network interfaces. Increased bandwidth usage can signal a high volume of incoming requests, which may be a sign of a DoS attack.

Here are 10 example values of a normal state in a web server over a 10-second duration, along with the corresponding values for CPU utilisation, memory utilisation, and network traffic volume.

Table 3.1 CPU utilisation, memory utilisation, and network traffic volume of a normal state.

Time (s)	CPU Utilisation (%)	Memory Utilisation (%)	Network Traffic (Mbps)
1	22	31	20
2	23	28	19
3	24	32	19
4	22	30	18
5	23	30	20
6	24	28	19
7	23	32	19
8	22	29	18
9	24	30	20
10	23	31	19

3.2 Establishing Baseline Values

Once the historical data is collected, the baseline values for each server-side parameter can be established. Baseline values represent the typical or average values of these parameters under normal operating conditions, serving as a reference point for detecting deviations that may indicate a potential DoS attack.

Monitoring and updating the baseline values can maintain an accurate reference point for detecting potential DoS attacks and reduce the risk of false positives.

To establish the baseline values for each parameter, the below are the average values for the historical data:

Average CPU utilisation = (22% + 23% + 24% + 22% + 23% + 24% + 23% + 22% + 24% + 23%) / 10 = 23%

Average memory utilisation = (31% + 28% + 32% + 30% + 30% + 28% + 32% + 29% + 30% + 31%) / 10 = 30.1%

Average network traffic = (20 + 19 + 19 + 18 + 20 + 19 + 19 + 18 + 20 + 19) / 10 = 19.1M bps

These average values serve as the baseline values for each parameter under normal operating conditions. The figure below explains the flow chart of the server monitoring process in the AMS monitoring tool.

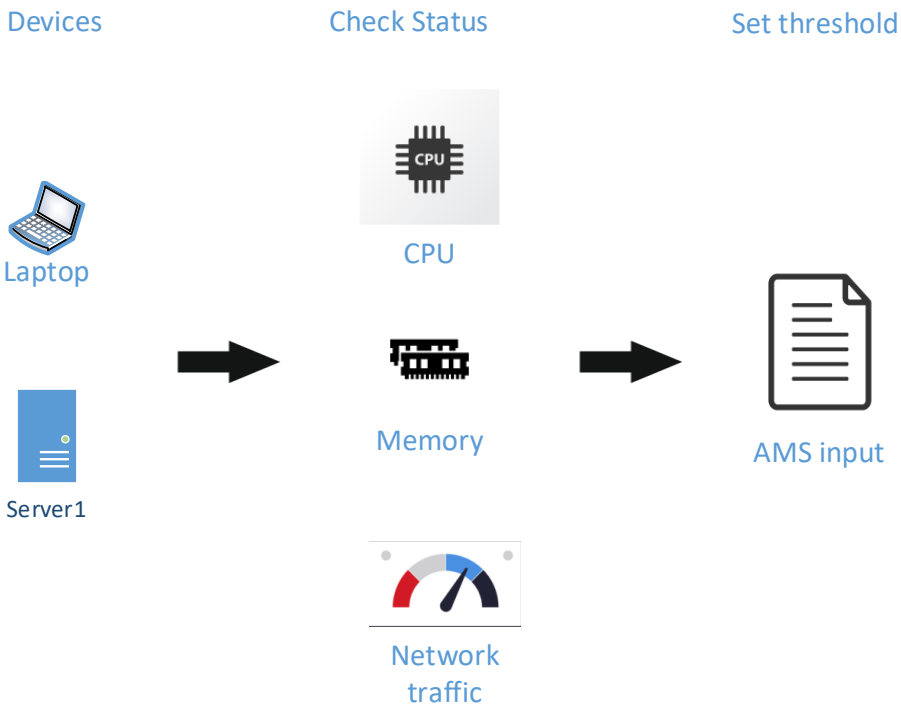

Figure 3.2 Flow chart for the AMS input parameters

3.3 Monitoring System Design

The monitoring system should be designed to track the current values of the server-side parameters, to compare them to the established baseline values, and to identify significant deviations that might indicate a potential DoS attack. These attacks achieve their goal by sending a stream of packets to overload a victim's network or its processing capabilities. Well-known examples of DoS attack are flooding the TCP SYN, UDP SYN packets, ICMP, and Http packets. Before launching an attack, attackers use tools such as port scans and host scans to discover what services they can break into. A specific technique has been used to evaluate several types of DoS attack: TCP SYN flood, UDP flood, ICMP flood, Http attack. Finally, the performance is compared. Accurate detection, CPU, and memory usage, as well as network bandwidth, are performance indicators. The results show that this method can identify all occurrences and all hosts associated with attack activities. Moreover, this method requires low memory.

3.3.1 DoS Attack design

In this section, the proposed DoS attack is presented including the methodology of our detection system. This research focuses on classifying the types of DoS attack, namely TCP

SYN flood, UDP flood, ICMP flood, and HTTP attack. Each attack is defined by examining its unique behaviours, as follows.

3.3.1.1 TCP SYN flood

SYN flood exploits the vulnerability of the TCP three-way handshake. During a SYN flood, attackers send a lot of TCP SYN packets with source IP addresses that do not exist or are not in use. Attackers also use many random source ports to connect to a single destination port of a victim. Since the number of requests is tremendous, the system will run out of resources and start dropping normal connection requests. This results in a graphlet with multiple source ports as shown in Figure 3.1(a).

3.3.1.2 UDP flood

UDPFlood is a UDP packet sender. It sends out UDP packets to the specified IP and port at a controllable rate. Packets can be made from a typed text string, a given number of random bytes, or data from a file. This results in a graphlet with multiple source ports as shown in Figure 3.1(b).

3.3.1.3 ICMP (Internet Control Message Protocol) Flood Attack

An ICMP (Internet Control Message Protocol) Flood Attack is a type of Denial-of-Service (DoS) attack that leverages the Internet Control Message Protocol to overwhelm a targeted network's resources. The attacker sends a large number of ICMP Echo Request (ping) packets to the target network or device. Because each ICMP Echo Request requires an ICMP Echo Reply, the system can be overwhelmed by the large number of requests and responses, consuming network bandwidth and system resources, potentially leading to a denial of service. ICMP Flood attacks exploit the fact that each request needs to be processed and responded to by the system that receives it. This means that even if the requests are illegitimate or malformed, they will still consume resources as the system tries to process them. If the volume of requests is high enough, it can overwhelm the system, leading to a slowed service or even complete unavailability.

3.3.1.4 Http attack

A HTTP (Hypertext Transfer Protocol) attack is a type of cyberattack that targets web servers, applications, or APIs (Application Programming Interfaces) by exploiting vulnerabilities or weaknesses in the HTTP protocol. This type of attack involves sending a

large number of HTTP requests to a server, often with the intent of exhausting server resources or causing application-level disruptions.

3.3.2 DoS attack tools

In this research, network traffic was generated using Low Orbit Ion Cannon (LOIC) tools, Nettools 5 and NetScantools specifically, which are briefly described below.

LOIC attacks a target site by flooding a server with TCP packets, UDP packets and Http packets. It also has the function to perform DoS attacks but uses the TCP/UDP packets to flood the target. LOIC can also be used as a network stress checking tool. The graphic user interface of LOIC is shown in Figure 3.3.

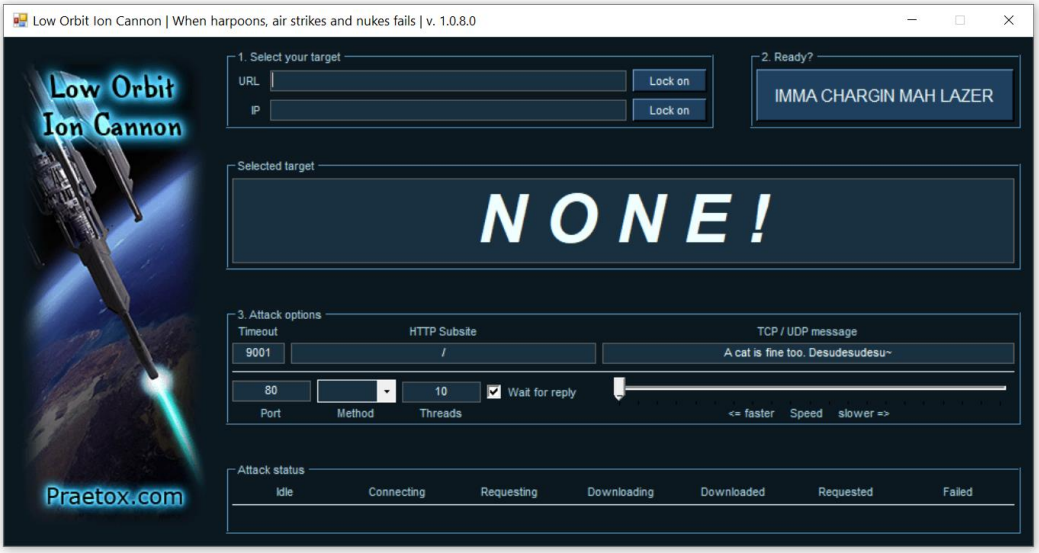

Figure 3.3 Low Orbit Ion Cannon GUI

Net Tools 5 includes a variety of network tools, some of which can be used for malicious activities such as launching Denial-of-Service (DoS) attacks, including UDP flood attacks. . In a UDP flood attack, the attacker sends a large number of User Datagram Protocol (UDP) packets to a target system with the aim of overwhelming the network or system resources, causing a denial of service. The tool in Net Tools 5 that can potentially carry out a UDP flood attack is the "UDP Flooder" tool. This tool allows for the sending of a high volume of UDP packets to a specified IP address and port number. The graphic user interface of Net Tools 5 is shown in Figure 3.4.

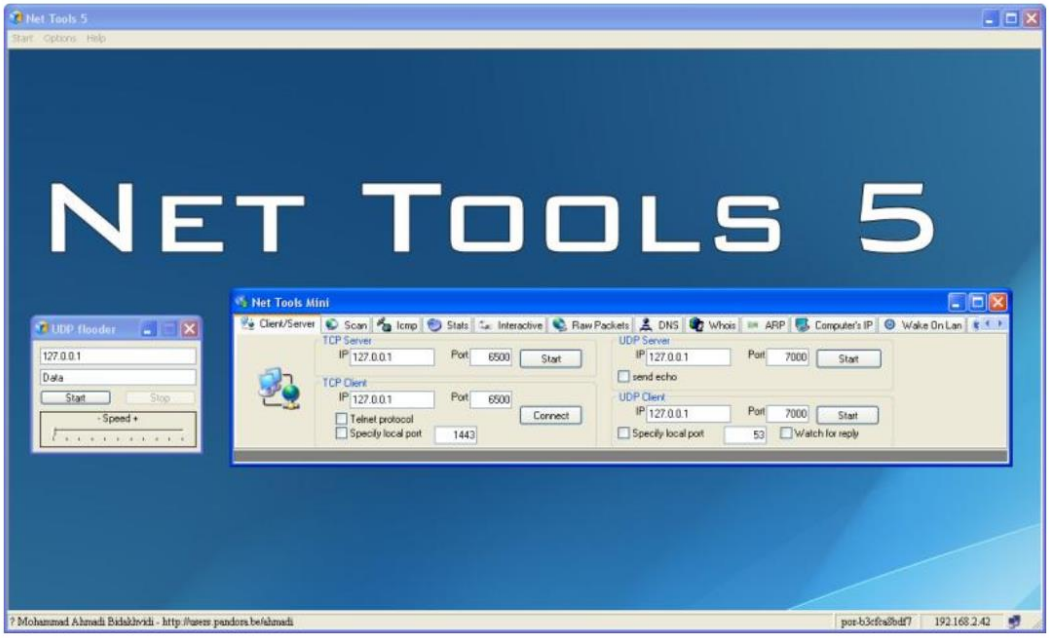

Figure 3.4 Net Tools 5

NetScantools is a suite of network discovery tools. One of the key features of NetScanTools is ICMP (Internet Control Message Protocol) operations. In an ICMP flood attack, a malicious actor overwhelms a target by rapidly sending a large number of ICMP packets. This can consume the target's network bandwidth or resources, resulting in service disruption for legitimate users. NetScanTools includes the ability to send ICMP packets for legitimate troubleshooting purposes, such as 'pinging' a server to check whether it is reachable, and launching ICMP flood attacks. The graphic user interface of NetScantools is shown in Figure 3.5.

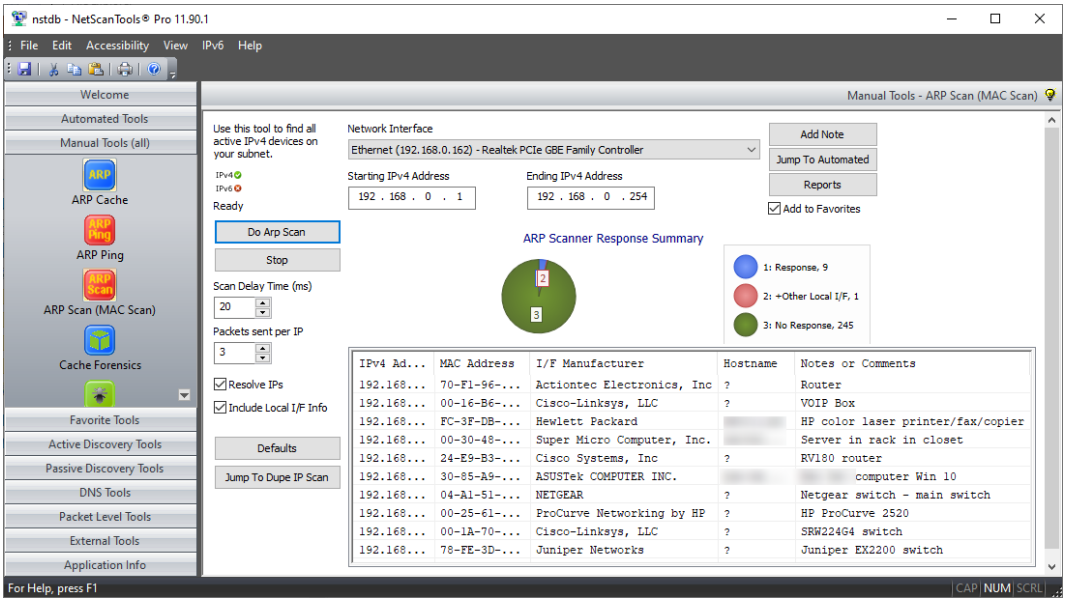

Figure 3.5 NetScantools

The software attack tools used in the testbed are shown in Table 3.2.

Table 3.2 DoS attack tools

Software Tools	Type of DoS attack
LOIC	TCP SYN flood attack
Net Tools 5	UDP flood attack
NetScantools	ICMP flood attack
LOIC	HTTP attack

3.4 Setting Thresholds

Determining an appropriate threshold for the DoS Attack is critical for detecting potential DoS attacks and minimising false positives. The threshold should be based on historical data, normal server behaviour, and the acceptable level of risk associated with false positives or false negatives.

This method can be used to set the threshold, including historical analysis, in order to analyse historical data to identify the values associated with past DoS attacks or periods of high server stress. These values can be used as a reference point for setting the threshold.

Initially, there are the input parameters for the monitoring system such as SNMP v2, CPU, memory utilisation, and network bandwidth. When AMS receives the input data from the devices and has already set up the threshold value, if something does happen such as port failure, the memory is full, etc. and reaches the specified threshold, a message will be sent to the API program where the API will follow the next action based on the information it receives. Then, the API program runs mechanisms to correlate with the rules from various input data. In addition, the detection of the anomaly on the API program depends not only on the individual parameters but also on the relationship between them. A weight can be allocated to each of the parameters and a total bound can be derived based on the weighted sum of parameters. Then, these parameter bounds can be adjusted dynamically.

This equation is based on traffic volume and resource utilisation-based anomaly detection:

$Y = \alpha X1 + \beta X2 + \gamma X3$

Where:

Y is the dependent variable, representing the presence or absence of a DoS attack.

X1 is the network traffic volume, measured in Mbits per second (Mbps).

X2 is the CPU utilisation, measured as a percentage.

X3 is the memory utilisation, measured as a percentage.

α, β, γ, are coefficients that represent the strength and direction of the relationship between each independent variable and the dependent variable. The coefficients are dynamic modified weight that $\alpha + \beta + \gamma = 1$

In the development of a methodology for the detection of Distributed Denial-of-Service (DoS) attacks, this research adopts a linear regression model centred on the pivotal indicators of network health and vulnerability: network traffic volume, CPU utilisation, and memory utilisation. The linear equation $Y=\alpha X1+\beta X2+\gamma X3$ serves as the analytical core, with Y representing the detection of a DoS attack and $X1$, $X2$, $X3$ denoting the aforementioned variables, respectively. The model's elegance lies in its simplicity and direct relevance to the

system's operational integrity, enhanced by the adaptability conferred through dynamic weights (α, β, γ), which are normalised to ensure balance and prevent overemphasis on a single parameter. This approach not only facilitates a comprehensive analysis by integrating diverse system metrics but also emphasises analytical clarity and methodological rigour, thereby providing a robust framework for the real-time detection of network anomalies.

Incorporating the linear model, as delineated within the methodology, serves as a foundational element for the anomaly detection framework, particularly in the identification of distributed Denial-of-Service (DoS) attack occurrences. This model meticulously integrates three pivotal parameters: network traffic volume, CPU utilisation, and memory utilisation. Such parameters are quintessential indicators of network system performance and security integrity, thus their inclusion is paramount. The subsequent discussion elucidates the rationale behind the employment of this formula and the significance of its central presentation within the research documentation.

- Relevance and analytical simplicity: The selection of network traffic volume, CPU utilisation, and memory utilisation as indicators is predicated on their direct relevance to network performance and susceptibility to security breaches. The linear equation, by virtue of its simplicity, adeptly encapsulates the relationships between these indicators and the potential for a DoS attack, thereby offering a potent yet straightforward analytical tool.
- Adaptive weight allocation for dynamic flexibility: The employment of coefficients (α, β, γ) as dynamic weights within the model augments its flexibility, enabling the adjustment of each parameter's significance in response to the evolving landscape of DoS attack methodologies. The constraint that the sum of these weights equals one.
- ($\alpha + \beta + \gamma = 1$) ensures a balanced scale of measurement, mitigating the risk of disproportionate influence from any singular parameter on the model's outcome.
- Integrated comprehensiveness: The amalgamation of disparate utilisation metrics and traffic volume within a singular analytical formula facilitates a holistic view of the system's operational state. This comprehensive approach is indispensable for the identification of anomalies that may remain obscured when parameters are analysed in isolation.
- Prominence for analytical clarity: The strategic placement and emphasis of the formula within the methodology section underscores its critical role in the anomaly detection process. This deliberate presentation acts as a beacon, guiding the reader through the

analytical underpinnings of the proposed detection strategy, thereby enhancing the manuscript's clarity and academic rigour.

- Foundation for discussion and empirical validation: By centring the discussion around the formula, the research invites scholarly discourse, allowing for the explication of the model's derivation, the determination and adjustment of coefficients, and the empirical validation of the model's efficacy. Such a structured presentation not only facilitates peer review but also encourages the replication of the study and the application of the model across various contexts.

Moreover, weights (α, β, γ) that can change in response to the network's current state are a strategic decision aimed at enhancing the model's accuracy and responsiveness to threats. The process begins with an analysis of past data, examining how variations in CPU, memory utilisation and network traffic have been correlated with security incidents. This historical insight is vital, as it informs the initial setting of the weights, ensuring the model is grounded in reality and capable of making meaningful predictions. However, the threat scenario and network behaviour are far from static, and are always evolving. Recognising this, the model is designed to adapt its weights based on ongoing network activity and emerging threat patterns. This adaptability is crucial for maintaining the relevance and effectiveness of the detection system amidst new and evolving cyber threats. It's a way to ensure that the model stays tuned to the nuances of network behaviour and continues to provide reliable predictions over time. A key feature of the model is the normalisation of weights, ensuring their sum equals one ($\alpha+\beta+\gamma=1$). This approach ensures that no single parameter disproportionately affects the prediction outcome, allowing for a balanced and holistic analysis of the network's health. It's about keeping the model's focus broad, ensuring it doesn't overlook or overemphasise particular aspects of network activity. Applying this model in practice involves navigating challenges, such as the continuous need for data to refine the weights, and the risk that the model might become too narrowly focused on the historical data it was trained on. Despite these hurdles, careful management and regular updates can maintain the model's accuracy and reliability.

So, the linear model delineated herein is not merely an analytical tool but a cornerstone of the research methodology, offering a nuanced, adaptable, and integrated approach to anomaly detection. Its prominent presentation within the thesis is designed to highlight its importance, facilitate scholarly discourse, and underscore the methodological rigour of this study.

The figure below shows the flow chart of the AMS system in which it analyses the monitored components. Because of a network malfunction, the traffic pattern may rise to the upper bound threshold caused by an attack on the system or due to other causes such as overloading, too many users access to the system, or system failure. The AMS Algorithm has to examine the cause of the malfunction. In the testbed, AMS monitored and recorded various parameter input data such as CPU, storage, memory, bandwidth utilisation, and Syslog into a database divided into two methods.

- Monitor and record the status of the server in the normal state.
- Monitor and record the server's status when it is attacked in different ways.

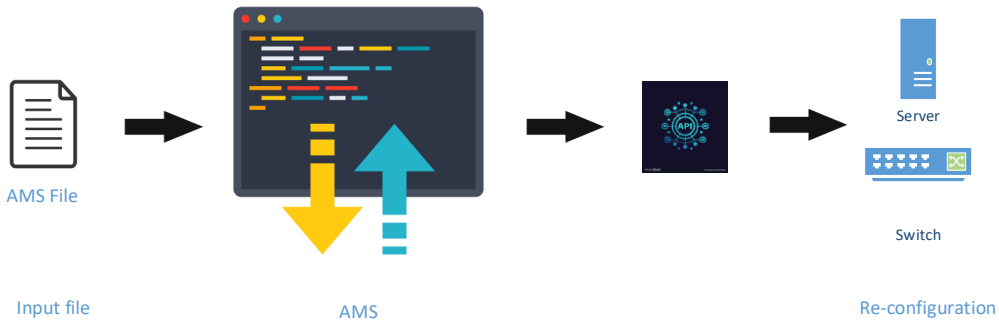

Figure 3.6 Flow chart for the AMS system

The process of the AMS system is shown in Figure 3.7.

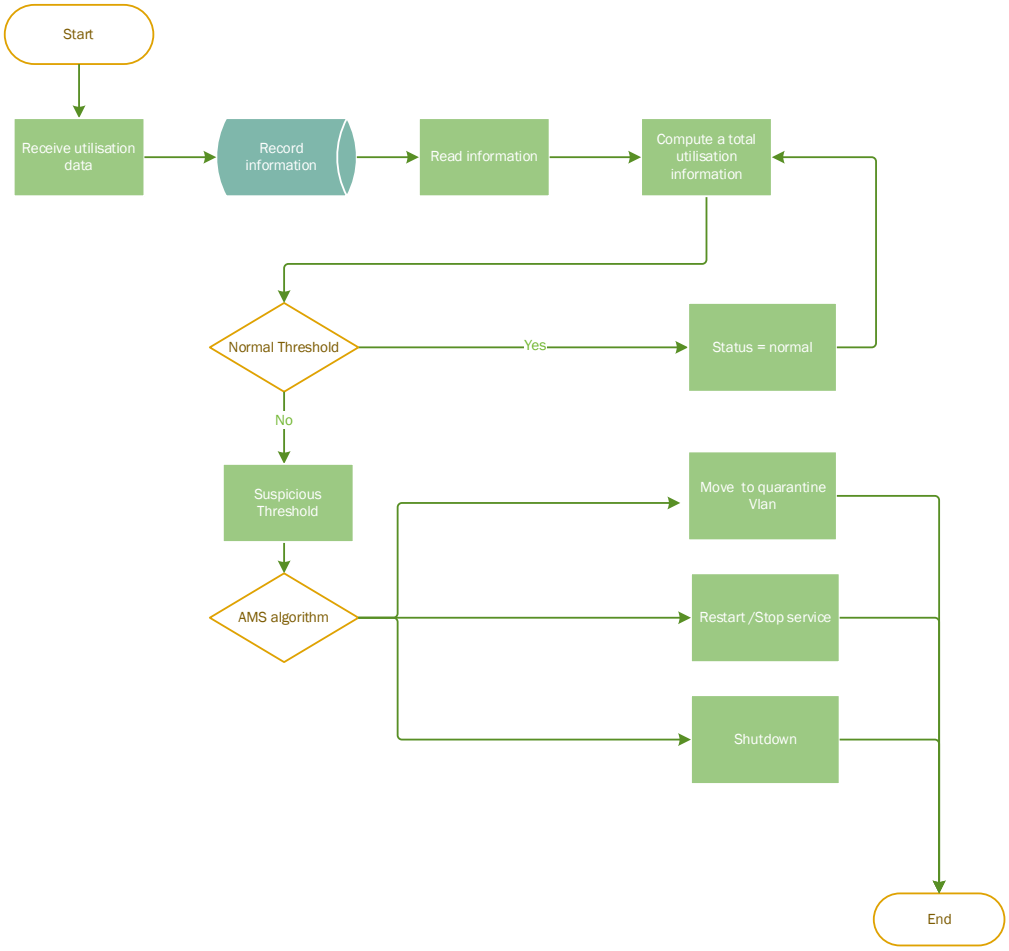

Figure 3.7 Process of the AMS system.

This comprehensive experimental testbed section provides a detailed presentation of two testbed architectures, each specifically tailored to assess the effectiveness of various DoS detection schemes in the context of real traffic and attack traffic under controlled experimental settings. The experimental design encompasses the configuration and deployment of two distinct primary testbed environments, which serve as platforms for simulating different attack scenarios.

3.4.1 Experimental testbed configuration - part 1

The first testbed environment, referred to as the real traffic testbed, represents normal, non-malicious user behaviour or it refers to the actual data packets exchanged between the user and server during normal operations.

Testbed configuration part 1: Normal traffic.

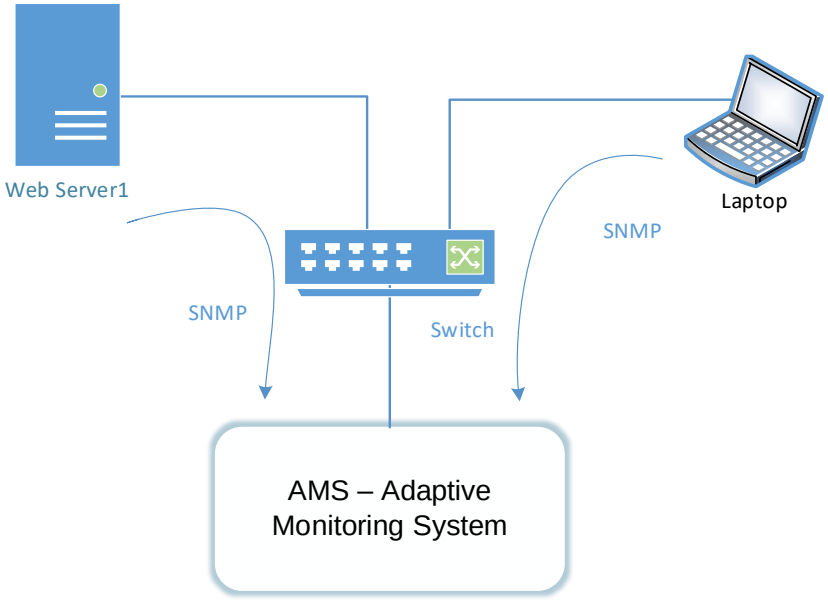

Figure 3.8 Normal traffic testbed architecture

As shown in Figure 3.8, the architecture of the normal traffic testbed consists of two computers such as laptop and a server. The two computers directly connect via a switch and ethernet cable.

The specifications of the two computers are listed:

- Laptop specification
  - OS: Windows 10
  - CPU: Intel Core i7-8550U (1.80GHz)
  - Memory: 16 GB RAM
  - Network Bandwidth: 100 Mbps
- Server specification
  - OS: Windows Server 2019
  - CPU: Quad-Core Intel Xeon Processor (2.4 GHz)
  - Memory: 16 GB RAM
  - Network Bandwidth: 100 Mbps

3.4.2 Experimental testbed configuration - part 2

The second testbed environment, known as the DoS attack testbed with real background traffic, introduces an additional layer of complexity by incorporating actual non-malicious traffic alongside the simulated DoS attack. This mixed traffic environment more closely

resembles real-world situations, providing valuable insights into the detection schemes' ability to accurately differentiate between benign and malicious traffic patterns, as well as its effectiveness at handling DoS attacks under more challenging conditions.

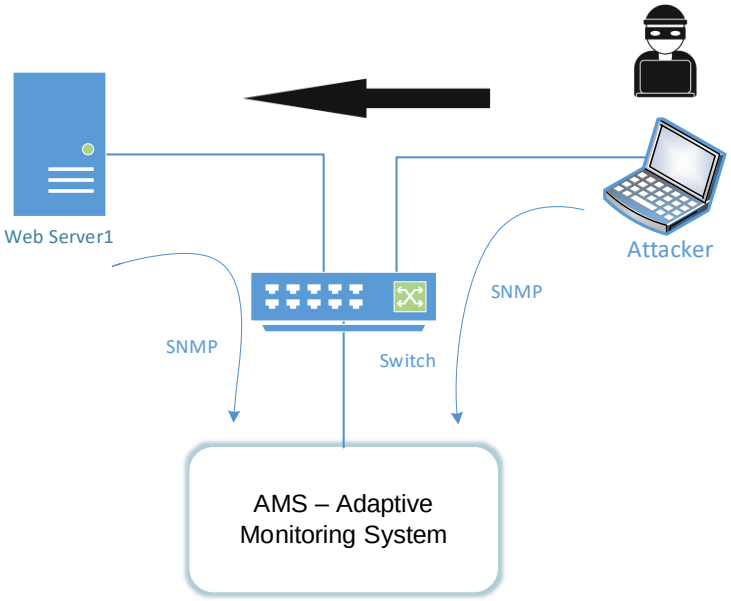

Figure 3.9 DoS attack testbed with normal background traffic architecture

3.5 Reconfiguration

After the modification of the device's configuration settings, a meticulous system examination was executed to confirm the restoration of normal operations. This involved a detailed analysis of various system parameters, ensuring that each was within their expected operational bounds. Once this was verified, an exhaustive report encapsulating the current status of the network - inclusive of potential issues and any corrective measures undertaken - was compiled. This report, aimed at providing administrators with a thorough understanding of the network's condition, was then dispatched electronically via e-mail, allowing for immediate and comprehensive access to the information contained within.

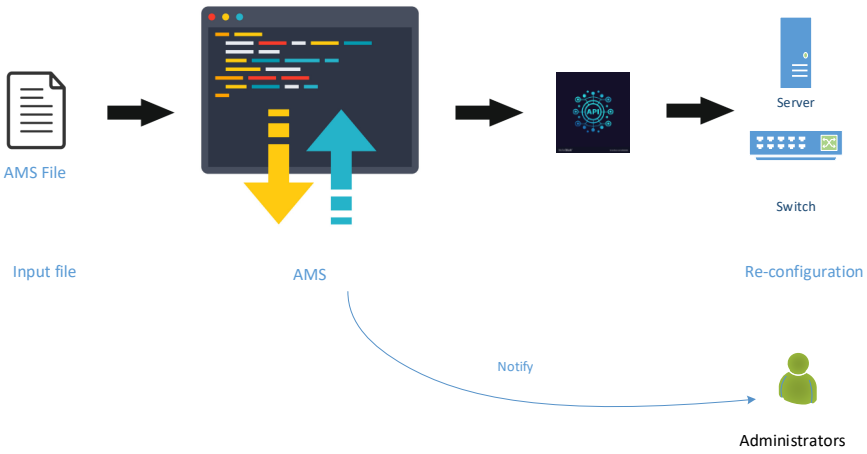

Figure 3.10 Auto-reconfiguration and notification

3.6 Validation

Validation of the AMS mechanism included assessing the system's ability to accurately differentiate between legitimate and malicious traffic. The system was tested under several types of DoS attack, such as TCP SYN flood, UDP flood, ICMP flood, and HTTP attacks. Its effectiveness was gauged on factors such as precision of detection, speed of identification, and false positive rates. The system's scalability was also tested by progressively increasing the volume and intensity of attacks. The validation process's overall objective was to ascertain the effectiveness of the proposed server monitoring system in achieving its primary goals: enhancing the server's resilience against DoS attacks, improving resource allocation, and minimising administrator intervention through automatic reconfigurations.

3.7 Chapter conclusion

Chapter 3outlines a detailed methodology for monitoring and detecting Denial-of-Service (DoS) attacks on web servers, focusing on establishing baseline values for server-side parameters, and comparing them to current values to detect anomalies. This methodology is designed to be adaptable to various server environments and traffic patterns, enhancing its effectiveness across different scenarios. The methodology employs a combination of historical data analysis and real-time monitoring to create a robust framework for identifying and responding to DoS attacks. Tools such as Low Orbit Ion Cannon (LOIC), NetTools 5, and

NetScanTools are discussed in respect of generating network traffic and simulating DoS attacks to test the system's resilience and effectiveness.

The findings from this methodology contribute significantly to the next chapter, which will delve into the experiments and results. Chapter 4 will apply the methodologies outlined to actual data and scenarios, testing the system's effectiveness in a controlled environment and real-world situations. This will provide empirical evidence to support the theoretical approaches discussed in Chapter 3, offering insights into the practical challenges and effectiveness of the monitoring system in detecting and mitigating DoS attacks.

4 EXPERIMENTS AND RESULTS

This chapter delves into the outcomes of the investigation carried out on the model put forth in Chapter 3. The model was devised to detect and counteract Denial-of-Service (DoS) attacks, particularly TCP SYN flood, UDP flood, ICMP flood, and HTTP attacks. The fundamental idea that drives this research is the necessity for a proficient monitoring system. Such a system should be capable of swiftly pinpointing any unusual activities that could be indications of DoS attacks, as well as quickly stepping in to counteract those threats. The proposed model achieves this by incorporating advanced statistical analysis techniques and anomaly detection algorithms to differentiate between legitimate traffic and potentially harmful activities. In this chapter, a detailed discussion is undertaken of the findings that have emerged from the implementation of a model, as well as its effectiveness. In the course of this research, three key server-side parameters are focused on: CPU utilisation, memory utilisation, and network throughput. The correlation of these parameters with the potential signs of DoS attacks allowed us to assess our monitoring system's precision in identifying potential threats. The primary objective of this study was to introduce a new approach to enhance network monitoring. This approach aimed at autonomously fine-tuning the server configuration as soon as any network irregularities were detected. The end goal was to lessen the dependency on network administrators while ensuring uninterrupted service, even in the face of DoS attacks.

4.1 Experimental Setup

4.1.1 Experimental testbed configuration part I

The first testbed environment, referred to as real traffic testbed, represents normal, non-malicious user behaviour, or the actual data packets exchanged between the user and server during normal operations. Table 4.1 illustrates the results for CPU utilisation, memory utilisation, and network throughput during normal usage on a web server for 20 minutes.

Table 4.1 CPU utilisation, memory utilisation, and network throughput during normal usage on a web server for a duration of 20 minutes.

Time (minutes)	CPU Utilisation (%)	Memory Utilisation (%)	Network Throughput (Mbps)
1	25	35	20
2	23	32	19
3	24	34	19
4	22	30	19
5	26	37	20
6	21	29	19
7	23	33	19
8	25	36	19
9	24	34	19
10	22	31	19
11	26	37	20
12	21	29	19
13	23	33	19
14	25	36	19
15	24	34	19
16	22	30	19
17	26	37	20
18	21	29	19
19	23	33	19
20	25	36	19

Average CPU utilisation : (25 + 23 + 24 + 22 + 26 + 21 + 23 + 25 + 24 + 22 + 26 + 21 + 23 + 25 + 24 + 22 + 26 + 21 + 23 + 25) / 20 = 23.6%

Average memory utilisation : (35 + 32 + 34 + 30 + 37 + 29 + 33 + 36 + 34 + 31 + 37 + 29 + 33 + 36 + 34 + 30 + 37 + 29 + 33 + 36) / 20 = 33.3%

Average network throughput: (20 + 19 + 19 + 19 + 20 + 19 + 19 + 19 + 19 + 19 + 20 + 19 + 19 + 19 + 19 + 19 + 20 + 19 + 19 + 19) / 20 = 385 / 20 = 19.2 Mbps

The average CPU utilisation is 23.6%, the average memory utilisation is 33.3%, and the average network throughput is 19.2 Mbps.

Figure 4.1 illustrates a visual representation of the results for CPU utilisation (%), memory utilisation (%), and network bandwidth (Mbps) under normal operations.

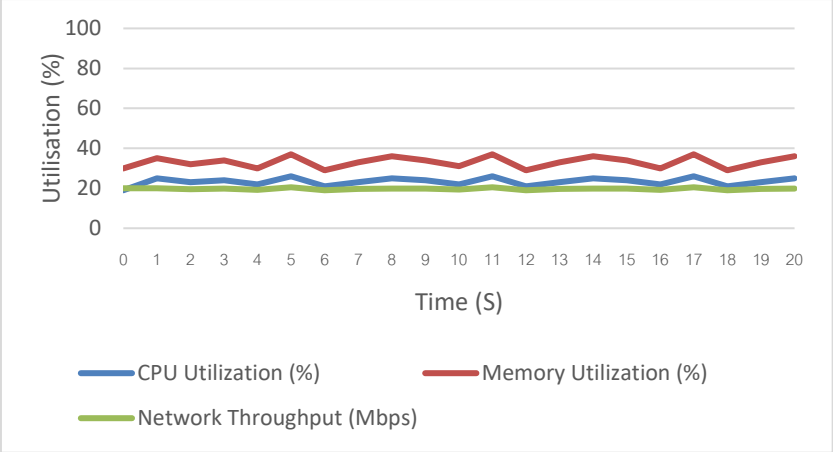

Figure 4. 1The results for CPU utilisation (%), memory utilisation (%), and network bandwidth (Mbps)

This equation is based on traffic volume and a resource utilisation-based anomaly detection equation:

$Y = \alpha X1 + \beta X2 + \gamma X3$

Where,

Y is the dependent variable, representing the presence or absence of a DoS attack.

X1 represents CPU utilisation (as a percentage),

X2 represents memory utilisation (as a percentage),

X3 represents network traffic volume (in Mbps),

and α, β, γ are coefficients that represent the strength and direction of the relationship between each independent variable and the dependent variable.

The provided averages are:

X1 = 23.6% (average CPU utilisation),

X2 = 33.3% (average memory utilisation).

X3 = 19.2 Mbps (average network throughput),

The values of the coefficients α, β, γ, which have to be dynamically adjusted to fit the data that $\alpha + \beta + \gamma = 1$, assumes α, β, γ as 0.3, 0.4, 0.3 respectively.

So, $Y = \alpha X1 + \beta X2 + \gamma X3$

$Y = 0.3(23.6) + 0.4(33.3) + 0.3(19.2)$

Y = 7.08 + 13.32 + 5.76 = 26.16

Then, these are added up:

Y = 26.16 (normal operations)

This value of Y represents the state of normal operations. Any significant deviation from this value could potentially indicate the occurrence of a DoS attack. The exact threshold or change that indicates an attack can vary and will typically be determined based on the specifics of the system.

In addition to calculating the mean, standard deviation (SD) is another statistical measure that provides valuable insights into the distribution and variability of data points within a dataset. Essentially, the SD indicates the extent to which individual data points deviate from the mean, thus offering a measure of dispersion or spread within the dataset. By assessing the SD alongside the mean, researchers can gain a more comprehensive understanding of the dataset's characteristics, aiding in the interpretation and analysis of said data. A smaller SD suggests that the data points are closely clustered around the mean, indicating a more consistent dataset, whereas a larger SD signifies greater variability among the data points, which may indicate the presence of outliers or inconsistencies. Therefore, the calculation of both the mean and standard deviation is essential in evaluating the consistency, reliability, and distribution of the data, ultimately facilitating more informed research interpretations and analyses.

The formula for calculating the standard deviation of the utilisation data is as follows:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(xi-\bar{x})^2}{n-1}}$$

Where:

xi represents each individual value.

$\bar{x}$ represents the mean of all values.

n is the total number of values.

The standard deviation (SD) of the CPU utilisation data = 1.93 (The mean CPU utilisation is 23.6).

The standard deviation (SD) of memory utilisation = 2.07 (The mean memory utilisation is 33.3).

The standard deviation (SD) of network throughput = 0.447 (The mean network throughput is 19.2).

These standard deviation values offer valuable insights into the dispersion of the data points around their respective means, aiding in the understanding of the variability within the dataset.

4.1.2 Experimental testbed configuration - part 2

The second testbed environment was the DoS attack testbed with normal background traffic. This controlled setting allows for a focused investigation of the DoS detection schemes' performance in detecting and mitigating the impact of such attacks.

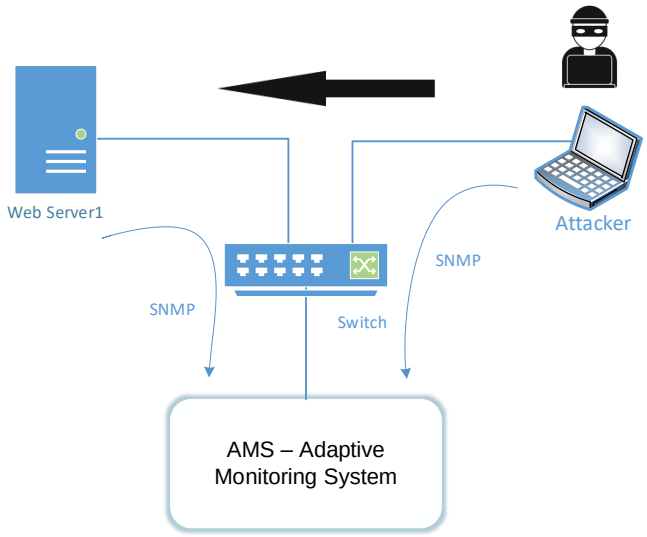

Figure 4. 2 DoS attack testbed with normal background traffic architecture

This section examines the effectiveness of a model used for identifying the different types of DoS attacks. This research focuses on classifying the types of DoS attack, namely TCP SYN flood, UDP flood, ICMP flood, and HTTP attack. After performing each of these distinct attacks on our system, the key metrics were collected and recorded in a data table and subsequently represented this data graphically for comparative analysis. In addition, an algorithm defined as $Y = \alpha X1 + \beta X2 + \gamma X3$ was used to calculate the value of Y, serving as an additional verification method to determine the presence or absence of a system attack. The value of Y, indicative of a DoS attack on a server, is subject to the standards or thresholds designated by system administrators. It may also be swayed by the server's robustness and ability to manage the load induced by an attack.

Assuming a sudden or significant escalation in the value of Y as evidence of a DoS attack, one might hypothetically establish an increase of 70% from the normal Y value as the benchmark for a DoS attack. Consequently, when Y exceeds 26.16 + (26.16 * 0.7) = 26.16 + 18.31 = 45, it may be inferred that the server is experiencing a DoS attack. Then, summing these values up equals Y = 45, which represents the threshold value.

4.1.2.1 In a TCP SYN flood

This sub-section elucidates the proficiency of the proposed system in identifying TCP SYN flood under varying conditions, specifically utilising different threads (sessions). These instances encompass 5, 10, 20, 50, and 100 threads respectively, presenting a spectrum of scenarios to comprehensively evaluate system performance. Figure 4.3 illustrates a visual representation of the experimental testbed part 2 with TCP attack via LOIC diagram.

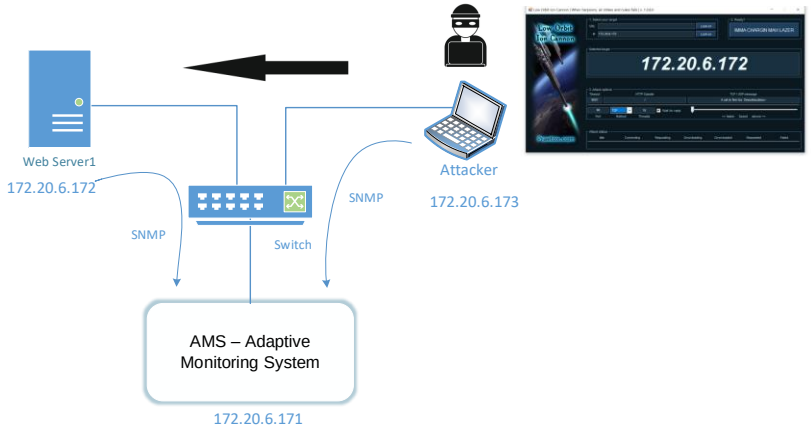

Figure 4. 3 Diagram of experimental testbed part 2 with TCP attack via LOIC tool.

4.1.2.1.1 In a TCP SYN flood using LOIC starting with 5 threads, the impact on CPU and memory utilisation, as well as network bandwidth, will generally be less compared to attacks with a larger number of threads. Here is presented a value for system resource utilisation and network bandwidth every second for 10 seconds. Table 4.2 shows the results for CPU utilisation, memory utilisation, and network throughput during TCP SYN flood using LOIC with 5 threads on a web server for a duration of 10 seconds.

Table 4.2 CPU utilisation, memory utilisation, and network throughput during TCP SYN flood using LOIC with 5 threads on a web server for a duration of 10 seconds

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	25	33	19
2	30	36	20
3	35	39	21
4	40	42	22
5	45	45	23
6	50	48	24
7	55	51	25
8	60	54	26
9	65	57	28
10	70	60	30

This data demonstrates that launching a LOIC attack can put considerable strain on the attacker's own system. As the attack progresses, it uses more of the computer's resources, potentially slowing down other applications or making the system unresponsive. The increasing network bandwidth use could also slow down the attacker's internet connection.

At the start (0 seconds), CPU utilisation was 23%, memory utilisation was 30%, and network bandwidth was 19 Mbps. For 10 seconds, all three parameters steadily increased. By the end of the 10-second period, CPU utilisation rose to 70%, an increase of 47 percentage points. Memory utilisation increased by 30 percentage points, from 30% to 60%. Network bandwidth increased 11 Mbps, from an initial value of 19 Mbps to 30 Mbps.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into the equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.4, and 0.3 respectively, results in the following values for Y:

At Time = 0 seconds: $Y = 0.3(23) + 0.4(30) + 0.3(19) = 6.9 + 12 + 5.7 = 24.6$

At Time = 1 second: $Y = 0.3(25) + 0.4(33) + 0.3(19) = 7.5 + 13.2 + 5.7 = 26.4$

At Time = 2 seconds: $Y = 0.3(30) + 0.4(36) + 0.3(20) = 9 + 14.4 + 6 = 29.4$

At Time = 3 seconds: $Y = 0.3(35) + 0.4(39) + 0.3(21) = 10.5 + 15.6 + 6.3 = 32.4$

At Time = 4 seconds: $Y = 0.3(40) + 0.4(42) + 0.3(22) = 12 + 16.8 + 6.6 = 35.4$

At Time = 5 seconds: $Y = 0.3(45) + 0.4(45) + 0.3(23) = 13.5 + 18 + 6.9 = 38.4$

At Time = 6 seconds: Y = 0.3(50) + 0.4(48) + 0.3(24) = 15 + 19.2 + 7.2 = 41.4

At Time = 7 seconds: Y = 0.3(55) + 0.4(51) + 0.3(25) = 16.5 + 20.4 + 7.5 = 44.4

At Time = 8 seconds: Y = 0.3(60) + 0.4(54) + 0.3(26) = 18 + 21.6 + 7.8 = 47.4

At Time = 9 seconds: Y = 0.3(65) + 0.4(57) + 0.3(28) = 19.5 + 22.8 + 8.4 = 50.7

At Time = 10 seconds: Y = 0.3(70) + 0.4(60) + 0.3(30) = 21 + 24 + 9 = 54

According to the given data and calculated values of Y, starting from the 8th second onwards, the value of Y exceeds the defined threshold of 45, indicating a DoS attack on the server.

4.1.2.1.2 A TCP SYN flood attack implemented with the Low Orbit Ion Cannon (LOIC) tool using 10 threads will generally induce a lesser impact on both the CPU and memory utilisation, as well as on the network bandwidth, compared to attacks employing a larger number of threads. The ensuing data represents the per-second metrics of system resource utilisation and network bandwidth over 10 seconds during such an attack scenario. Table 4.3 encapsulates the outcomes for CPU utilisation, memory utilisation, and network throughput for 10 seconds during a TCP SYN flood attack executed using LOIC with 10 threads on a web server.

Table 4.3 CPU utilisation, memory utilisation, and network throughput during TCP SYN flood using LOIC with 10 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	30	35	20
2	40	40	22
3	50	45	25
4	60	50	30
5	70	55	35
6	80	60	40
7	85	65	45
8	90	70	50
9	95	75	55
10	98	80	60

CPU utilisation exhibits a steep ascent, hitting a peak of 98% at the 10-second mark, indicating an increasing workload on the processor. Similarly, memory utilisation escalates from 30% to 80% within the same duration, illustrating a substantial demand on the server's memory. Network bandwidth also sees a significant surge, from 19 Mbps initially to 60 Mbps at the end of the 10-second period, which indicates an amplified data transfer rate.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.4, and 0.3 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.3(23) + 0.4(30) + 0.3(19) = 6.9 + 12 + 5.7 = 24.6$

At time 1 second: $Y = 0.3(30) + 0.4(35) + 0.3(20) = 9 + 14 + 6 = 29$

At time 2 seconds: $Y = 0.3(40) + 0.4(40) + 0.3(22) = 12 + 16 + 6.6 = 34.6$

At time 3 seconds: $Y = 0.3(50) + 0.4(45) + 0.3(25) = 15 + 18 + 7.5 = 40.5$

At time 4 seconds: $Y = 0.3(60) + 0.4(50) + 0.3(30) = 18 + 20 + 9 = 47$

At time 5 seconds: $Y = 0.3(70) + 0.4(55) + 0.3(35) = 21 + 22 + 10.5 = 53.5$

At time 6 seconds: $Y = 0.3(80) + 0.4(60) + 0.3(40) = 24 + 24 + 12 = 60$

At time 7 seconds: $Y = 0.3(85) + 0.4(65) + 0.3(45) = 25.5 + 26 + 13.5 = 65$

At time 8 seconds: $Y = 0.3(90) + 0.4(70) + 0.3(50) = 27 + 28 + 15 = 70$

At time 9 seconds: $Y = 0.3(95) + 0.4(75) + 0.3(55) = 28.5 + 30 + 16.5 = 75$

At time 10 seconds: $Y = 0.3(98) + 0.4(80) + 0.3(60) = 29.4 + 32 + 18 = 79.4$

Given the threshold of $Y = 45$, the system would be considered to be under a DoS attack starting from the 4th second.

4.1.2.1.3 Here is the value for how CPU and memory utilisation, as well as network bandwidth, change every second for a duration of 10 seconds during a TCP SYN flood with LOIC using 20 threads. The details provided in Table 4.4 reveal the outcomes associated with CPU utilisation, memory utilisation, and network throughput during a TCP SYN flood attack executed via LOIC, utilising 20 threads on a web server, all recorded for 10 seconds.

Table 4.4 CPU utilisation, memory utilisation, and network throughput during TCP SYN flood using LOIC with 20 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	40	45	20
2	60	60	30
3	75	70	40
4	85	80	50
5	90	85	60
6	95	90	70
7	97	92	80
8	98	94	90
9	99	96	100
10	99	97	100

Over a duration of 10 seconds during a TCP SYN flood attack executed using LOIC with 20 threads, resource utilisation and network bandwidth increased significantly. CPU utilisation started from 20% at time zero and rapidly rose to 99% by the 9th second, where it remained steady. Similarly, memory utilisation exhibited a swift increment from 30% at the outset, escalating to 97% by the 10th second. In parallel, network bandwidth showed a substantial increase. Starting at 19 Mbps, it rose rapidly and by the 9th second, bandwidth utilisation had reached its peak at 100 Mbps, where it continued until the 10th second. This data indicates the high resource utilisation and network load during a TCP SYN flood attack executed using 20 threads.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.4, and 0.3 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.3(23) + 0.4(30) + 0.3(19) = 6.9 + 12 + 5.7 = 24.6$

At time 1 second: $Y = 0.3(40) + 0.4(45) + 0.3(20) = 12 + 18 + 6 = 36$

At time 2 seconds: $Y = 0.3(60) + 0.4(60) + 0.3(30) = 18 + 24 + 9 = 51$

At time 3 seconds: $Y = 0.3(75) + 0.4(70) + 0.3(40) = 22.5 + 28 + 12 = 62.5$

At time 4 seconds: $Y = 0.3(85) + 0.4(80) + 0.3(50) = 25.5 + 32 + 15 = 72.5$

At time 5 seconds: $Y = 0.3(90) + 0.4(85) + 0.3(60) = 27 + 34 + 18 = 79$

At time 6 seconds: Y = 0.3(95) + 0.4(90) + 0.3(70) = 28.5 + 36 + 21 = 85.5

At time 7 seconds: Y = 0.3(97) + 0.4(92) + 0.3(80) = 29.1 + 36.8 + 24 = 89.9

At time 8 seconds: Y = 0.3(98) + 0.4(94) + 0.3(90) = 29.4 + 37.6 + 27 = 94

At time 9 seconds: Y = 0.3(99) + 0.4(96) + 0.3(100) = 29.7 + 38.4 + 30 = 98.1

At time 10 seconds: Y = 0.3(99) + 0.4(97) + 0.3(100) = 29.7 + 38.8 + 30 = 98.5

With a threshold of Y = 45, it shows that the system is under a DoS attack, starting from the 2nd second.

4.1.2.1.4 The provided data reveals the CPU and memory utilisation fluctuation, alongside network bandwidth, during a TCP SYN flood assault instigated via LOIC employing 50 threads. These measurements were collected on a second-by-second basis over a 10-second interval. The presented data in Table 4.5 illustrates the values recorded for CPU utilisation, memory utilisation, and network bandwidth over a span of 10 seconds during a TCP SYN flood attack on a web server. The attack was conducted using the Low Orbit Ion Cannon (LOIC) tool with 50 concurrent threads.

Table 4.5 CPU utilisation, memory utilisation, and network throughput during TCP SYN flood using LOIC with 50 threads on a web server for a duration of 10 seconds

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	60	70	50
2	80	85	100
3	90	90	100
4	95	95	100
5	97	97	100
6	98	98	100
7	99	99	100
8	99	99	100
9	99	99	100
10	99	99	100

Over the course of a 10-second TCP SYN flood attack employing LOIC with 50 threads, both CPU and memory utilisation, as well as network bandwidth, experience significant increases. At time zero, CPU and memory utilisation started at 20% and 30%

respectively, with network bandwidth at 19 Mbps. CPU and memory utilisation escalated rapidly, with both reaching 99% by the 7th second and maintaining this peak for the remaining duration. Similarly, network bandwidth rose sharply from 19 Mbps to 100 Mbps within the first 2 seconds and remained at this peak throughout the rest of the attack. These trends suggest a high resource load and network saturation during a TCP SYN flood attack when conducted with 50 concurrent threads, demonstrating the severe impact of such an attack on the targeted web server.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.4, and 0.3 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.3(23) + 0.4(30) + 0.3(19) = 6.9 + 12 + 5.7 = 24.6$

At time 1 second: $Y = 0.3(60) + 0.4(70) + 0.3(50) = 18 + 28 + 15 = 61$

At time 2 seconds: $Y = 0.3(80) + 0.4(85) + 0.3(100) = 24 + 34 + 30 = 88$

At time 3 seconds: $Y = 0.3(90) + 0.4(90) + 0.3(100) = 27 + 36 + 30 = 93$

At time 4 seconds: $Y = 0.3(95) + 0.4(95) + 0.3(100) = 28.5 + 38 + 30 = 96.5$

At time 5 seconds: $Y = 0.3(97) + 0.4(97) + 0.3(100) = 29.1 + 38.8 + 30 = 97.9$

At time 6 seconds: $Y = 0.3(98) + 0.4(98) + 0.3(100) = 29.4 + 39.2 + 30 = 98.6$

At time 7 seconds: $Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3$

At time 8 seconds: $Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3$

At time 9 seconds: $Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3$

At time 10 seconds: $Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3$

Given a threshold of $Y = 45$, the system is detected as being under a DoS attack starting from the 1st second.

4.1.2.1.5 The following data represents the per-second fluctuations in CPU utilisation, memory utilisation, and network bandwidth for a 10-second duration. These metrics were recorded during a TCP SYN flood attack initiated using the Low Orbit Ion Cannon (LOIC) tool with 100 threads. Table 4.6 displays the relevant outcomes. This attack was implemented using a Low Orbit Ion Cannon (LOIC) tool employing 100 threads targeting a web server over a span of 100 seconds

Table 4.6 CPU utilisation, memory utilisation, and network throughput during TCP SYN flood using LOIC with 100 threads on a web server for a duration of 10 seconds

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	80	90	100
2	95	95	100
3	98	97	100
4	99	98	100
5	99	99	100
6	99	99	100
7	99	99	100
8	99	99	100
9	99	99	100
10	99	99	100

The provided data records the second-by-second changes in CPU utilisation, memory utilisation, and network bandwidth over a 10-second interval during a TCP SYN flood attack executed using the Low Orbit Ion Cannon (LOIC) tool with 100 threads. Initially, at time zero, CPU utilisation, memory utilisation, and network bandwidth were recorded at 20%, 30%, and 19 Mbps respectively. However, by the 1st second, CPU and memory utilisation had escalated to 80% and 90%, and network bandwidth had reached 100 Mbps. By the 2nd second, CPU and memory utilisation had reached 95%, and network bandwidth remained at its peak of 100 Mbps. Between the 3rd and 10th second, CPU and memory utilisation were at their peak values (99% and 98-99%, respectively), indicating a state of maximum load on the system resources. Network bandwidth remained at its maximum of 100 Mbps from the 1st second onwards, indicating that the system was operating at full network capacity. This data signifies that a TCP SYN flood attack carried out using 100 threads can quickly maximise system resource utilisation and network bandwidth, causing a potential disruption to a web server's operations.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.4, and 0.3 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.3(23) + 0.4(30) + 0.3(19) = 6 + 12 + 5.7 = 24.6$

At time 1 second: $Y = 0.3(80) + 0.4(90) + 0.3(100) = 24 + 36 + 30 = 90$

At time 2 seconds: Y = 0.3(95) + 0.4(95) + 0.3(100) = 28.5 + 38 + 30 = 96.5

At time 3 seconds: Y = 0.3(98) + 0.4(97) + 0.3(100) = 29.4 + 38.8 + 30 = 98.2

At time 4 seconds: Y = 0.3(99) + 0.4(98) + 0.3(100) = 29.7 + 39.2 + 30 = 98.9

At time 5 seconds: Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3

At time 6 seconds: Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3

At time 7 seconds: Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3

At time 8 seconds: Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3

At time 9 seconds: Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3

At time 10 seconds: Y = 0.3(99) + 0.4(99) + 0.3(100) = 29.7 + 39.6 + 30 = 99.3

Given a threshold of Y = 45, it would be detected that the system is under a DoS attack starting from the 1st second.

It's clear that there is a correlation between the number of threads involved in the task and the time it takes for a TCP attack to be identified. This correlation suggests that as the number of threads increases, the time it takes for the system to identify a TCP attack decreases. With only 5 threads, the system is capable of sustaining normal operations for up to 7 seconds before the values exceed the defined threshold of Y = 45, indicating a TCP attack. As the number of threads doubles to 10, the time to detect the attack significantly reduces by half to the 4th second. An even more significant change is observed as the thread count is further increased to 20. The time to detect a TCP attack reduces by half again to the 2nd second. This pattern suggests that the increase in thread count exponentially increases the system's susceptibility to TCP attack, likely due to the higher utilisation of system resources. Interestingly, from 50 threads and beyond, the system is under a TCP attack right from the first second. This indicates that beyond a certain threshold of threads (in this case, 50), the system becomes immediately overwhelmed, suggesting a severe limitation in the server's ability to handle large numbers of simultaneous connections.

Building on the results accrued from the Experimental Testbed Configuration - Part 2, an in-depth examination of CPU utilisation patterns was undertaken. This inspection spanned a duration of 10 seconds, coinciding with the execution of a TCP SYN flood attack. To ensure a comprehensive evaluation, various thread counts were employed, specifically 5, 10, 20, 50,

and 100 threads. The intent of this appraisal was to discern any correlations or trends in CPU Utilisation, as the intensity of the attack – determined by the number of threads – increases.

Figure 4.4 provides a graphical depiction of the resultant CPU utilisation (%), with specific reference to the distinct thread counts: 5, 10, 20, 50, and 100. This figure elucidates the relationship between the volume of threads and the corresponding impact on CPU utilisation.

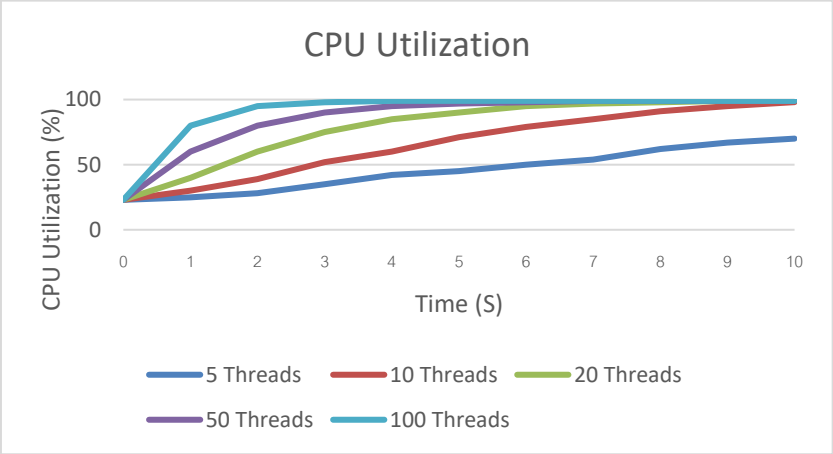

Figure 4. 4 CPU utilisation (%), specifically TCP attack 5, 10, 20, 50, and 100 threads.

The provided data details the progression of CPU utilisation over 10 seconds during a TCP SYN flood attack using different thread counts (5, 10, 20, 50, 100). CPU utilisation is represented as a percentage, reflecting the load on the processor caused by the attack. With 5 threads, CPU utilisation starts at 23% and increases slowly and consistently, reaching a maximum of 70% after 10 seconds. When the attack is executed with 10 threads, it begins at the same initial value (23%) but escalates more rapidly than in the 5-thread scenario, reaching 98% after 10 seconds. This indicates that doubling the number of threads roughly doubles the load on the CPU. An attack with 20 threads shows an even sharper increase in CPU utilisation. The load begins at 23% but hits the saturation point (99%) as early as 9 seconds into the attack, staying there in the 10th second. When the number of threads increases to 50, the saturation point (99%) is reached even faster, within the 7th second. CPU utilisation stays at this level for the remainder of the time. The trend of rapid CPU saturation continues with 100 threads, where 99% utilisation is achieved already in the 4th second, remaining there for the rest of the attack duration. This data highlights how increasing the number of threads in a TCP SYN flood attack

leads to more rapid saturation of CPU resources, potentially causing more significant disruption and damage to the targeted server.

The results derived from Experimental Testbed Configuration - Part 2 enable a thorough analysis of memory utilisation trends. This analysis was conducted over a period of 10 seconds, during a TCP SYN flood attack. The attack used different numbers of threads, 5, 10, 20, 50, and 100, to allow for a broad and detailed evaluation. This analysis aims to identify any patterns in memory utilisation that correspond to the severity of the attack, dictated by the number of threads used.

Figure 4.5 below presents a visual representation of memory utilisation (%), specifically for the different thread counts: 5, 10, 20, 50, and 100. This figure helps illustrate how the number of threads used in the attack influences memory utilisation.

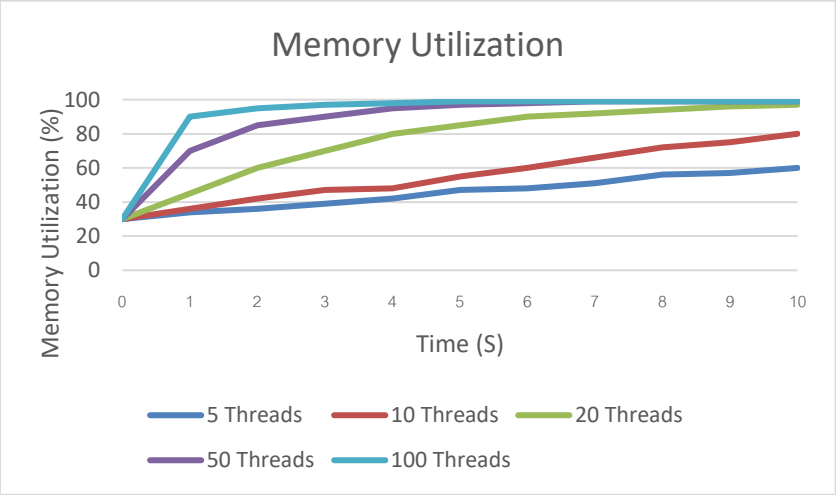

Figure 4.5 Percentage of memory utilisation specific to TCP attacks using different thread counts: 5, 10, 20, 50, and 100.

The data presented above displays the progression of memory utilisation, expressed in percentages, over a time frame of 10 seconds during a TCP SYN flood attack. The test involved varied the number of threads used in the attack, specifically 5, 10, 20, 50, and 100 threads, to discern any correlational changes in memory utilisation. For the TCP SYN flood attack with 5 threads, memory utilisation started at 30% at time 0 and progressively increased each second, reaching 60% after 10 seconds. The steady increase depicts the resource usage by these threads over the period. When the attack employed 10 threads, there was a similar increase, albeit at a faster rate. Starting from 30%, memory utilisation reached 80% after 10 seconds, illustrating

the higher strain on the system with more threads. The trend of faster memory utilisation becomes apparent as the number of threads increases. For an attack with 20 threads, memory utilisation started at 30% and reached 97% after 10 seconds. With 50 threads, memory utilisation went from 30% to 99% in the same duration. Finally, an attack employing 100 threads saw memory utilisation rise rapidly from 30% to 99% within the first 6 seconds, remaining stable at 99% for the remaining 4 seconds.

Overall, this data showcases the direct relationship between the number of threads employed in a TCP SYN flood attack and the memory utilisation rate. As the number of threads increases, the speed at which memory utilisation increases becomes faster, demonstrating the heightened system strain under more intense attacks.

The Experimental Testbed Configuration - Part 2 data allows for a complete investigation of network bandwidth (Mbps) trends. The study was done during a 10-second TCP SYN flood attack. The attack employed a variety of thread counts, including 5, 10, 20, 50, and 100, to enable a thorough and in-depth analysis. This analysis's objective was to find any trends in network bandwidth related to the attack's severity, determined by the number of threads employed. In Figure 4.6, a graphical interpretation of network bandwidth is depicted, specifically emphasising varying thread counts: 5, 10, 20, 50, and 100. This illustrative representation aids in discerning the influence exerted by the number of threads utilised in the attack on network bandwidth (Mbps).

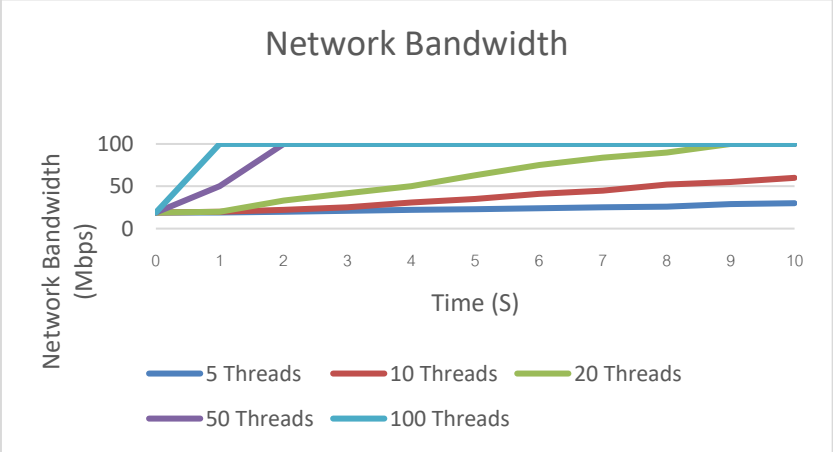

Figure 4.6 Percentage of network bandwidth (Mbps) specific to TCP attacks using different thread counts: 5, 10, 20, 50, and 100

Figure 4.6 above presents data for network bandwidth measured in Mbps during a TCP SYN flood attack with thread counts of 5, 10, 20, 50, and 100. Observations were recorded each second for 10 seconds. At the outset (Time = 0 seconds), all thread counts began with a network bandwidth utilisation of 19 Mbps, which suggests a similar baseline for all scenarios. For attacks with 5 and 10 threads, there is a relatively gradual and linear increase in network bandwidth utilisation over time. After 10 seconds, network bandwidth for the 5-thread and 10-thread attacks reached 30 Mbps and 60 Mbps, respectively. With a 20-thread attack, the network bandwidth usage exhibited a more accelerated progression, reaching 100 Mbps at the 9-second mark and maintaining that level for the remainder of the observation period. Attacks with 50 and 100 threads showed the most pronounced increase, with the network bandwidth skyrocketing to 100 Mbps as early as the 2-second mark for the 50-thread attack, and by the first second in the case of the 100-thread attack. This maximum bandwidth utilisation of 100 Mbps was sustained throughout the remainder of the observation period. In summary, as the number of threads used in the TCP SYN flood attack increases, there is a more immediate and significant impact on network bandwidth utilisation. This indicates that more intense attacks, characterised by a higher number of threads, consume network resources more rapidly and sustain this consumption for the attack's duration.

4.1.2.2 In a UCP flood

This subsection clarifies the effectiveness of the proposed system in detecting UDP flood attacks using the Nettools 5 attack tool under various conditions, particularly employing differing numbers of threads (sessions). These variations include scenarios with 5, 10, 20, 50, and 100 threads respectively, providing a broad range of circumstances for a thorough assessment of system performance. Notably, the packet size used in these scenarios is 1000 bytes. Figure 4.7 displays an image of the Experimental Testbed - Part 2 with UDP flood via Nettools 5 diagram.

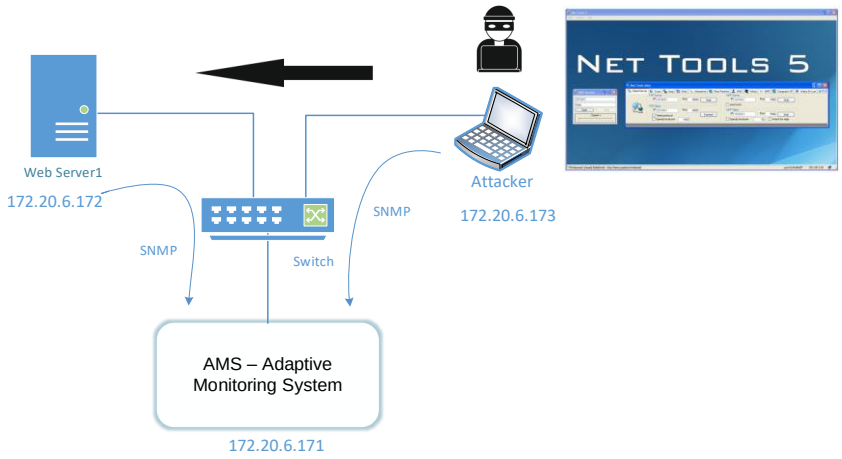

Figure 4.7 Diagram of experimental testbed part 2 with UDP attack via Nettools 5.

4.1.2.2.1 In a UDP flood using Nettools 5 starting with 5 threads, the impact on CPU and memory utilisation, as well as network bandwidth, will generally be less compared to attacks with a larger number of threads. Here, a value of the system's resource utilisation and network bandwidth is taken every second for 10 seconds. Table 4.7 shows the results for CPU utilisation, memory utilisation, and network bandwidth during UDP flood using Nettools 5 with 5 threads on a web server for a duration of 10 seconds:

Table 4.7 CPU utilisation, memory utilisation, and network bandwidth during UDP flood using Nettools 5 with 5 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	25	33	28
2	30	37	35
3	34	42	45
4	40	48	55
5	47	57	70
6	52	63	80
7	60	69	90
8	65	72	98
9	70	78	100
10	75	80	100

With the UDP attack increasing the load, CPU and memory utilisation also gradually increase. Network bandwidth spikes because of the flood of UDP packets. The most significant rise in resource utilisation occurs between the 4th and 5th second, especially for network bandwidth which jumps from 55 Mbps to 70 Mbps. From then on, network bandwidth keeps increasing rapidly, reaching its peak at the 9th second. This sharp increase can indicate the onset of the attack. After reaching the switch's capacity (100 Mbps), it remains at 100 Mbps, indicating a saturation point, assuming the attack intensity stays the same.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.3(23) + 0.3(30) + 0.4(19) = 6.9 + 9 + 7.6 = 23.5$

At time 1 second: $Y = 0.3(25) + 0.3(33) + 0.4(28) = 7.5 + 9.9 + 11.2 = 28.6$

At time 2 seconds: $Y = 0.3(30) + 0.3(37) + 0.4(35) = 9 + 11.1 + 14 = 34.1$

At time 3 seconds: $Y = 0.3(34) + 0.3(42) + 0.4(45) = 10.2 + 12.6 + 18 = 40.8$

At time 4 seconds: $Y = 0.3(40) + 0.3(48) + 0.4(55) = 12 + 14.4 + 22 = 48.4$

At time 5 seconds: $Y = 0.3(47) + 0.3(57) + 0.4(70) = 14.1 + 17.1 + 28 = 59.2$

At time 6 seconds: $Y = 0.3(52) + 0.3(63) + 0.4(80) = 15.6 + 18.9 + 32 = 66.5$

At time 7 seconds: $Y = 0.3(60) + 0.3(69) + 0.4(90) = 18 + 20.7 + 36 = 74.7$

At time 8 seconds: $Y = 0.3(65) + 0.3(72) + 0.4(98) = 19.5 + 21.6 + 39.2 = 80.3$

At time 9 seconds: $Y = 0.3(70) + 0.3(78) + 0.4(100) = 21 + 23.4 + 40 = 84.4$

At time 10 seconds: $Y = 0.3(75) + 0.3(80) + 0.4(100) = 22.5 + 24 + 40 = 86.5$

The system stays within safe operational limits for the initial few seconds (0 to approximately 3 seconds). However, after this period, the composite metric Y surpasses the threshold and continues to increase, indicating that the system is under substantial load or stress.

4.1.2.2.2 In a UDP flood using Nettools 5 start with 10 threads, the impact on CPU and memory utilisation, as well as a network bandwidth, will generally be less compared to attacks with a larger number of threads. Here, the values are given for system resource utilisation and network bandwidth every second for 10 seconds. Table 4.8 shows the results for CPU

utilisation, memory utilisation, and network bandwidth during a UDP flood using Nettools 5 with 10 threads on a web server for 10 seconds:

Table 4.8CPU utilisation, memory utilisation , and network bandwidth during UDP flood using Nettools 5 with 10 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	28	37	35
2	35	45	50
3	42	55	66
4	50	66	80
5	58	77	89
6	65	82	100
7	70	88	100
8	75	92	100
9	80	95	100
10	85	98	100

This data set indicates a persistent upward trend in system load over time. Network bandwidth, notably, reaches full capacity at the 6th second and stays at the peak for the remaining duration, suggesting a severe strain on network resources. The notable increase in resource usage is observed between the 4th and 5th second, particularly for network bandwidth, which experiences a surge from 80 Mbps to 89 Mbps. After this point, network bandwidth swiftly saturates, remaining at its peak for the remainder of the time.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into the equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.3(23) + 0.3(30) + 0.4(19) = 6.9 + 9 + 7.6 = 23.5$

At time 1 second: $Y = 0.3(28) + 0.3(37) + 0.4(35) = 8.4 + 11.1 + 14 = 33.5$

At time 2 seconds: $Y = 0.3(35) + 0.3(45) + 0.4(50) = 10.5 + 13.5 + 20 = 44$

At time 3 seconds: $Y = 0.3(42) + 0.3(55) + 0.4(66) = 12.6 + 16.5 + 26.4 = 55.5$

At time 4 seconds: $Y = 0.3(50) + 0.3(66) + 0.4(80) = 15 + 19.8 + 32 = 66.8$

At time 5 seconds: $Y = 0.3(58) + 0.3(77) + 0.4(89) = 17.4 + 23.1 + 35.6 = 76.1$

At time 6 seconds: Y = 0.3(65) + 0.3(82) + 0.4(100) = 19.5 + 24.6 + 40 = 84.1

At time 7 seconds: Y = 0.3(70) + 0.3(88) + 0.4(100) = 21 + 26.4 + 40 = 87.4

At time 8 seconds: Y = 0.3(75) + 0.3(92) + 0.4(100) = 22.5 + 27.6 + 40 = 90.1

At time 9 seconds: Y = 0.3(80) + 0.3(95) + 0.4(100) = 24 + 28.5 + 40 = 92.5

At time 10 seconds: Y = 0.3(85) + 0.3(98) + 0.4(100) = 25.5 + 29.4 + 40 = 94.9

The calculated Y values indicate an upward trend over time, from 23.5 to 94.9, signalling an increasing resource utilisation. A notable shift occurs between the 2nd and 3rd seconds, when the Y value crosses the set threshold of 45, indicating a substantial increase in system load. The persistent high Y values (55.5 to 94.9) beyond the 3rd second imply that the system is continuously operating beyond the set threshold, which could potentially lead to performance issues or system failure.

4.1.2.2.3 A UDP flood attack using Nettools 5 with just 20 threads. In this scenario, the impact on CPU usage, memory usage, and network bandwidth is generally smaller compared to attacks that use more threads. This part presents how the system resources and network bandwidth are used every second for 10 seconds during this attack. Table 4.9 displays the results for CPU usage, memory usage, and network traffic during this 10-second-long UDP flood attack using Nettools 5 with 10 threads on a web server.

Table 4.9 CPU utilisation, memory utilisation, and network bandwidth during UDP flood using Nettools 5 with 20 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	35	45	40
2	47	60	61
3	58	75	77
4	70	85	100
5	80	92	100
6	85	96	100
7	90	98	100
8	93	99	100
9	95	100	100
10	97	100	100

The data show a pronounced increase in all three parameters of CPU utilisation, memory utilisation, and network bandwidth over the 10-second period. CPU utilisation rises from an initial 23% to a high of 97%. Memory utilisation likewise sees a dramatic increase from 30% at the outset to full usage (100%) by the 9th second. Lastly, network bandwidth use accelerates from 19 Mbps at the start to reaching its maximum capacity (100 Mbps) by the 4th second, remaining at this peak for the rest of the period. Moreover, the sharp increase in CPU and memory utilisation from the 3rd to the 4th second, with CPU utilisation jumping from 58% to 70% and memory utilisation from 75% to 85%, signals a critical point in the attack.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.3(23) + 0.3(30) + 0.4(19) = 6.9 + 9 + 7.6 = 23.5$

At time 1 second: $Y = 0.3(35) + 0.3(45) + 0.4(40) = 10.5 + 13.5 + 16 = 40$

At time 2 seconds: $Y = 0.3(47) + 0.3(60) + 0.4(61) = 14.1 + 18 + 24.4 = 56.5$

At time 3 seconds: $Y = 0.3(58) + 0.3(75) + 0.4(77) = 17.4 + 22.5 + 30.8 = 70.7$

At time 4 seconds: $Y = 0.3(70) + 0.3(85) + 0.4(100) = 21 + 25.5 + 40 = 86.5$

At time 5 seconds: $Y = 0.3(80) + 0.3(92) + 0.4(100) = 24 + 27.6 + 40 = 91.6$

At time 6 seconds: $Y = 0.3(85) + 0.3(96) + 0.4(100) = 25.5 + 28.8 + 40 = 94.3$

At time 7 seconds: $Y = 0.3(90) + 0.3(98) + 0.4(100) = 27 + 29.4 + 40 = 96.4$

At time 8 seconds: $Y = 0.3(93) + 0.3(99) + 0.4(100) = 27.9 + 29.7 + 40 = 97.6$

At time 9 seconds: $Y = 0.3(95) + 0.3(100) + 0.4(100) = 28.5 + 30 + 40 = 98.5$

At time 10 seconds: $Y = 0.3(97) + 0.3(100) + 0.4(100) = 29.1 + 30 + 40 = 99.1$

Looking at the evolution of Y over time, the initial value starts relatively low at 23.5, then undergoes a significant jump between the 1st and 2nd seconds (from 40 to 56.5), crossing the given threshold of 45. Beyond the 2nd second, the Y values remain consistently high (56.5 to 99.1), indicating that the system is continuously operating above the set threshold. Given how these are substantial increases sustained over time, it might imply that the system is under heavy load and could be at risk of instability or performance degradation.

4.1.2.2.4 A UDP flood attack using Nettools 5 with 50 threads. In this scenario, the impact on CPU usage, memory usage, and network bandwidth is generally smaller compared to attacks that use more threads. This part presents how the system resources and network bandwidth are used every second for 10 seconds during this attack. Table 4.10 displays the results for CPU usage, memory usage, and network bandwidth during this 10-second-long UDP flood attack using Nettools 5 with 10 threads on a web server.

Table 4.10 CPU utilisation, memory utilisation, and network bandwidth during UDP flood using Nettools 5 with 50 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	45	55	50
2	65	75	80
3	85	90	100
4	95	95	100
5	98	98	100
6	100	99	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

There is an exponential increase in CPU utilisation, memory utilisation, and network bandwidth throughout the 10 seconds. CPU utilisation jumps from an initial 23% to the peak 100% by the 6th second. Similarly, memory utilisation also accelerates drastically from 30% initially to reaching its maximum (100%) by the 7th second. On the other hand, network bandwidth exhausts its full capacity (100 Mbps) by the 3rd second and maintains it for the remaining period. The effects of the UDP flood attack become more significantly severe as the number of threads increases. Compared to the scenarios with fewer threads (5, 10, 20), the system reaches maximum resource utilisation much more rapidly when the attack is launched with 50 threads. The network bandwidth is fully exploited within just 3 seconds, an alarmingly fast rate. Also, CPU and memory usage reach saturation by the 6th and 7th seconds respectively, indicating that the system's capacity to handle the load is quickly overwhelmed under this attack level. The parameters remaining at their peak values from these points onward suggest a sustained strain on the system.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.3(23) + 0.3(30) + 0.4(19) = 6.9 + 9 + 7.6 = 23.5$

At time 1 second: $Y = 0.3(45) + 0.3(55) + 0.4(50) = 13.5 + 16.5 + 20 = 50$

At time 2 seconds: $Y = 0.3(65) + 0.3(75) + 0.4(80) = 19.5 + 22.5 + 32 = 74$

At time 3 seconds: $Y = 0.3(85) + 0.3(90) + 0.4(100) = 25.5 + 27 + 40 = 92.5$

At time 4 seconds: $Y = 0.3(95) + 0.3(95) + 0.4(100) = 28.5 + 28.5 + 40 = 97$

At time 5 seconds: $Y = 0.3(98) + 0.3(98) + 0.4(100) = 29.4 + 29.4 + 40 = 98.8$

At time 6 seconds: $Y = 0.3(100) + 0.3(99) + 0.4(100) = 30 + 29.7 + 40 = 99.7$

At time 7 seconds: $Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100$

At time 8 seconds: $Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100$

At time 9 seconds: $Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100$

At time 10 seconds: $Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100$

An initial examination of Y shows that it starts at a relatively modest value of 23.5 at time 0, implying the system is in a state of low utilisation. However, we observe a significant leap in the combined system score at the 1st second, where $Y = 50$. From the 2nd second onwards, the system load rises markedly and stays consistently high, ranging from 74 to 100. From the 3rd second onwards, the system appears to be running at or near its maximum capacity, as indicated by Y values above 90. By the 7th second, the system reaches full capacity load, where $Y = 100$, and remains at that level for the remaining time.

4.1.2.2.5 The following data represents the per-second fluctuations in CPU utilisation, memory utilisation, and network bandwidth for a 10-second duration. These metrics were recorded during a UDP attack initiated using Nettools5 with 100 threads. Table 4.11 displays the outcomes for the CPU utilisation, memory utilisation, and network throughput metrics throughout a UDP attack. The attack was implemented using Nettools 5, employing 100 threads targeting a web server for 100 seconds

Table 4.11 CPU utilisation, memory utilisation, and network bandwidth during UDP flood using Nettools 5 with 100 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	55	65	70
2	85	85	100
3	95	95	100
4	100	98	100
5	100	100	100
6	100	100	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

The data shows an alarming escalation in CPU utilisation, memory utilisation, and network bandwidth usage in just two seconds. The CPU utilisation dramatically rises from an initial 23% to reaching its peak at 100% by the 4th second. Memory utilisation also increases swiftly, starting from 30% and reaching full capacity (100%) by the 5th second. Network bandwidth hits its maximum value (100 Mbps) by the 2nd second, indicating full saturation of the network resources. It's clear that the system is severely affected by the flood attack as the number of threads increases to 100. Compared to previous cases with lower thread counts (5, 10, 20, 50), the system resources are exhausted extremely rapidly. Network bandwidth, in particular, maxes out within just two seconds, which is concerning. Furthermore, CPU and memory usage also reach saturation quite quickly, indicating that the system is under severe stress. The fact that these values remain at their peak for the rest of the period indicates that the system is likely unable to process any additional requests, essentially rendering it non-functional.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.3(23) + 0.3(30) + 0.4(19) = 6.9 + 9 + 7.6 = 23.5$

At time 1 second: $Y = 0.3(55) + 0.3(65) + 0.4(70) = 16.5 + 19.5 + 28 = 64$

At time 2 seconds: $Y = 0.3(85) + 0.3(85) + 0.4(100) = 25.5 + 25.5 + 40 = 91$

At time 3 seconds: Y = 0.3(95) + 0.3(95) + 0.4(100) = 28.5 + 28.5 + 40 = 97

At time 4 seconds: Y = 0.3(100) + 0.3(98) + 0.4(100) = 30 + 29.4 + 40 = 99.4

At time 5 seconds: Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100

At time 6 seconds: Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100

At time 7 seconds: Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100

At time 8 seconds: Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100

At time 9 seconds: Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100

At time 10 seconds: Y = 0.3(100) + 0.3(100) + 0.4(100) = 30 + 30 + 40 = 100

The overall system utilisation, represented by the metric Y, rapidly increases from 23.5 at time 0 seconds to 100 by the 5th second, suggesting a fast escalation in the demand on resources. The acceleration is so swift that all resources are saturated by the 5th second, a state that persists for the remaining period. The rapid escalation is particularly alarming for network bandwidth, which reaches full capacity within just two seconds, pointing to the extreme intensity of the flood attack. This saturation of network bandwidth is concerning because it means that the system would be unable to accommodate additional network requests. Similarly, CPU and memory utilisation reach saturation within the first five seconds. This situation suggests that the system is severely strained and potentially unable to handle any further computational or storage demands.

The provided data appears to depict the CPU utilisation (%) over time (measured in seconds) under different load conditions, simulated by varying the number of active threads (5, 10, 20, 50, and 100 threads). This is Experimental Testbed Configuration - Part 2 involving a UDP attack. Figure 4.8 provides a graphical depiction of the resultant CPU utilisation (%), with specific reference to the distinct thread counts: 5, 10, 20, 50, and 100. This figure elucidates the relationship between the volume of threads and the corresponding impact on CPU utilisation.

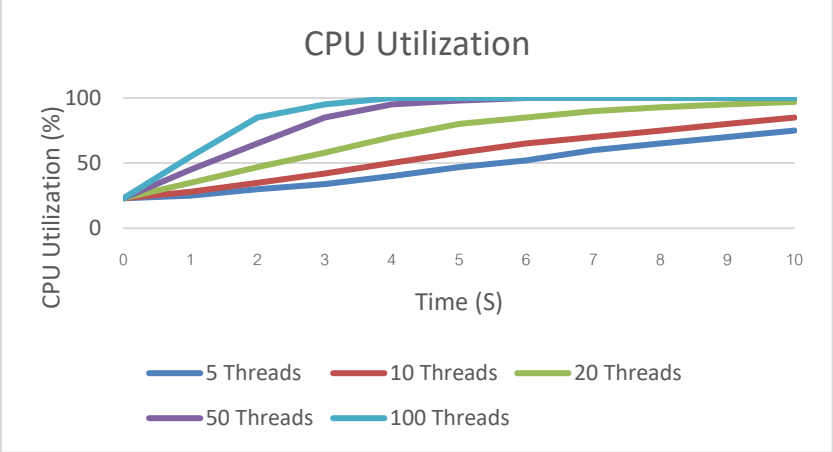

Figure 4.8 CPU utilisation (%), specifically for a UDP attack with 5, 10, 20, 50, and 100 threads.

At the start (0 seconds), all thread scenarios start at a CPU utilisation rate of 23%. As time progresses and threads increase, the CPU utilisation dramatically escalates. At 5 threads, CPU utilisation increases in a comparatively controlled manner, reaching 75% at 10 seconds. However, the CPU load significantly intensifies with a higher thread count. With 100 threads, the CPU hits its full capacity (100%) as early as 4 seconds.

The results derived from the Experimental Testbed Configuration - Part 2 enable a thorough analysis of the memory utilisation trends. This analysis was conducted over a period of 10 seconds during a UDP attack. The attack used different numbers of threads, 5, 10, 20, 50, and 100, to allow for a broad and detailed evaluation. This analysis aimed to identify any patterns in memory utilisation that corresponded to the severity of the attack, dictated by the number of threads used. Figure 4.9 below presents a picture of memory utilisation (%), specifically for different thread counts: 5, 10, 20, 50, and 100. This figure helps to illustrate how the number of threads used in the attack influences memory utilisation.

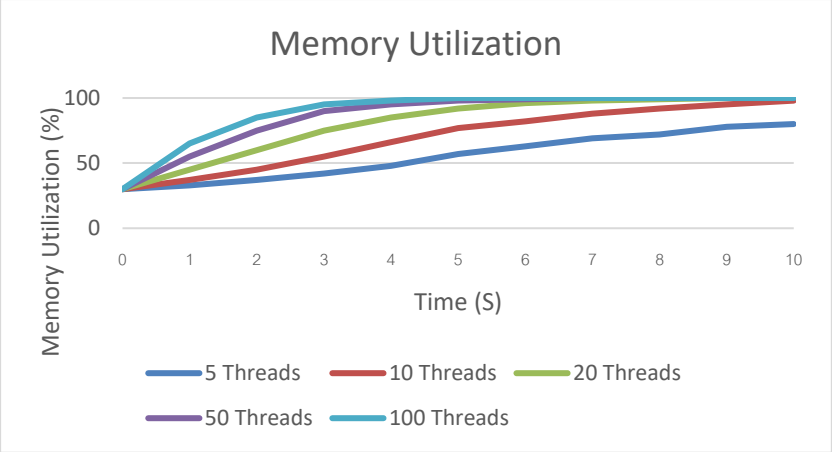

Figure 4.9 Percentage of memory utilisation specific to UDP attacks using different thread counts: 5, 10, 20, 50, and 100.

The data from Experimental Testbed Configuration - Part 2 reveals a significant trend in memory utilisation under a UDP attack over 10 seconds, with varying thread counts of 5, 10, 20, 50, and 100. Starting at an initial 30% utilisation across all thread counts, it's evident that memory usage rises with the increase in threads. At a lower thread count of 5, memory utilisation climbs steadily to 80% over 10 seconds, showing the system's reasonable handling of smaller loads. In stark contrast, under the highest load of 100 threads, memory utilisation maxes out to 100% in just 5 seconds, pointing to a considerable strain on the system's memory resources under intense load.

The data from Experimental Testbed Configuration - Part 2 presents an opportunity for a comprehensive evaluation of how network bandwidth (Mbps) changes. This observation was made during a 10 second period of a UDP attack, a common type of network attack. The attack used different numbers of threads (5, 10, 20, 50, and 100) to enable a detailed and wide-ranging assessment. The aim of this investigation was to identify if there are any patterns in network bandwidth related to how intense the attack was, controlled by the number of threads used. Figure 4.10 below provides a visual display of how network bandwidth changes, with special focus on the effect of the different thread counts: 5, 10, 20, 50, and 100. This picture helps to understand the impact of the number of threads used in the attack on network bandwidth (in Mbps).

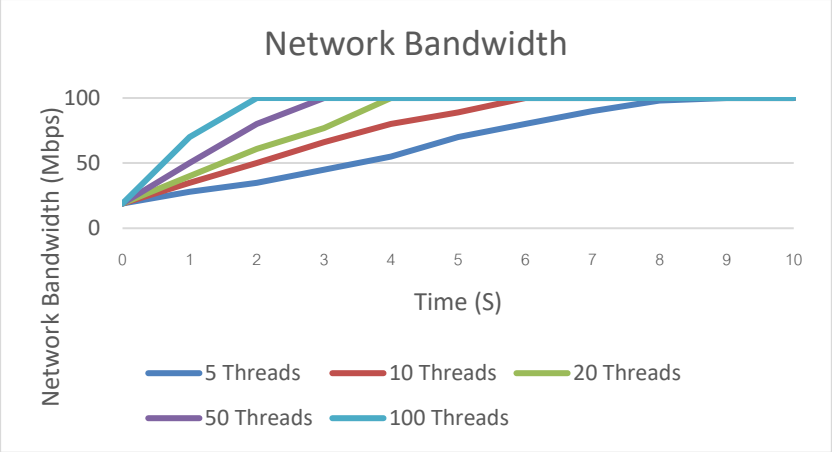

Figure 4.10 Percentage of network bandwidth (Mbps) specific to UDP attacks using different thread counts: 5, 10, 20, 50, and 100.

Starting with an identical network bandwidth of 19 Mbps across all thread counts, the bandwidth consumption escalated with an increase in threads. For the minimal load of 5 threads, bandwidth rose steadily to full utilisation (100 Mbps) in 9 seconds, indicating a moderate response to less intense attacks. In contrast, under a maximum load of 100 threads, bandwidth hit peak usage within just 2 seconds, implying an accelerated saturation and potential strain on network resources under severe attacks. This rapid bandwidth exhaustion at higher thread counts suggests possible network performance degradation or even system failure during high-intensity UDP attacks. The findings also hint at a potential scalability issue, where the system struggles to maintain performance under heavier loads.

4.1.2.3 ICMP flood

This part of the analysis focuses on the performance of the proposed system in spotting ICMP flood attacks. These attacks were executed using the NetScantools attack tool, conducted under various conditions for a thorough examination. The analysis considers different severity levels, reflected by the number of concurrent threads or sessions in the attack, specifically cases with 5, 10, 20, 50, and 100 threads. Notably, each packet employed in these scenarios had a size of 1,024 bytes. These diverse scenarios offer a comprehensive look at the system's response to different intensities of the same attack type. A graphic representation of the diagram Experimental Testbed part 2 with ICMP flood via NetScantools is shown in Figure 4.11 below.

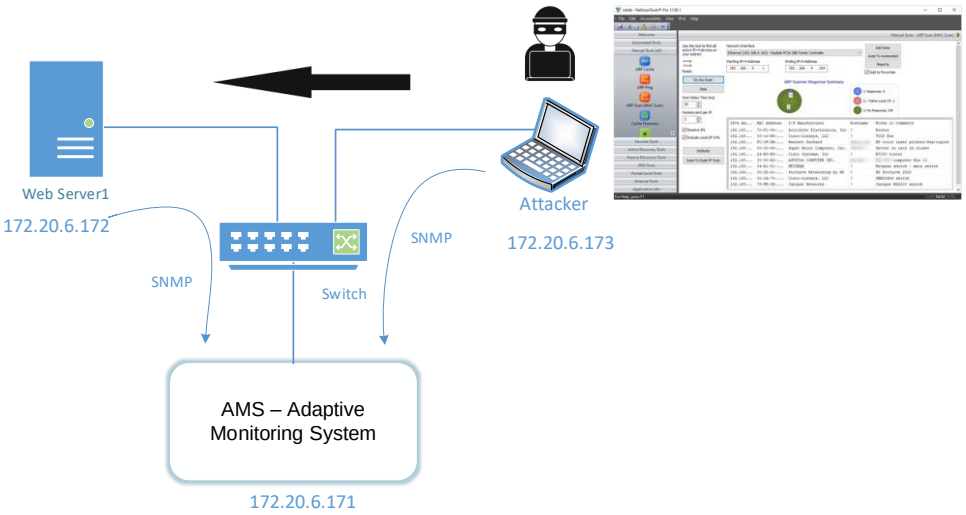

Figure 4.11 Diagram of experimental testbed part 2 with ICMP attack via NetScantools.

4.1.2.3.1 In a ICMP flood using NetScantools start with 5 threads.

Under these circumstances, CPU and memory utilisation, along with network bandwidth, experience a lesser impact compared to the impact of attacks with a higher thread count. The specific values of these resource utilisations are presented every second over 10 seconds. For a detailed examination, Table 4.12 showcases the figures about CPU utilisation, memory utilisation, and network bandwidth during this specific assault on the web server.

Table 4.12 CPU utilisation, memory utilisation, and network bandwidth during ICMP flood using NetScantools with 5 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	27	33	30
2	32	37	41
3	35	39	52
4	39	42	63
5	44	47	74
6	47	50	85
7	52	51	96
8	55	54	100
9	59	57	100
10	63	59	100

Regarding CPU utilisation, the initial value starts at 23% and progressively increases to 63% by the 10th second. Although there is a steady rise, the utilisation does not reach saturation, indicating that the system may still have capacity to handle additional tasks. Memory utilisation shows a similar trend, beginning at 30% and reaching 59% by the end of the attack. The gradual and less drastic increase reflects the lower thread count in the attack and suggests a less severe strain on system resources compared to attacks with a larger number of threads.

Regarding network bandwidth, it's noted that while the initial usage is 19 Mbps, it reaches its maximum capacity of 100 Mbps by the 8th second. This rapid saturation of the network bandwidth is concerning as it could limit the system's ability to handle legitimate network traffic.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.25, 0.35, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.25(23) + 0.35(30) + 0.4(19) = 23.85$

At time 1 second: $Y = 0.25(27) + 0.35(33) + 0.4(30) = 30.3$

At time 2 seconds: $Y = 0.25(32) + 0.35(37) + 0.4(41) = 37.35$

At time 3 seconds: $Y = 0.25(35) + 0.35(39) + 0.4(52) = 43.2$

At time 4 seconds: $Y = 0.25(39) + 0.35(42) + 0.4(63) = 49.65$

At time 5 seconds: $Y = 0.25(44) + 0.35(47) + 0.4(74) = 57.05$

At time 6 seconds: $Y = 0.25(47) + 0.35(50) + 0.4(85) = 63.25$

At time 7 seconds: $Y = 0.25(52) + 0.35(51) + 0.4(96) = 69.25$

At time 8 seconds: $Y = 0.25(55) + 0.35(54) + 0.4(100) = 72.65$

At time 9 seconds: $Y = 0.25(59) + 0.35(57) + 0.4(100) = 74.7$

At time 10 seconds: $Y = 0.25(63) + 0.35(59) + 0.4(100) = 76.4$

Analysing the trend, there is a continuous and steady increase in the values of Y from time 0 to time 10 seconds. Y increases from 23.85 at time 0 to 76.4 at time 10 seconds, showing a rise in system utilisation over this period. This may imply that the system is experiencing an escalating load. A closer look at the respective contributions to Y indicates that network

bandwidth (with the highest coefficient of 0.4) tends to contribute the most to the total system load, increasing significantly over the given time period. This points to a surge in network activity or data traffic which could be due to a variety of factors, such as a potential cyberattack. CPU and memory utilisation, although also increasing, do so more modestly. They do not exhibit the same rapid growth as the network bandwidth, suggesting that these resources are not as strained or as immediately impacted. However, the total system load, represented by Y, is below the critical threshold of 45 until the 4th second, after which it exceeds the threshold. This signifies that the system may be able to handle the increased load in the initial seconds. However, as time progresses, the system load goes beyond the stipulated capacity, indicating a potential risk of system slowdown or failure.

4.1.2.3.2 In an ICMP flood using NetScantools start with 10 threads.

Under these conditions, the CPU and memory utilisation, along with network bandwidth, experience a lesser impact compared to the impact of attacks with a higher thread count. The specific values of these resource utilisations are presented every second over 10 seconds. For a detailed examination, Table 4.13 showcases the figures for CPU utilisation, memory utilisation, and network bandwidth during this specific assault on the web server.

Table 4.13 CPU utilisation, memory utilisation, and network bandwidth during ICMP flood using NetScantools with 10 threads on a web server for a duration of 10 seconds

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	35	42	40
2	47	52	64
3	58	60	85
4	71	72	100
5	84	80	100
6	95	91	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

The data reveals a steadily increasing trend in CPU and memory utilisation. CPU usage, which starts at a relatively low 23%, gradually escalates to its maximum capacity (100%) by

the 7th second and sustains this level for the remainder of the attack duration. Memory utilisation follows a similar trajectory, rising from an initial 30% to peak at 100% in the 7th second, demonstrating that the attack fully engages the system's memory resources in the later stages. However, the network bandwidth utilisation in this scenario presents an urgent issue. Despite commencing from 19 Mbps, it reaches its maximum limit (100 Mbps) as early as the 4th second and maintains this saturation for the remainder of the attack. This demonstrates the significant threat posed by the ICMP flood attack as it can rapidly consume available network bandwidth, potentially leading to service disruptions or slowdowns.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.25(23) + 0.35(30) + 0.4(19) = 5.75 + 10.5 + 7.6 = 23.85$

At time 1 second: $Y = 0.25(35) + 0.35(42) + 0.4(40) = 8.75 + 14.7 + 16 = 39.45$

At time 2 seconds: $Y = 0.25(47) + 0.35(52) + 0.4(64) = 11.75 + 18.2 + 25.6 = 55.55$

At time 3 seconds: $Y = 0.25(58) + 0.35(60) + 0.4(85) = 14.5 + 21 + 34 = 69.5$

At time 4 seconds: $Y = 0.25(71) + 0.35(72) + 0.4(100) = 17.75 + 25.2 + 40 = 82.95$

At time 5 seconds: $Y = 0.25(84) + 0.35(80) + 0.4(100) = 21 + 28 + 40 = 89$

At time 6 seconds: $Y = 0.25(95) + 0.35(91) + 0.4(100) = 23.75 + 31.85 + 40 = 95.6$

At time 7 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 8 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 9 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 10 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

In the given timeframe, system load Y exhibits a linear growth pattern, moving from a lower load state (23.85) to full saturation (100) by the 7th second. This escalation corresponds to a synchronous rise in CPU utilisation, memory utilisation, and network bandwidth. As the system crosses the critical threshold (45) at around the 2nd second, it's evident that the system capacity is overstretched.

4.1.2.3.3 In an ICMP flood using NetScantools start with 20 threads.

In the context of an ICMP flood instigated via Nettools5 with 20 threads, there are tangible impacts on the CPU and memory utilisation, as well as the network bandwidth. The consumption levels of these system resources and the network bandwidth are specified at each one-second interval over a 10-second duration. Table 4.14 displays the consequential data for CPU, memory utilisation, and network bandwidth incurred during an ICMP flood attack executed using Nettools5 with 20 threads on a web server, sustained for 10 seconds.

Table 4.14 CPU utilisation, memory utilisation, and network bandwidth during ICMP flood using NetScantools with 20 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	45	50	50
2	67	70	80
3	89	90	100
4	100	100	100
5	100	100	100
6	100	100	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

CPU utilisation surges from 23% at the onset to a staggering 100% in just 4 seconds and maintains this peak level for the remaining duration. Similarly, memory utilisation experiences a sharp rise, reaching 100% within the same 4-second time frame. A key point of note here is the rapid saturation of the network bandwidth. It starts at a manageable 19 Mbps, only to shoot up to its maximum limit of 100 Mbps within 3 seconds of the attack commencement. Once the threshold is hit, it remains at its peak for the rest of the attack duration.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.25(23) + 0.35(30) + 0.4(19) = 5.75 + 10.5 + 7.6 = 23.85$

At time 1 second: Y = 0.25(45) + 0.35(50) + 0.4(50) = 11.25 + 17.5 + 20 = 48.75

At time 2 seconds: Y = 0.25(67) + 0.35(70) + 0.4(80) = 16.75 + 24.5 + 32 = 73.25

At time 3 seconds: Y = 0.25(89) + 0.35(90) + 0.4(100) = 22.25 + 31.5 + 40 = 93.75

At time 4 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 5 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 6 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 7 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 8 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 9 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 10 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

From the data, it can be seen that the system load Y, calculated using the equation, rapidly escalates over time. It exceeds the defined threshold of 45 in just one second. By the 4th second, each of the three variables has reached its maximum value of 100, suggesting that they contribute equally to the total system load from this point forward.

4.1.2.3.4 In an ICMP flood using NetScantools start with 50 threads.

During an ICMP flood attack executed using Nettools5 with 50 threads, significant impacts were observed on CPU and memory utilisation, as well as network bandwidth. The variations in both the system resources and network bandwidth were recorded every second for 10 seconds. Table 4.15 presents a detailed account of CPU utilisation, memory utilisation, and network bandwidth during an ICMP flood attack instigated by Nettools5, operating with 50 threads on a web server over 10 seconds.

Table 4.15 CPU utilisation, memory utilisation, and network bandwidth during ICMP flood using NetScantools with 50 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	60	65	70
2	97	100	100
3	100	100	100
4	100	100	100
5	100	100	100
6	100	100	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

CPU utilisation begins at 23% at the start of the attack and swiftly escalates to 100% by the third second, maintaining at this peak for the remainder of the attack. Memory utilisation, likewise, starts at 30%, reaching its peak at 100% by the 2nd second and remains fully utilised until the end of the examined period. Network bandwidth also surges from 19 Mbps to its maximum capacity of 100 Mbps within the same timeframe, indicating the serious consequences of this attack on network availability. This data underscores the overwhelming pressure that an ICMP flood attack with 50 threads can place on system resources and network bandwidth. In particular, the speed at which both CPU and memory utilisation reach their maximum underscores the potency and urgency of such an attack. Such rapid consumption can lead to the exhaustion of system resources, severely affecting the system's functionality and possibly leading to a system shutdown.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y= 0.25(23) +0.35(30) + 0.4(19) = 5.75 + 10.5 + 7.6=23.85$

At time 1second: $Y = 0.25(60) + 0.35(65) + 0.4(70) = 15 + 22.75 + 28 = 65.75$

At time 2seconds:$Y= 0.25(97) + 0.35(100) + 0.4(100) = 24.25 + 35 + 40 = 99.25$

At time 3 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 4 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 5 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 6 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 7 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 8 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 9 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

At time 10 seconds: Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100

The system load Y breaches the threshold of 45 in under a second. This indicates an alarmingly fast saturation of the system resources, culminating in full utilisation by the 3rd second. The system stays at peak capacity from the 3rd second onward, indicating a sustained state of maximum strain. This swift and sustained resource saturation under the ICMP flood attack indicates a potentially fatal vulnerability.

4.1.2.3.5 In an ICMP flood using NetScantools start with 100 threads.

In this context, the utilisation of system resources such as CPU and memory, in addition to the network bandwidth, are evaluated. These particular measurements are recorded at one-second intervals over a 10-second period. For an in-depth understanding, Table 4.16 offers values related to CPU utilisation, memory utilisation, and network bandwidth during this distinct type of assault on the server.

Table 4.16 CPU utilisation, memory utilisation, and network bandwidth during ICMP flood using NetScantools with 100 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	75	83	91
2	100	100	100
3	100	100	100
4	100	100	100
5	100	100	100
6	100	100	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

The table starts with CPU utilisation at 23%, memory utilisation at 30%, and network bandwidth at 19 Mbps at the initial stage of the attack. A striking increase is evident from the 2nd second of the attack, with all parameters reaching 100%. This full utilisation continues for the remaining duration of the attack, signifying the high level of strain such an attack can place on the system. Critically analysing this data, it becomes evident how devastating an ICMP flood attack with 100 threads can be. The rapid escalation of system resource utilisation to its maximum capacity within just two seconds demonstrates the immense potency of this attack. This can lead to a significant hindrance to the regular operation of the system and, in extreme cases, may even result in a complete system shutdown.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.25(23) + 0.35(30) + 0.4(19) = 5.75 + 10.5 + 7.6 = 23.85$

At time 1 second: $Y = 0.25(75) + 0.35(83) + 0.4(91) = 18.75 + 29.05 + 36.4 = 84.2$

At time 2 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 3 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 4 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 5 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 6 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 7 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 8 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 9 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 10 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

Initially, at time 0, the system metric Y starts at 23.85, which is under the set threshold of 45. However, Y escalated to 84.2 by the 1st second, significantly surpassing the threshold. This swift increase indicates a rapid intensification of system resource utilisation. From the 2nd second onward, Y reaches and maintains a peak value of 100, implying full saturation of system resources and bandwidth. The system experiences a drastic escalation in resource utilisation within one second, surpassing the threshold of 45 and reaching full capacity by the 2nd second.

This saturation persists throughout the observation period, pointing towards a critical system vulnerability under these circumstances.

4.1.2.3.6 In an ICMP flood using NetScantools start with 5 threads and packet size 6,535 bytes.

The next scenario was an ICMP flood with NetScantools deploying a packet size of 6,535 bytes. Specifically, situations with 5 and 10 threads were taken into consideration. Considerable effects on CPU and memory utilisation, as well as on network bandwidth, became evident. The system resources and the network bandwidth were measured at one-second intervals over a 10-second timeframe. Table 4.17 provides a comprehensive report of the CPU usage, memory usage, and network bandwidth during this particular type of cyber assault, which was executed using Nettools5 with 5 threads on a web server over 10 seconds.

Table 4.17 CPU utilisation, memory utilisation, and network bandwidth during an ICMP flood using NetScantools with a packet size of 6,535 bytes and 5 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	35	43	40
2	47	50	65
3	62	58	88
4	71	70	100
5	83	80	100
6	90	90	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

In this scenario, an ICMP flood attack using Nettools5 with 5 threads and a packet size of 6,535 bytes resulted in noticeable impacts on CPU, memory utilisation, and network bandwidth. Within a span of 10 seconds, CPU and memory utilisation increased from 23% and 30% to 100% respectively, while the network bandwidth utilisation rose from 19 Mbps to full capacity. This swift escalation in system resource usage demonstrates the severity and effectiveness of this form of attack. The results presented in Table 4.17 are indicative of the substantial strain that an ICMP flood attack can exert on a system, even when instigated with a relatively low thread count of 5. Starting at fairly low levels of CPU and memory utilisation (23% and 30% respectively) at the onset of the attack, both parameters reached their maximum

capacity by the 7th second, clearly demonstrating the attack intensity. The network bandwidth was also significantly impacted, reaching its peak within the 4th second. The rapid escalation in resource utilisation is a testament to the potency of this type of attack. Moreover, the use of a larger packet size, in this case, 6,535 bytes, might have contributed to the more immediate and drastic exhaustion of the system resources, reflecting the potential gravity of such attacks. This underlines the necessity for robust and efficient defensive mechanisms capable of countering such aggressive onslaughts in real-time to protect critical system resources and maintain optimal performance levels.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.25(23) + 0.35(30) + 0.4(19) = 5.75 + 10.5 + 7.6 = 23.85$

At time 1 second: $Y = 0.25(35) + 0.35(43) + 0.4(40) = 8.75 + 15.05 + 16 = 39.8$

At time 2 seconds: $Y = 0.25(47) + 0.35(50) + 0.4(65) = 11.75 + 17.5 + 26 = 55.25$

At time 3 seconds: $Y = 0.25(62) + 0.35(58) + 0.4(88) = 15.5 + 20.3 + 35.2 = 71$

At time 4 seconds: $Y = 0.25(71) + 0.35(70) + 0.4(100) = 17.75 + 24.5 + 40 = 82.25$

At time 5 seconds: $Y = 0.25(83) + 0.35(80) + 0.4(100) = 20.75 + 28 + 40 = 88.75$

At time 6 seconds: $Y = 0.25(90) + 0.35(90) + 0.4(100) = 22.5 + 31.5 + 40 = 94$

At time 7 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 8 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 9 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 10 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

By the 2nd second, Y rises to 55.25, surpassing the threshold. At the 4th second, Y reaches 82.25, indicating a significant strain on system resources and at the 7th second, Y reaches its maximum value of 100, representing a full utilisation of the system resources. From the seventh second onward, Y maintains this peak value, reflecting the sustained severity of the attack. The system experiences rapid and sustained exhaustion of its resources due to the ICMP flood attack with a relatively low thread count and large packet size.

4.1.2.3.7 In an ICMP flood using NetScantools start with 10 threads and a packet size of 6,535 bytes.

In the scenario of an ICMP flood using Nettools5 with 10 threads, notable changes were seen in the usage of CPU, memory, and network bandwidth. The data, captured every second across 10 seconds, showed how the system resources and network bandwidth fluctuate. For a comprehensive understanding, please see Table 4.18. It details the impact on CPU, memory utilisation, and network bandwidth during the specific ICMP flood attack carried out by Nettools5 with 10 threads on a web server for 10 seconds.

Table 4.18 CPU utilisation, memory utilisation, and network bandwidth during ICMP flood using NetScantools with a packet size of 6,535 bytes and 10 threads on a web server for a duration of 10 seconds

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	50	55	50
2	77	80	80
3	100	100	100
4	100	100	100
5	100	100	100
6	100	100	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

In the specific scenario of an ICMP flood attack conducted with Nettools5 using 10 threads and a packet size of 6,535 bytes, there were significant increases in CPU and memory utilisation, along with network bandwidth consumption. Starting from the initial utilisations of 23% for CPU, 30% for memory, and 19 Mbps for network bandwidth, all parameters reached full capacity by the 3rd second and remained at this level for the remainder of the 10-second interval. The findings presented in Table 4.18 underscore the extreme stress such an ICMP flood attack can place on a system, even within an extremely short time frame. The rapid escalation in resource utilisation from modest levels to full capacity in just three seconds demonstrates the power of such an attack, significantly when it leverages a higher thread count of 10 and a packet size of 6,535 bytes. The intensity of the attack's impact on network bandwidth is particularly noteworthy, as it peaked at 100 Mbps as quickly as the 3rd second, reflecting the substantial strain on network resources and potential service disruptions.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.3, 0.3, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.25(23) + 0.35(30) + 0.4(19) = 5.75 + 10.5 + 7.6 = 23.85$

At time 1 second: $Y = 0.25(50) + 0.35(55) + 0.4(50) = 12.5 + 19.25 + 20 = 51.75$

At time 2 seconds: $Y = 0.25(77) + 0.35(80) + 0.4(80) = 19.25 + 28 + 32 = 79.25$

At time 3 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 4 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 5 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 6 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 7 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 8 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 9 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At time 10 seconds: $Y = 0.25(100) + 0.35(100) + 0.4(100) = 25 + 35 + 40 = 100$

At the onset, Y is at 23.85, below the threshold of 45. However, by the 1st second, Y rises to 51.75, exceeding the threshold, and continuing to climb to 79.25 at the 2nd second. By the 3rd second, Y hits the maximum value of 100, representing the full utilisation of system resources. From this point forward, Y maintains its peak value, signifying the sustained severity of the attack. The system experiences a rapid exhaustion of resources due to an ICMP flood attack with a high thread count and large packet size.

The data from Experimental Testbed Configuration - Part 2 during the ICMP attack seems to show how CPU utilisation (measured in percentages) changes over time (in seconds) when the system is put under different amounts of stress. This stress is created by using different numbers of active threads (5, 10, 20, 50, and 100 threads). Figure 4.12 uses a graph to help us understand how the CPU usage changes when we change the number of threads used. This helps to highlight how the number of threads used can affect how much of the CPU is being used.

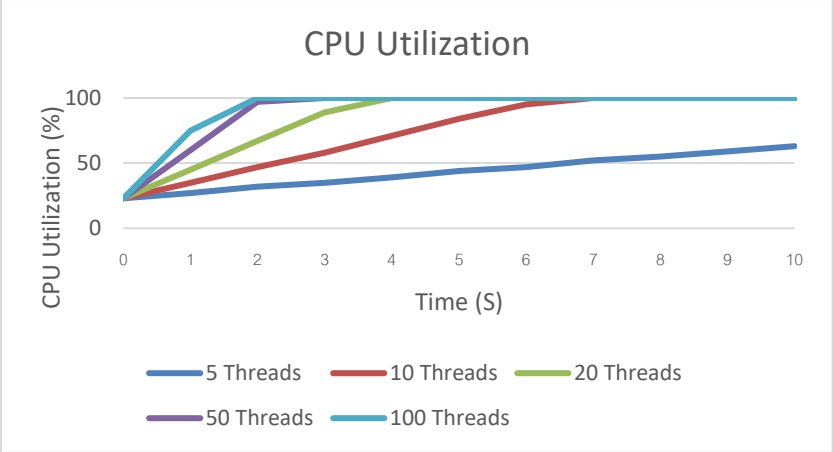

Figure 4.12 CPU utilisation (%), specifically under ICMP attack at 5, 10, 20, 50, and 100 threads.

A critical analysis of the data reveals an escalating trend of CPU utilisation as the number of threads increases. At 5 threads, CPU usage rises gently from 23% to 63% over the 10-second period, suggesting that the system effectively handles lesser loads. Conversely, at 100 threads, CPU utilisation surges to its maximum within just 2 seconds, indicating the system's potential to quickly become overwhelmed under heavy loads. The swift saturation of CPU usage at higher thread counts suggests a vulnerability to intense ICMP attacks and may lead to performance degradation or system failure.

The data from Experimental Testbed Configuration - Part 2 during an ICMP attack presents a snapshot of how memory utilisation (%) evolves over a certain period of time (seconds) while the system undergoes varying levels of load. The load levels are modulated by altering the number of active threads (5, 10, 20, 50, and 100 threads). The graph presented in Figure 4.13 illustrates the memory utilisation pattern as the number of threads changes, underscoring the direct impact of thread count on CPU usage.

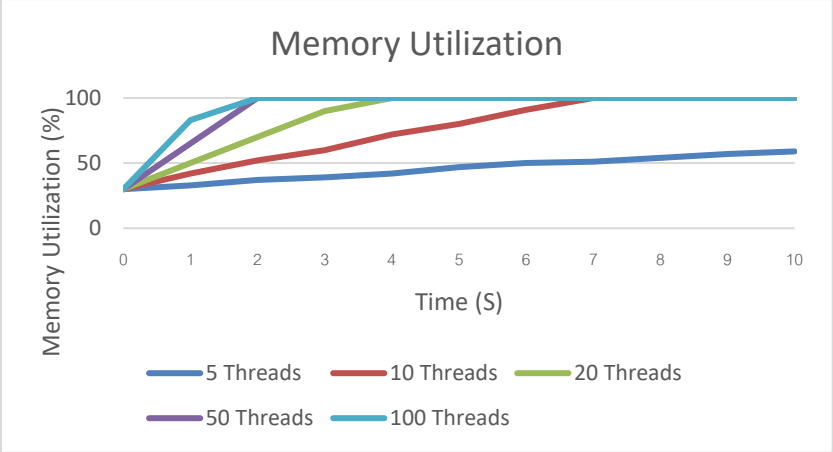

Figure 4.13 Memory utilisation (%), specifically an ICMP attack with 5, 10, 20, 50, and 100 threads.

The stress levels are adjusted by changing the number of active threads: 5, 10, 20, 50, and 100. The analysis of the data revealed distinct patterns in memory utilisation relative to the thread count. For a minimal load of 5 threads, memory utilisation gradually increases from 30% to 59% over 10 seconds, demonstrating the system's capability to manage low-intensity attacks. However, when subjected to a heavy load of 100 threads, memory usage saturates to its maximum within the first 2 seconds, indicating a rapid response to intense attacks that can potentially lead to resource exhaustion.

Experimental Testbed Configuration - Part 2 provides data on how network bandwidth changes over time during an ICMP attack. This study measured the network bandwidth (in Mbps) every second while applying different loads on the system. These loads are represented by varying the number of active threads: 5, 10, 20, 50, and 100. Figure 4.14 illustrates these changes, helping to show the relationship between the number of threads and the percentage of network bandwidth. The graph highlights how increasing the number of threads can result in a higher percentage of network bandwidth.

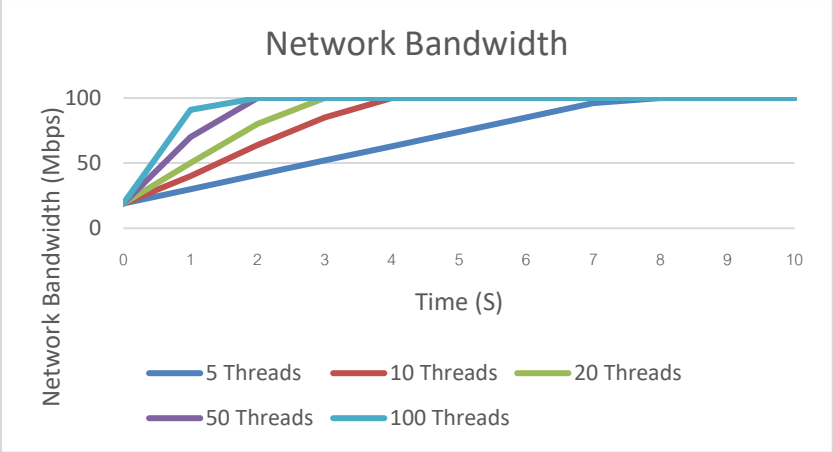

Figure 4.1 Network bandwidth (Mbps) specifically under an ICMP attack with 5, 10, 20, 50, and 100 threads.

A critical examination of the data highlights distinctive patterns correlating the number of threads to the network bandwidth consumption. With a minimal load of 5 threads, the network bandwidth usage increases gradually from 19 Mbps to 100 Mbps over the span of 10 seconds, showing the system's efficient handling of low-intensity loads. However, with an intensive load of 100 threads, network bandwidth saturates to 100 Mbps within the first 2 seconds, revealing the system's vulnerability to high-intensity attacks.

4.4.2.4 HTTP attack.

This sub-section elucidates the proficiency of the proposed system in identifying HTTP attack under varying conditions, specifically utilising different threads (sessions). These instances encompass 5, 10, 20, 50, and 100 threads respectively, presenting a spectrum of scenarios to evaluate system performance comprehensively. Figure 4.15 shows the HTTP attack via LOIC in the Experimental Testbed - Part 2.

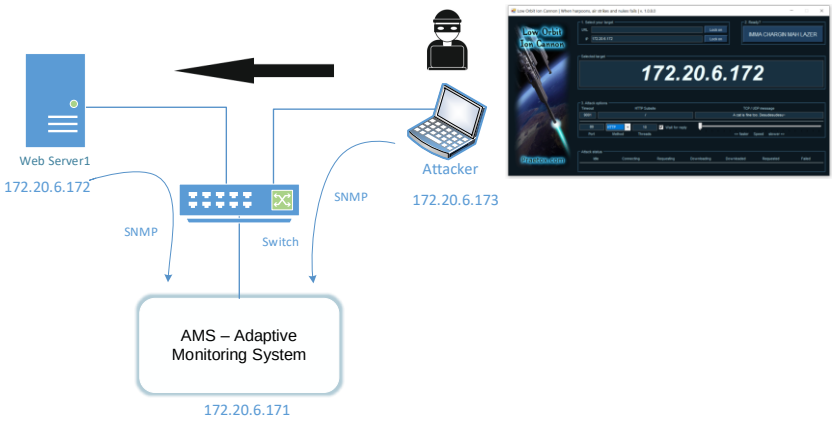

Figure 4.2 Diagram of experimental testbed part 2 with HTTP attack via LOIC tool.

4.4.2.1.1 In a HTTP attack using LOIC starting with 5 threads, the impact on CPU and memory utilisation, as well as network bandwidth, will generally be less compared to attacks with a larger number of threads. A value for system resource utilisation and network bandwidth was obtained every second for 10 seconds. Table 4.19 shows the results for CPU utilisation, memory utilisation, and network throughput during a HTTP attack using LOIC with 5 threads on a web server for a duration of 10 seconds.

Table 4.19 CPU utilisation, memory utilisation, and network throughput during a HTTP attack using LOIC with 5 threads on a web server for 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	26	33	24
2	29	37	30
3	33	42	38
4	37	48	47
5	42	55	57
6	47	62	68
7	53	70	80
8	60	78	92
9	67	85	100
10	79	94	100

The data collected during 10 seconds of a HTTP attack utilising the LOIC tool with 5 threads indicates a progressive impact on CPU, memory, and network bandwidth. As illustrated

in Table 4.19, the resource utilisation percentage for both CPU and memory increases over time, starting from 23% and 30% respectively at the onset of the attack, to 79% and 94% at the end of the 10 seconds. Similarly, network bandwidth escalates from an initial 19 Mbps to eventually reaching full capacity (100 Mbps) by 9 seconds. Network bandwidth reaching saturation point by the 9th second suggests a relatively rapid exhaustion of resources, hinting towards a potentially greater impact if the attack continues for a more extended period. It indicates the severity of the threat that such attacks can pose to network availability, further underlining the importance of efficient and robust countermeasures.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.35, 0.25, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.35(23) + 0.25(30) + 0.4(19) = 8.05 + 7.5 + 7.6 = 23.15$

At time 1 second: $Y = 0.35(26) + 0.25(33) + 0.4(24) = 9.1 + 8.25 + 9.6 = 26.95$

At time 2 seconds: $Y = 0.35(29) + 0.25(37) + 0.4(30) = 10.15 + 9.25 + 12 = 31.4$

At time 3 seconds: $Y = 0.35(33) + 0.25(42) + 0.4(38) = 11.55 + 10.5 + 15.2 = 37.25$

At time 4 seconds: $Y = 0.35(37) + 0.25(48) + 0.4(47) = 12.95 + 12 + 18.8 = 43.75$

At time 5 seconds: $Y = 0.35(42) + 0.25(55) + 0.4(57) = 14.7 + 13.75 + 22.8 = 51.25$

At time 6 seconds: $Y = 0.35(47) + 0.25(62) + 0.4(68) = 16.45 + 5.5 + 27.2 = 59.15$

At time 7 seconds: $Y = 0.35(53) + 0.25(70) + 0.4(80) = 18.55 + 17.5 + 32 = 68.05$

At time 8 seconds: $Y = 0.35(60) + 0.25(78) + 0.4(92) = 21 + 19.5 + 36.8 = 77.3$

At time 9 seconds: $Y = 0.35(67) + 0.25(85) + 0.4(100) = 23.45 + 21.25 + 40 = 84.7$

At time 10 seconds: $Y = 0.35(79) + 0.25(94) + 0.4(100) = 7.65 + 23.5 + 40 = 91.15$

At the start (0 seconds), Y equals 23.15, a value well below the threshold of 45. The values for Y increase incrementally each second, with the next values at 26.95 (1 second) and 31.4 (2 seconds). By the third second, Y rises to 37.25, still under the threshold. At the 4th second, Y is at 43.75, nearly reaching the threshold. At the 5th second, Y crosses the threshold for the first time, hitting 51.25. This indicates a heightened level of system resource utilisation.

4.4.2.1.2 In a HTTP attack using LOIC start with 10 threads.

In the context of a HTTP flood attack, initiated by the LOIC tool and utilising an initial count of 10 threads, it is expected that the toll on system resources such as CPU and memory usage, as well as network bandwidth, is considerably lesser than would be the case under an assault involving a greater number of threads. The data corresponding to the fluctuation of the system resources and network bandwidth have been chronicled every second over 10 seconds. To present a clear and detailed account, the data is collated in Table 4.20, which illustrates the CPU and memory usage along with the network throughput for a 10-second HTTP flood attack via LOIC with 10 threads targeting a web server.

Table 4.20 CPU utilisation, memory utilisation, and network throughput during a HTTP attack using LOIC with 10 threads on a web server for 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	31	40	35
2	40	50	52
3	52	61	68
4	65	78	88
5	71	85	100
6	82	96	100
7	89	100	100
8	98	100	100
9	100	100	100
10	100	100	100

The presented data provides insights into a HTTP attack scenario using the LOIC tool with 10 threads. Table 4.20 shows that over a span of 10 seconds, there is a steady increase in the percentage utilisation of CPU, memory, and network bandwidth. Starting from the initial 23% CPU utilisation, 30% memory utilisation, and 19 Mbps network bandwidth, these figures steadily rise to 100% in all three categories by the end of the 10-second duration. Furthermore, the fact that network bandwidth reaches 100% by the 5th second shows a rapid depletion of resources and potentially significant impact on the system's operation. This further emphasises the need for the prompt detection and mitigation of such attacks.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.35, 0.25, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.35(23) + 0.25(30) + 0.4(19) = 8.05 + 7.5 + 7.6 = 23.15$

At time 1 second: $Y = 0.35(31) + 0.25(40) + 0.4(35) = 10.85 + 10 + 14 = 34.85$

At time 2 seconds: $Y = 0.35(40) + 0.25(50) + 0.4(52) = 14 + 12.5 + 20.8 = 47.3$

At time 3 seconds: $Y = 0.35(52) + 0.25(61) + 0.4(68) = 18.2 + 15.25 + 27.2 = 60.65$

At time 4 seconds: $Y = 0.35(65) + 0.25(78) + 0.4(88) = 22.75 + 19.5 + 35.2 = 77.45$

At time 5 seconds: $Y = 0.35(71) + 0.25(85) + 0.4(100) = 24.85 + 21.25 + 40 = 86.1$

At time 6 seconds: $Y = 0.35(82) + 0.25(96) + 0.4(100) = 28.7 + 24 + 40 = 92.7$

At time 7 seconds: $Y = 0.35(89) + 0.25(100) + 0.4(100) = 31.15 + 25 + 40 = 96.15$

At time 8 seconds: $Y = 0.35(98) + 0.25(100) + 0.4(100) = 34.3 + 25 + 40 = 99.3$

At time 9 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 10 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

Starting at zero seconds, the total score (Y) is 23.15. By the time one second has passed, it has jumped to 34.85. At two seconds, the score breaks the 'worry threshold' of 45, reaching 47.3. This means that the computer's resources are being heavily used.

4.4.2.1.3 In a HTTP attack using LOIC start with 20 threads.

A HTTP attack scenario, initiated using LOIC with 20 threads, induces significant impacts on CPU usage, memory utilisation, and network bandwidth. The recorded measurements of the system parameters and consumed network bandwidth have been denoted for every second across 10 seconds. To provide a detailed representation, Table 4.21 contains the specific data outlining CPU, memory utilisation, and network bandwidth during the duration of this particular HTTP attack. This attack, executed via LOIC employing 20 threads on a web server, was monitored and recorded for 10 seconds.

Table 4.21 CPU utilisation, memory utilisation, and network throughput during a HTTP attack using LOIC with 20 threads on a web server for 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	45	57	50
2	70	80	81
3	89	100	100
4	100	100	100
5	100	100	100
6	100	100	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

The data presented illustrates the effects of a HTTP attack using the LOIC tool with 20 threads on a web server for a period of 10 seconds. Table 4.21 clearly outlines a dramatic surge in the utilisation of CPU, memory, and network bandwidth. Starting from 23% CPU utilisation, 30% memory utilisation, and a network bandwidth of 19 Mbps, these values escalate to 100% by the 4th second and remain at full capacity for the remainder of the attack duration. Network bandwidth, another critical system resource, also experiences a rapid consumption rate, reaching its limit within the third second. This rapid exhaustion of network bandwidth underlines the severity of the attack, potentially causing significant disruption to the system's operations and services.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.35, 0.25, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.35(23) + 0.25(30) + 0.4(19) = 8.05 + 7.5 + 7.6 = 23.15$

At time 1 second: $Y = 0.35(45) + 0.25(57) + 0.4(50) = 15.75 + 14.25 + 20 = 50$

At time 2 seconds: $Y = 0.35(70) + 0.25(80) + 0.4(81) = 24.5 + 20 + 32.4 = 76.9$

At time 3 seconds: $Y = 0.35(89) + 0.25(100) + 0.4(100) = 31.15 + 25 + 40 = 96.15$

At time 4 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 5 seconds: Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100

At time 6 seconds: Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100

At time 7 seconds: Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100

At time 8 seconds: Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100

At time 9 seconds: Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100

At time 10 seconds: Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100

In the initial timestamp (0 seconds), the computation results in a value of 23.15, indicating the moderate utilisation of resources. However, a significant leap is observed in the 1st second with a computed value of 50, exceeding the set threshold of 45. This marks a drastic shift from moderate to high resource utilisation. The system transitions from moderate resource utilisation at the outset to a rapid escalation within a second, culminating in sustained, full-capacity operation from the fourth second onwards.

4.4.2.1.4 In a HTTP attack using LOIC start with 50 threads.

A HTTP attack enacted via LOIC using 50 threads has a marked effect on the utilisation of CPU, memory, and network bandwidth. The system resources and network bandwidth utilisation were meticulously measured at one-second intervals over a 10-second duration. Table 4.22 collates the metrics corresponding to CPU, memory utilisation, and network bandwidth throughout the HTTP attack. This particular attack, orchestrated using LOIC with 50 threads on a web server, was methodically tracked and logged over 10 seconds.

Table 4.22 CPU utilisation, memory utilisation, and network throughput during a HTTP attack using LOIC with 50 threads on a web server for 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	70	85	100
2	100	100	100
3	100	100	100
4	100	100	100
5	100	100	100
6	100	100	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

The data provides insight into the effects of a HTTP attack launched using LOIC with 50 threads on a web server for 10 seconds. As depicted in Table 4.22, the utilisation of CPU, memory, and network bandwidth undergoes a drastic increase. The CPU and memory utilisation initiate from 23% and 30% respectively and the network bandwidth begins at 19 Mbps. However, by the 2nd second of the attack, all resources reach full utilisation and maintain this 100% utilisation for the rest of the attack duration.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.35, 0.25, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.35(23) + 0.25(30) + 0.4(19) = 8.05 + 7.5 + 7.6 = 23.15$

At time 1 second: $Y = 0.35(70) + 0.25(85) + 0.4(100) = 24.5 + 21.25 + 40 = 85.75$

At time 2 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 3 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 4 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 5 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 6 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 7 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 8 seconds: Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100

At time 9 seconds: Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100

At time 10 seconds: Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100

At the beginning (time 0), the calculated value of Y is 23.15, which is under the threshold of 45. This suggests that system use is relatively normal at this point. Just a second later, the situation changes significantly. The value of Y jumps to 85.75, nearly twice the established threshold. This signals a sharp increase in system demand.

4.4.2.1.5 In a HTTP attack using LOIC start with 100 threads.

In the case of a HTTP attack triggered by LOIC involving 100 threads, notable changes are observed in the CPU, memory, and network bandwidth usage. The data for these system resources, along with the network bandwidth, was captured every second over 10 seconds. Table 4.23 presents the individual CPU, memory usage, and network bandwidth measurements during this specific HTTP attack. This attack, carried out using LOIC with 100 threads on a web server, was documented for a full 10-second duration.

Table 4.23 CPU utilisation, memory utilisation, and network throughput during a HTTP attack using LOIC with 100 threads on a web server for a duration of 10 seconds.

Time (Seconds)	CPU Utilisation (%)	Memory Utilisation (%)	Network Bandwidth (Mbps)
0	23	30	19
1	100	100	100
2	100	100	100
3	100	100	100
4	100	100	100
5	100	100	100
6	100	100	100
7	100	100	100
8	100	100	100
9	100	100	100
10	100	100	100

Table 4.23 presents the effects of a HTTP attack initiated using LOIC with 100 threads on a web server over 10 seconds. In this case, the CPU utilisation, memory utilisation, and network bandwidth started at 23%, 30%, and 19 Mbps respectively. However, just one second into the attack, the values surged to 100% and maintained this utilisation level for the remainder of the attack duration. This data provides a stark portrayal of the potential severity of a HTTP attack that involves as many as 100 threads. The fact that the CPU, memory, and network bandwidth reach full utilisation within the 1st second of the attack underscores the intensity of this type of HTTP flood attack. This is a quintessential illustration of a severe Denial-of-Service (DoS) attack. In this scenario, the web server would likely become unresponsive almost immediately as the attack begins due to the extreme utilisation of CPU and memory resources. Similarly, the network would instantly become congested as all available bandwidth is consumed. Compared to scenarios with fewer threads, this immediate and sustained saturation of resources reflects how increasing the number of threads can escalate the severity of a HTTP flood attack.

Substituting the values for CPU utilisation, memory utilisation, and network bandwidth at each timestamp into equation $Y = \alpha X1 + \beta X2 + \gamma X3$, where the coefficients α, β, γ are 0.35, 0.25, and 0.4 respectively, results in the following values for Y:

At time 0 seconds: $Y = 0.35(23) + 0.25(30) + 0.4(19) = 8.05 + 7.5 + 7.6 = 23.15$

At time 1 second: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 2 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 3 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 4 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 5 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 6 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 7 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 8 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 9 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At time 10 seconds: $Y = 0.35(100) + 0.25(100) + 0.4(100) = 35 + 25 + 40 = 100$

At the outset (0 seconds), Y equals 23.15, a value well below the server's limits. However, from the 1-second mark onwards, Y rapidly escalates to 100, hitting the server's

maximum capacity. This value remains constant through the 10 seconds, signalling that the system is operating at full tilt throughout. In conclusion, this scenario underscores the swift and relentless saturation of resources that can occur during a high-thread HTTP flood attack. This stark escalation in severity compared to attacks with fewer threads offers critical insights into the potent threat these attacks can pose to web servers.

The data provided depicts the CPU utilisation (%) over time (seconds) under different load conditions, simulated by varying the number of active threads (5, 10, 20, 50, and 100 threads). This is Experimental Testbed Configuration - Part 2 involving a HTTP attack. Figure 4.16 provides a graphical depiction of the resultant CPU Utilisation (%), with specific reference to the distinct thread counts: 5, 10, 20, 50, and 100. This figure elucidates the relationship between the volume of threads and the corresponding impact on CPU utilisation.

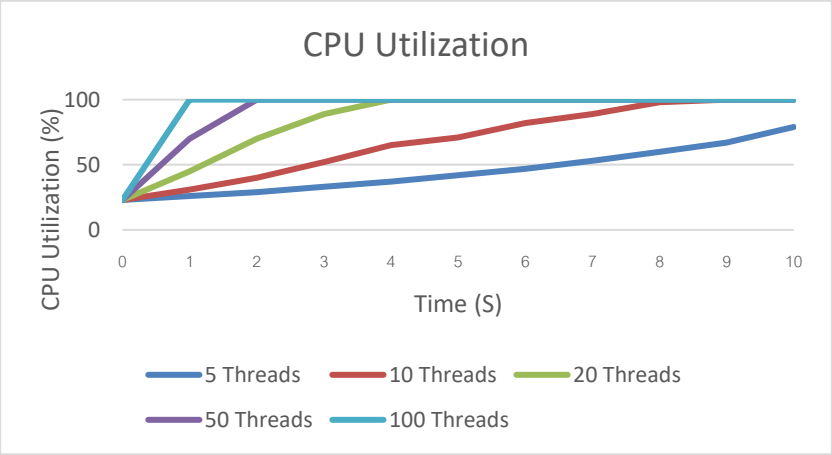

Figure 4.3 CPU utilisation (%), specifically HTTP attacks of 5, 10, 20, 50, and 100 threads.

A careful inspection of the data reveals a clear link between thread volume and its consequent influence on CPU usage. A thread count as low as 5 only gradually escalates CPU utilisation from 23% to 79% over the duration of 10 seconds, signifying competent load management under low-stress conditions. On the contrary, a maximum thread count of 100 exhibits an immediate surge in CPU utilisation, reaching 100% within the 1st second itself. This swift saturation suggests the system's susceptibility to high-stress conditions, potentially leading to CPU overload and affecting overall system performance during intensive HTTP attacks.

The given information purports to show the memory utilisation (%) over a period of time (seconds) under various load situations, simulated by changing the number of active threads (5, 10, 20, 50, and 100). This was Experimental Testbed Configuration - Part 2 involving a HTTP attack. The resulting memory utilisation (%) is graphically represented in Figure 4.17 regarding the different thread counts: 5, 10, 20, 50, and 100. This graph explains the relationship between the number of threads and their effect on memory utilisation.

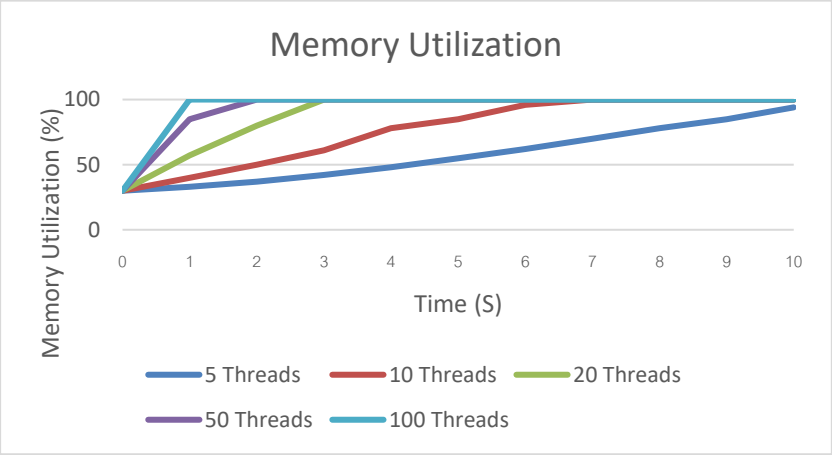

Figure 4.4 Memory utilisation (%), specifically HTTP attacks with 5, 10, 20, 50, and 100 threads.

The data suggests a robust correlation between the number of threads used and memory utilisation. Notably, lower thread counts such as 5 show a gradual increase in memory utilisation from 30% to 94% over the 10-second period, indicating efficient memory management under less intensive conditions. However, high thread counts, such as 100, reveal a sharp escalation, reaching full memory utilisation within the 1st second. The system, therefore, shows considerable strain under high-intensity conditions, leading to full memory utilisation almost immediately. This rapid saturation suggests potential challenges for the system under high-stress HTTP attacks, with repercussions on performance and system stability.

The information from Experimental Testbed Configuration - Part 2 offers the chance to assess how network bandwidth (Mbps) varies thoroughly. The analysis was made during a HTTP attack, a frequent network attack, for 10 seconds. For a thorough analysis, the attack used several thread counts, specifically 5, 10, 20, 50, and 100. This investigation aimed to find any trends in the network bandwidth that might be connected to the attack's intensity,

determined by the number of threads employed. The network bandwidth is shown visually in Figure 4.18, emphasising how varying the thread counts 5, 10, 20, 50, and 100 affected it.

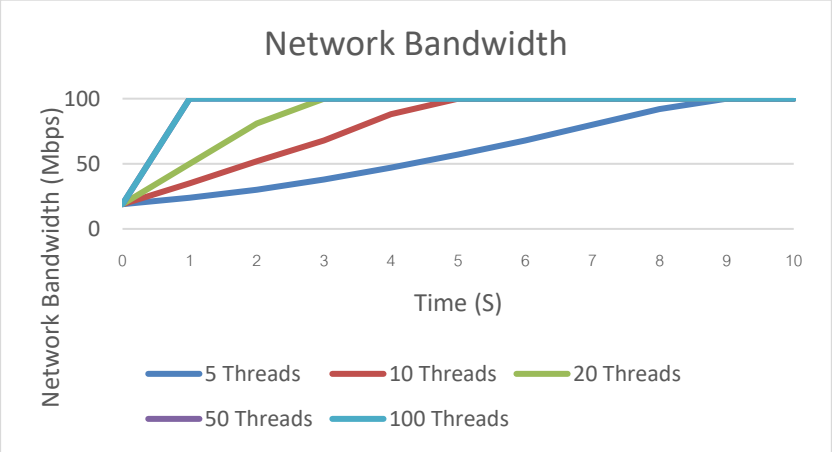

Figure 4.5 Percentage of network bandwidth (Mbps) specific to HTTP attacks using different thread counts: 5, 10, 20, 50, and 100.

The trends visible in the data suggest a direct correlation between the intensity of the attack (determined by the number of threads) and network bandwidth utilisation. Notably, for lower thread counts such as 5, the network bandwidth usage increased gradually from 19 Mbps to 100 Mbps over the 10-second duration. In contrast, under more intense attack scenarios (50 and 100 threads), the network bandwidth was fully utilised (100 Mbps) almost immediately, highlighting a significant impact. Therefore, the system appears to be more vulnerable to higher-intensity attacks, reaching full network capacity swiftly, which might hamper its performance and stability under such conditions.

4.2 Reconfiguration

According to the experiment, once the AMS system successfully receives the input parameters (CPU utilisation, memory utilisation, and network bandwidth) through SNMP from the web server, the AMS monitoring system will record these input values in a text file, continuously recording over time. The data from the text file will then be sent to calculate mechanisms with to correlate the rules from the various input data every 5 seconds to find the value of Y. If the value of Y reaches the threshold, the AMS script will send a command to reconfigure according to the specified conditions.

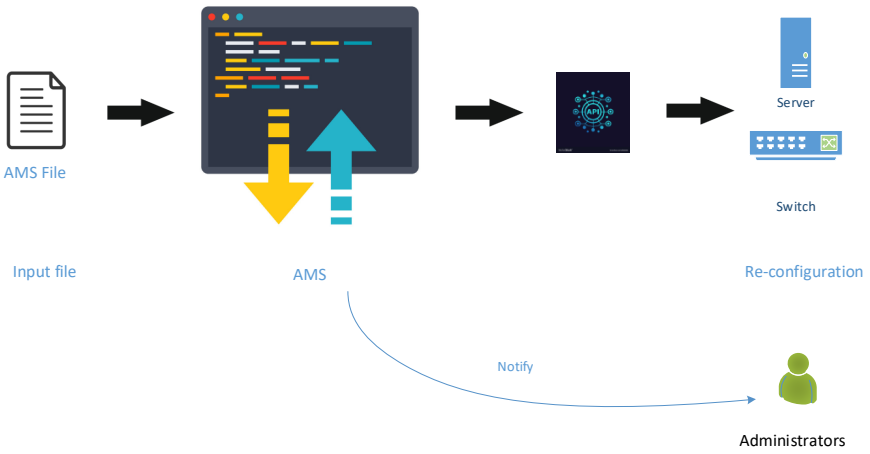

Figure 4.6 Auto-reconfiguration and notification

From the Experimental Testbed Configuration - Part 2, it was found that the value of Y increased to the predetermined threshold of 45. Therefore, the AMS sent a command script via an API and the Python Programming Language to perform the following reconfiguration.

4.2.1 TCP SYN flood attack

In a TCP SYN flood attack using different numbers of threads (5, 10, 20, 50, 100), it results in different times for sending a command script via an API as follows.

Table 4.24 Time to send command based on the number of threads

Threads	Time(s)
5	8
10	4
20	2
50	1
100	1

This shows that when the TCP SYN flood attack uses a varying number of threads, the time it takes to send a command script via an API changes. As the number of threads increases, the time required to send the command decreases significantly.

4.2.2 UDP attack

In a UDP attack using different numbers of threads (5, 10, 20, 50, 100), it results in different times for sending a command script via an API as follows.

Table 4.25 Time to send a command based on the number of threads

Threads	Time(s)
5	4
10	3
20	2
50	1
100	1

4.2.3 ICMP attack

In a ICMP attack using different numbers of threads (5, 10, 20, 50, 100) and using a packet size of 1024 bytes, it results in different times for sending a command script via an API as follows.

Table 4.26 Time to send a command based on the number of threads

Threads	Time(s)
5	4
10	2
20	1
50	1
100	1

In a ICMP attack using different numbers of threads (5, 10, 20, 50, 100) and using a packet size of 6535 bytes, it results in different times for sending a command script via an API as follows.

Table 4.27 Time to send a command based on the number of threads

Threads	Time(s)
5	2
10	1

4.2.4 HTTP attack

In a HTTP attack using different numbers of threads (5, 10, 20, 50, 100), it results in different times for sending a command script via an API as follows.

Table 4.28 Time to send a command based on the number of threads

Threads	Time(s)
5	5
10	2
20	1
50	1
100	1

If the value of Y does not reach any of the preset threshold values, the AMS algorithm will adjust the parameter boundaries on its own and check them again to see if there are indeed any unusual occurrences in the system. Additionally, the AMS has the added feature of automatically solving problems. For instance, it can automatically shut down and restart or halt the server's services, allowing the system to resume normal operations.

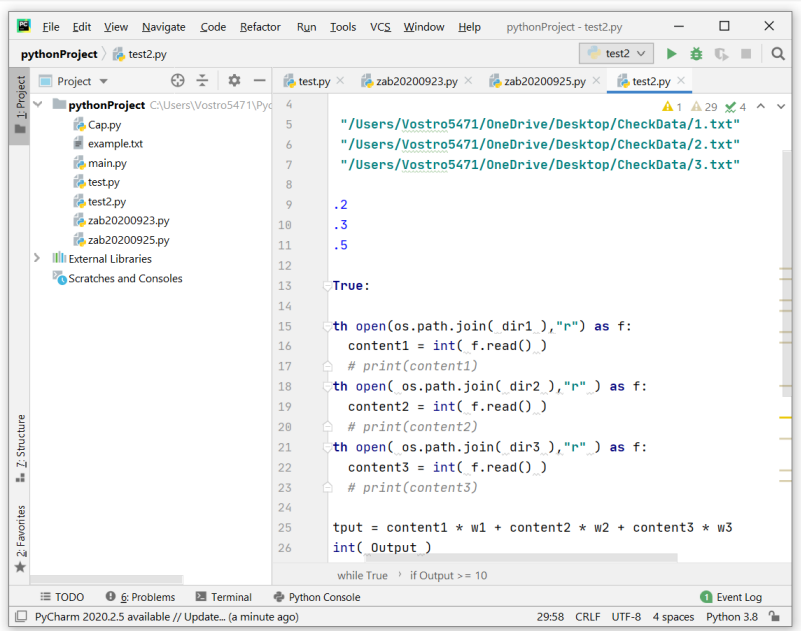

Figure 4.20 Command script via an API

4.3 Chapter conclusion

Chapter 4 meticulously explores the performance of the proposed model for detecting and mitigating Denial-of-Service (DoS) attacks under a variety of conditions. The key findings from our experimental testbeds indicate that the model is highly effective at identifying and responding to TCP SYN floods, UDP floods, ICMP floods, and HTTP attacks.

The effectiveness of the model in maintaining network performance and continuity during attacks highlights its potential to significantly reduce the workload for network administrators and enhance the overall security posture of the infrastructure. The next chapter, Chapter 5, will build on these findings to discuss the broader implications of the AMS in various operational environments. It will explore the potential enhancements that can be integrated into the system to handle sophisticated attacks and improve scalability. The chapter will also address the limitations of the current threshold-based detection mechanism and propose future research directions to refine the AMS's effectiveness and applicability in larger network scenarios.

5 DISCUSSION

5.1 Discussion of the efficacy and adaptability of the AMS

This thesis has proposed and implemented an AMS – Adaptive Monitoring System (an enhanced server monitoring system) for detecting and responding to DoS attacks. This system is designed to be simple, efficient, and effective, using statistical analysis and threshold-based rules to identify anomalous traffic patterns that may indicate a DoS attack. When a potential attack is detected, the system can also be adapted to fix problems automatically and responds by alerting the network administrator. The system's performance was assessed in a variety of scenarios, including both simulated and real-world attacks. The evaluation results indicate that the system effectively detects and mitigates DoS attacks, achieving high accuracy.

The integration of standard deviation into the dataset represents a critical enhancement of the system's experimental framework. This methodological refinement significantly bolsters the AMS's ability to accurately analyse network traffic. By accounting for natural fluctuations in data traffic, the AMS enhances its detection mechanism, allowing for the more precise identification of anomalous activities without over-relying on static thresholds. This approach is especially beneficial in countering sophisticated DoS strategies that might not conform to traditional traffic patterns, thereby improving the system's adaptability and responsiveness.

One limitation of the system is its reliance on threshold-based rules to detect DoS attacks. This approach may not be suitable for detecting sophisticated attacks involving a low traffic volume or attacks designed to bypass threshold-based rules. Further research could be done to investigate the effectiveness of the system under these scenarios and to incorporate additional data sources, such as intrusion detection systems or network flow data.

Another limitation of this system is its need for scalability. This system is designed for a single server or network segment and may not be suitable for large-scale deployments. Further research could be done to investigate the scalability of the system and to identify ways to optimise its performance in large-scale environments.

In conclusion, this research has shown that a straightforward threshold-based server monitoring system can effectively detect and mitigate DoS attacks. This system is easy to deploy and use, achieving high accuracy. However, further research is needed to investigate

the effectiveness and scalability of the system under various scenarios and to identify ways to optimise its performance in large-scale environments.

5.2 Chapter conclusion

This chapter provides full details of the discussion by explaining the development and validation of the Adaptive Monitoring System (AMS), focusing on its efficiency and effectiveness in identifying and mitigating Denial-of-Service (DoS) attacks. Key achievements of this system include efficient anomaly detection, adaptive response mechanisms, and methodological enhancements. Despite these successes, the system faces challenges with scalability and handling low-volume sophisticated attacks that could bypass conventional detection methods. These limitations frame the focus for future research, as argued in Chapter 6. There, we will explore potential enhancements related to the AMS's scalability and the integration of more sophisticated detection mechanisms, aiming to extend its applicability to larger network environments and improve its resilience against more complex attack vectors. This transition sets the stage for the concluding remarks and future research directions, reinforcing the thesis's contributions to the field of cybersecurity and network management.

6 CONCLUSION

6.1 Answering the research questions

The implementation of Adaptive Monitoring System (AMS) has proven to be a pivotal advancement in the management and security of web servers, particularly in the context of mitigating Denial-of-Service (DoS) attacks. This conclusion synthesises the research findings, revisits the objectives and research question, and illustrates the efficacy of AMSs in enhancing network monitoring and security.

6.1.1 Overview of the research achievements

This research embarked on a detailed exploration of network vulnerabilities and the necessity for robust monitoring systems that can proactively detect, respond to, and mitigate cyber threats, especially DoS attacks. The Adaptive Monitoring System (AMS), developed through this research, integrates cutting-edge technologies and methodologies to offer a comprehensive solution capable of addressing these challenges.

6.1.2 Detailed examination of the research objectives

The objectives set forth at the beginning of this research were aimed at developing a new and enhanced method of network monitoring that could adaptively respond to network threats and anomalies without requiring extensive manual intervention. Here's how each objective was addressed:

Objective 1: Develop a new method for enhanced network monitoring.

Approach: Leveraged Python programming and advanced algorithms to create a flexible and dynamic monitoring system.

Outcome: AMS was successfully implemented, demonstrating superior capabilities in real-time data processing and anomaly detection compared to traditional systems.

Objective 2: Automate server configuration adjustments.

Approach: Integrated API scripts that allowed for automatic reconfigurations based on the detection of potential security threats.

Outcome: Reduced downtime and minimised the need for manual adjustments, enhancing operational efficiency.

Objective 3: Improve network monitoring automation and performance.

Approach: Deployed machine learning algorithms to predict and respond to patterns indicative of cyberattacks.

Outcome: AMS demonstrated high accuracy in threat detection and significant improvements in network performance under stress conditions.

Objective 4: Advance network security techniques.

Approach: Integrated the latest security protocols and encryption methods to safeguard data transmissions.

Outcome: AMS enhanced the overall security posture of network systems, making it a formidable tool against a wide range of cyber threats.

6.1.3 Addressing the research question

The central research question posed was, "What are the most effective and efficient methods, algorithms for developing a real-time server monitoring system to detect and mitigate Denial-of-Service (DoS) attacks, ensuring optimal server performance and uninterrupted service delivery?" This was explored through extensive theoretical research and practical experiments which involved the following:

Literature Review (Chapter 2): Analysed the existing research and identified gaps in the current monitoring technologies.

Methodology (Chapter 3): Detailed the design and development process of the AMS, focusing on innovative algorithmic solutions.

Experiments and Results (Chapter 4): Conducted rigorous testing of the AMS under simulated attack scenarios to validate its effectiveness.

Discussion (Chapter 5): Interpreted the results, discussing the implications for network security and the potential for future enhancements.

6.1.4 Synthesis of the findings and future directions

AMS has shown remarkable success in enhancing the resilience of network systems against disruptions caused by DoS attacks. The system's ability to autonomously adjust and respond to threats has markedly reduced the incidence of system failures and service interruptions. The detailed assessment of AMS under varied conditions has not only

demonstrated its robustness and scalability but also highlighted areas for further research, particularly in the integration of even more sophisticated AI-driven predictive models.

The research undertaken in this thesis directly addresses and fulfils the aims and objectives outlined in Chapter 1, proving that AMS can significantly enhance the security and efficiency of network monitoring systems. The successful implementation and testing of AMS within varied attack scenarios has not only demonstrated its efficacy and adaptability but also its potential to significantly reduce the administrative burden, making it an invaluable asset in the realm of network security. This alignment with this thesis underscores the research's contribution to advancing knowledge and practical solutions in cybersecurity, specifically protecting web servers against increasingly sophisticated DoS attacks.

6.2 Final Summary

In conclusion, implementing an AMS – Adaptive Monitoring System is essential to effectively managing web servers. The system provides valuable information for monitoring, detecting, and responding to DoS (Denial-of-Service) attacks (TCP SYN flood, UDP flood, ICMP flood, HTTP attack), ensuring the availability and reliability of the server, and optimising performance.

The proposed system has thoroughly reviewed the literature on DoS attacks, server monitoring systems, and related research in order to achieve its goal, then identified the key requirements and features that a server monitoring system for DoS attacks should possess and used this knowledge to design and implement the system. This thesis proposed an Adaptive Monitoring System that leverages complex algorithms, data collection, threshold-based rules, and statistical techniques to monitor, detect, and respond to DoS attacks on a web server. This system uses multiple variables, including CPU utilisation, memory utilisation and traffic bandwidth, to enable the more accurate and robust detection of DoS attacks. This system can also respond to DoS attacks in real-time, making it an effective tool for ensuring the security of the web server. Implementing an Adaptive Monitoring System involves several key steps, including selecting appropriate monitoring tools and techniques, configuring the system to monitor relevant metrics, and analysing the data to identify potential problems. The system must be configured and maintained to ensure that it is providing accurate and relevant information.

Furthermore, the Adaptive Monitoring System can also be used to implement API scripts on open-source tools and Python Programming Language to help improve the algorithm

methods, analysis, and SNMP for managing and changing device configurations. This information can be used to optimise the web server's performance and ensure that users have a positive experience when accessing the server. Additionally, the Adaptive Monitoring System can also be adapted to fix problems automatically, such as the automatic shutdown of the server and restart/stopping of the service of the server so then the system can return to work normally. The AMS can diagnose problems and fix them without needing the administrator at all. This can reduce the workload of the system administrator as well. The response times for different attacks (TCP SYN flood, UDP, ICMP, HTTP) show a consistent trend; as the number of threads used in the attack increases, the time to send a reconfiguration command via an API significantly decreases. This inverse relationship suggests that the AMS system is well-equipped to deal with increased threat levels and demonstrates impressive scalability.

The methodical framework for the experiment was distinguished by conducting tests at the same time each day, which guaranteed stable testing conditions unaffected by external factors like varying network traffic or server demands that could potentially distort the outcomes. By upholding such rigorous consistency, the approach effectively reduced disruptions to the web server's regular operations, ensuring that the server could perform its essential duties without notable declines in performance. This meticulous strategy also supported the progressive refinement of the Adaptive Monitoring System (AMS). With every test carried out under uniform conditions, it became straightforward to identify how specific changes to the system influenced the AMS's proficiency at recognising and countering DoS attacks. Such a cycle of ongoing enhancement was vital for evolving AMS into a sturdy and efficient mechanism. In essence, this systematic procedure unveiled significant insights into the capabilities and adaptability of the AMS in combatting DoS attacks, representing a noteworthy progression in network security and server administration realms. Through this detailed assessment, the AMS proved its worth as an instrumental asset for boosting web server defences against digital threats, enriching the broader comprehension of security strategies in the online environment.

One of the key advantages of the proposed system is its simplicity and ease of use. Unlike some of the other solutions that rely on complex machine learning algorithms, the proposed system is easy to implement and does not require extensive training or expertise. This proposed system makes it accessible to a broader range of users, including those with limited resources or knowledge in the field of network security.

It is important to note that while the Adaptive Monitoring System provides a valuable solution for detecting DoS attacks, it is not a silver bullet solution. The system must be used in conjunction with other security measures, such as firewalls, intrusion detection systems, and access control mechanisms, to provide a comprehensive and effective solution for ensuring the security and performance of web servers.

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APPENDICES

Appendix A: Software and Environment Setup

This section provides a detailed description of the software setup and implementation steps used in the development and deployment of the Adaptive Monitoring System (AMS) for server monitoring and DoS attack detection.

1. Virtualization Software (Virtual Machine)

To begin, the chosen virtualization software, Oracle VM VirtualBox Manager, was installed on the primary machine. Subsequently, a virtual machine was established with the preferred operating system, CentOS 7. The configuration process was extended to set up the networking parameters, creating a simulated network environment meticulously designed for the testing of the Adaptive Monitoring System (AMS).

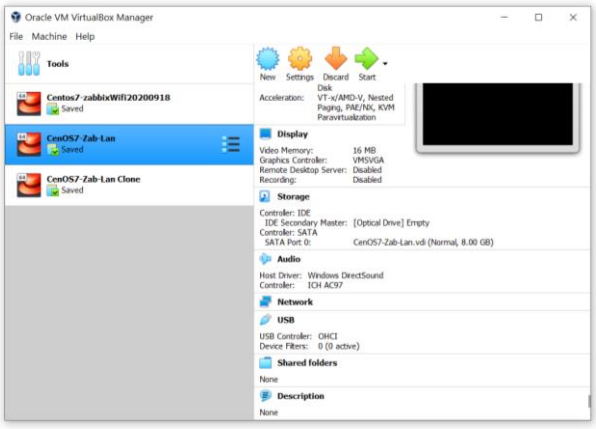

Figure 1. Installing VM

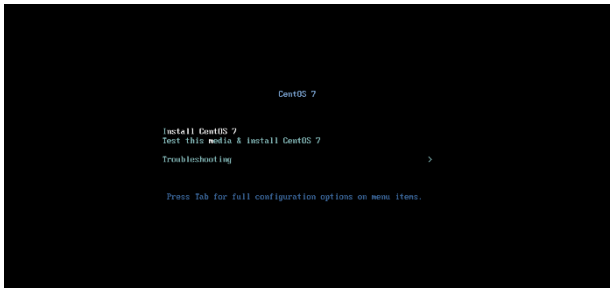

Figure 2. Installing CentOS7

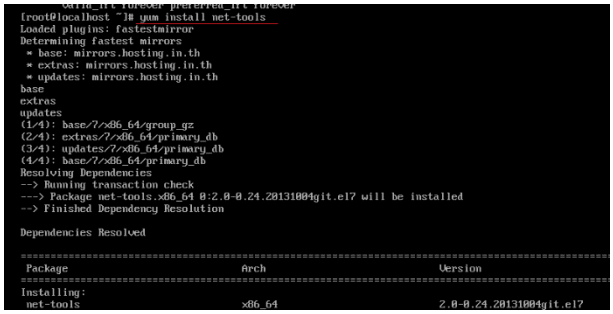

Figure 3. Installing the Zabbix monitoring software

2. Python Libraries and Dependencies

Python was used as the primary language for developing the AMS algorithm and scripts. Python can be downloaded from the official Python website.

(https://www.python.org/downloads/).

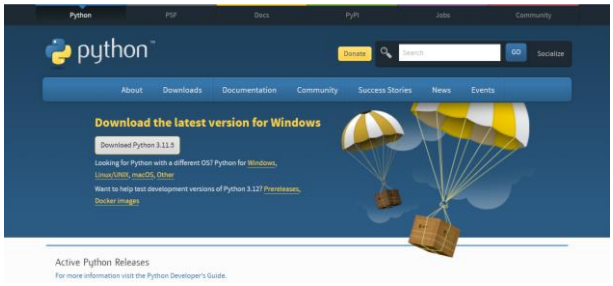

Figure 4. Download python

Appendix B: Data Collection Scripts

This section includes snippets of the data collection scripts used to gather the server metrics through various protocols such as SNMP.

```
snmp-server community Aot-Apps RO
snmp-server enable traps cpu threshold
snmp-server host 10.100.40.220 version 2c Aot-Apps
```

Figure 5. SNMP-server enables traps CPU threshold script

Appendix C: Anomaly Detection and Reconfiguration Algorithm

The anomaly detection algorithm and reconfiguration algorithm were implemented within the AMS, and the below explains the logical flow of the algorithm.

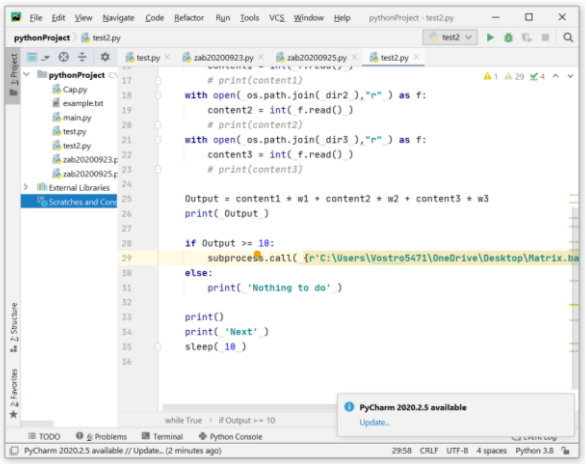

Figure 6. Detection and reconfiguration algorithm script