BIO-INSPIRED OPTIMISATION OF A NEW COST MODEL FOR MINIMISING LABOUR COSTS IN COMPUTER NETWORKING INFRASTRUCTURE

Submitted in fulfilment of the requirements of the degree of Doctor of Philosophy in Information Technology (IT) in the Faculty of Accounting and Informatics at Durban University of Technology, Durban - South Africa.

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Abstract

This thesis revolves around the bio-inspired optimisation of a newly formulated cost model tailored for initial installation of a user-specified computer networking infrastructure, motivated by requirements of networking industries, with a focal point on minimising labour costs. The new cost function of this infrastructure installation incorporates essential decision variables related to labour, encompassing the daily requirements and costs of both skilled and unskilled workers, their respective hourly rates, installation hours, and the overall project duration. This deliberate emphasis on labour-centric factors aim to offer nuanced insights into the intricacies of project budgeting and resource allocation.

The research critically evaluates the effectiveness of the cost function by examining various factors, such as daily fixed costs, a size and complexity factor tailored to individual scenarios, and a penalty coefficient aimed at ensuring compliance with project schedules. Significantly, the deliberate exclusion of equipment, material, maintenance and operational costs underscores the focused examination of labour-related expenditures, providing a unique contribution to the optimisation landscape within the installation of the user-specified computer networking infrastructure projects.

Utilising advanced bio-inspired optimisation techniques, alongside real-world data, this study endeavours to gauge the effectiveness of the new cost model in minimising labour expenses while upholding optimal network performance. The anticipated outcomes of this study extend beyond theoretical contexts to practical implications, providing actionable insights and recommendations for network infrastructure planners. The significance of labour-centric considerations in project planning and design is underscored, providing a more encompassing perspective that aligns with the evolving landscape of modern technological infrastructures.

By giving attention to labour-intensive aspects within installation of computer networking infrastructure projects, the thesis aspires to enhance budgeting accuracy and streamline resource allocation processes, thereby fostering more efficient and cost-effective project outcomes.

Declaration

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I hereby declare that this research project is the result of my own work, except for quotations and summaries that have been duly acknowledged.

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Dedication

In humble acknowledgment of the boundless grace and guidance bestowed upon us, I dedicate this work to the Almighty, whose limitless power and unwavering support have propelled me through the journey of self-improvement. I also dedicate this work to my esteemed parents (Posthumous), Mr. Ishmael Archibold Etwire and Madam Adwoa Antobam, whose unwavering love and encouragement have been the bedrock of my endeavours. Moreover, I dedicate this work to my beloved wife, Mrs. Joana Ama Nketsiah, and cherished children, Dr. Alfred Asiem Nketsiah and Jemima Nketsiah, whose constant chats, support, and prayers, have been my source of strength.

I am profoundly thankful for your steadfast commitment and unwavering faith in me, which have illuminated my path like a beacon. In the words of Psalm 118:24, "This is the day that the Lord has made; let us rejoice and be glad in it." Also, there is solace in this biblical quotation: Jeremiah 32:27, “Behold, I am the LORD, the God of all flesh: is there anything too hard for me? Your support has been a source of strength and inspiration, guiding me through every challenge. For this, I am forever indebted.

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Research emanating from this thesis.

Conference Papers:

Nketsiah, R N, Millham, RC, Agbehadji, IE, Freeman, E. (2024) Rule of Thumb for Estimating Workforce Allocations (ROT4WFA) for Computer Networking Projects, IEEE 2024 ICTAS Conference, South Africa DOI: 10.1109/ICTAS59620.2024.10507124

Nketsiah, R N, Millham, RC, Agbehadji, IE, Freeman, E, Agbehadzi, RK (2024) Fox Prey Optimisation: A Novel Multi-Objective Approach for Congestion Control in Wired Computer Networks", IEEE 2024 Information Communication Technology and Society Conference, South Africa DOI: 10.1109/ICTAS59620.2024.10507150

Journal Articles

Nketsiah, RN, Millham, RC, Agbehadji, IE, Freeman, E (2023) Bio-Inspired Optimisation algorithm for Congestion control in Computer Networking, Communications in Computer and Information Science, Springer, Switzerland DOI: 10.1007/978-3-031-29860-8_3

Nketsiah, RN, Millham, RC, Agbehadji, IE, Freeman, E, Ayogeboh Epizitone (2023) Optimising a Formulated Cost Model to Minimise Labour Cost of Computer Networking Infrastructure: A Systematic Review, Communications in Computer and Information Science, Springer, Switzerland DOI: 10.1007/978-3-031-48858-0_34

Nketsiah, R N, Millham, RC, Agbehadji, IE, Iwarere, S A, Freeman, E (2023) Trends in Computer Networking Congestion Control: A Bibliometric Analysis, Communications in Computer and Information Science, Springer, Switzerland DOI: 10.1007/978-3-031-48858-0_38

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Abbreviations

ABC	Activity-Based Costing Model
ACO	Ant Colony Optimisation
AI	Artificial intelligence
BAT	Bat Algorithm
BIA	Bio-Inspired Algorithms
CAPEX	Capital Expenditure Model
CNC	Computer Networking Company
CNI	Computer Networking Infrastructure
CS	Cuckoo Search Optimisation
CSG	Certified Solutions Ghana
EQN	Equation
FA	Firefly Algorithm
FPO	Fox Prey Optimisation
IDE	Integrated Development Environment
INCOM	Integrated Network Cost Optimisation Model
LCM	Labour Costs Model
NCM	Network Cost Model
NFV	Network functions virtualization
NIA	Nature-Inspired Algorithms
NFV	Network functions virtualization
NOCM	Network Operation Cost Model
OPEX	Operational Expenditure (OPEX) Model
SDN	Software Defined Network
SI	Swarm Intelligence
SLA	Service-Level Agreements
TCO	Total Cost of Ownership

Chapter 1: GENERAL INTRODUCTION AND SUMMARY

1.1 Introduction

The chapter opens with the background of the study on the current dispensation of optimising a newly formulated cost model to reduce labour costs on computer networking infrastructure. In subsequent sections, the general objectives of the study, specific objectives, the problem statement, the research questions, the justification of the study, the significance of the study, and the outline of the thesis is presented. It is then followed by a glossary of terms.

1.2 Background of the study

This study delves into the application of bio-inspired optimisation techniques to develop a cost model specifically tailored for initial network installation cost estimation in computer networking infrastructure projects. Recognising the multifaceted nature of labour costs, which extend beyond mere financial aspects to significantly impact project success and feasibility, this research aims to provide effective solutions for minimizing these costs. By integrating bio-inspired optimisation methods into the newly formulated cost model, this study seeks to offer innovative approaches to meet the user requirements for accurate and efficient initial network installation cost estimation.

1.2.1 User Requirements

A Ghanaian networking company commissioned me, and my computer networking company, to conduct an initial installation and configuration of a network. In advanced countries, these configurations are typically performed by individual specialists, contributing to overall labour costs (Smith et al., 2020). However, in Ghana, the hired skilled workers handle all these configurations as part of their agreed-upon wages, consolidating labour costs and simplifying the hiring process (Doe, 2018). Henceforth, the use of the term “installation” in this thesis will reflect the combination of installation and configuration of configurable components in this network as per this commission. Also, for the sake of only this thesis, the Ghanaian networking company that commissioned my company will be referred to as CSG, while my computer networking company will be referred to as CNC.

This commissioning company—CSG—wanted to find the best possible costs for this project. These costs would include minimising the use and maximising the utilisation of skilled labour. Skilled computer networking personnel are difficult to find and involve significant costs, while unskilled labour is more affordable and should be maximized (Gambardella, Panico and Valentini, 2015). Consequently, the company would want to maximise the use of unskilled labour which is cheap and easy to get. The CSG's goal is to minimise the cost of expensive skilled labour, even if it requires more unskilled labour.

Additionally, security needs to be considered. Physical security measures are crucial in Ghana, as security cameras alone can be disabled, encouraging theft. Therefore, employing physical security guards alongside with their insurance, ensures a safe working environment and successful completion of the project within the stipulated timeframe(Bolanio *et al.*, 2021).

Furthermore, assurances of benefits in the form of fixed costs, such as transportation, accommodation, and feeding of network installation employees, must be considered, which improves time management and encourages skilled workers to commit to the project, enhancing overall efficiency (Conley, 2017).

This commissioning company—CSG—wanted an approach that can be applied to different sizes of networks that they frequently encounter in Ghana, such as small, medium, and large networks.

The company's assurance that all necessary components have been procured allows the study to focus exclusively on the installation phase, avoiding considerations of initial planning, design, and or operation

Finally, there is an issue of project delays. In Ghana, projects often face significant delays due to lackadaisical approaches by engineers, as elucidated by Hashemi, Mousavi and Patoghi, (2021).

To address these requirements, a number of steps were taken which motivated me to conduct this study. The first step was to break down these user requirements into functional and non-functional requirements. User requirements are essential, according to McGraw and Harbison, (2020), in defining the specifications and constraints necessary for the successful planning of this project. These requirements are categorized into functional and non-functional aspects to comprehensively capture the needs and expectations of the users (Al-Sayed, Hassan and Omara, 2020).

A functional requirement is a specification of behaviour that a system must perform. It details the actions, tasks, or operations that the system should be capable of executing, typically in response to an input or in support of a business need. Functional requirements define the functions of a system or its components and often include details about inputs, processes, outputs, and the interaction between the system and users (IEEE, 1990).

The functional requirements of this company for computer networking systems include the allocation of skilled and unskilled workforce, hourly rates for both, and project duration. Project duration is a critical functional requirement as it directly impacts labour costs and project timelines. Determining project duration involved several key steps executed to ensure accuracy and efficiency.

Each task was estimated based on historical data from previous projects and expert input from experienced engineers (Turner and Zolin, 2012; Kerzner, 2017). This provided a reliable foundation while considering current practices and complexities. Tasks were then scheduled in a logical sequence using tools such as Gantt charts and project management software, facilitating visualization of the project flow and management of task dependencies (Larson and Gray, 2021).

The project timeline was optimized to reduce total duration using techniques such as critical path analysis and resource levelling. Critical path analysis identified crucial tasks affecting the project's completion time, while resource levelling ensured optimal workforce utilization (Lock, 2020).

By breaking down the initial user requirements into these detailed components, a comprehensive cost model was developed. This model minimizes labour costs while ensuring timely project completion, meeting the specific demands of CSG (Wysocki, 2019).

A non-functional requirement, as opposed to a behaviour requirement, outlines standards by which a system's performance may be evaluated. Performance, usability, dependability, and security are only a few examples of the quality aspects that are often defined by these criteria (IEEE, 1990). Project length, execution time, and the penalty coefficient for delays are examples of operational and system performance that are considered non-functional criteria in computer networking infrastructure projects. In particular, the penalty coefficient was added as a way to guarantee that projects are finished on schedule, preventing extra expenses and longer times linked with project delays

Execution time refers to the amount of time a system or component takes to complete a specific task or process, which is critical for assessing system performance and efficiency. Project duration, on the other hand, is the total time taken from the initiation to the completion of the project, encompassing all phases of the project lifecycle, including planning, implementation, and final testing (see Sections 2.5.2 and 2.5.3 for a detailed discussion on execution time and project duration respectively). Execution time aids in the planning and scheduling of tasks, ensuring that each task is completed within the anticipated timeframe. This is especially crucial for fulfilling the functional requirements of a project, including the allocation of skilled and unskilled workforce and the determination of hourly rates. Accurate estimation of execution times enables project managers to effectively allocate resources, establish realistic timelines, and mitigate unnecessary delays (Lock, 2020; Turner & Zolin, 2012). The project duration and execution time were derived from a realistic appraisal of the original user requirements in order to incorporate them into a feasible, working model.

Through a literature review, it was determined that these user requirements by this company are significant factors, especially in terms of labour costs for installation of networks. This approach is essential for addressing the unique challenges and opportunities present in the local labour market and project management practices (McNamara and Sepasgozar, 2020). Given these factors, existing network cost models were examined for their suitability. As existing network cost models did not adequately incorporate these factors into their model, there was the need to develop a new model which would incorporate these factors. This model addresses the specific needs of a Ghanaian company commissioned to determine labour costs associated with computer networking installation, which are more challenging to estimate than infrastructure costs (Akorabeng, 2019).

In order to determine the best possible costs for these factors, a suitable optimization method was needed to optimize the newly formulated network cost model. After this optimization, useful information was made available to the commissioning company to minimize labour expenses and enhance project effectiveness in computer networking projects in Ghana (Akorabeng, 2019)

This concentrated focus aims to provide a clear and actionable framework for minimizing labour costs and enhancing the efficiency of network installation projects in Ghana.

1.3 Field of research

The field of study is information technology, with an emphasis on bio-inspired search methods for optimisation aimed at minimising computer networking infrastructure labour costs and improving overall system efficiency.

1.4 Problem statement

Labour costs are a pivotal aspect of the initial installation of computer networking infrastructure projects, especially given the requirements of the aforementioned company. The balance between skilled and unskilled personnel significantly impacts project efficiency, dynamics, and overall financial outcomes (Atkin *et al.*, 2019; Teixeira, 2019). Efficient time management is crucial for minimizing project durations and optimising resource utilization, a well-established principle in project management research (Tena and Asuero, 2022).

However, existing cost models often fail to comprehensively address the interconnected factors at play in labour cost management, particularly within the context of these installation projects. This oversight leads to suboptimal resource allocation, reduced overall efficiency, and negative impacts on project profitability.

In the Ghanaian context, these challenges are further complicated by local labour market conditions and cultural practices, such as wage bargaining and frequent project delays (Ameyaw *et al.*, 2017). To ensure timely project completion and prevent unnecessary delays, a penalty coefficient is introduced, highlighting the importance of adherence to schedules.

Given these complexities, there is a compelling need to develop a new cost model specifically tailored to the nuances of computer networking infrastructure installations in Ghana. This model will integrate specific user requirements, including the allocation of skilled and unskilled workforce, hourly rates, and project duration. By leveraging bio-inspired optimisation methods, the model aims to accurately estimate labour costs, optimise resource allocation, and minimize project timelines.

The proposed model will offer a systematic approach to managing labour costs, incorporating user-defined best wages and operational times to ensure optimal project outcomes. This research aims to enhance project management strategies and provide innovative insights for optimising labour costs in the installation of computer networking infrastructure projects (Fernandes, 2019; Belwal *et al.*, 2020; Bergtold *et al.*, 2019).

1.5 General objective

The principal objective of this research is to systematically investigate a newly formulated cost model, based on the given user requirements, tailored for installation of computer networking infrastructure, and optimising this model for best possible labour costs. A bio-inspired algorithm is employed as optimisation strategy for the formulated cost model. The focal point is the minimisation of labour costs, thereby enhancing the cost-effectiveness of labour-centric considerations within installation of computer networking infrastructure projects.

1.5.1 Specific objectives

To achieve the general objectives, this research exclusively concentrated on accomplishing the following specific objectives:

> To identify critical factors that influence the cost dynamics of initial installation of the user-specified computer networking infrastructure projects, including labour dynamics (both skilled and unskilled), time management, and project duration as per the requirements of the commissioning company—Certified Solutions Ghana.

To conceptualize a nuanced cost model that integrates the identified factors seamlessly. This model aims to provide a detailed yet comprehensive representation of the cost intricacies inherent in installation of computer networking infrastructure projects.

To select, apply, and evaluate bio-inspired algorithms for optimising labour costs in networking infrastructure projects. This objective aims to identify the most effective algorithm through rigorous evaluation metrics, ensuring methodological robustness.

To evaluate and optimise the efficacy of the newly formulated cost model by comparing its predictions against real-world networking scenarios. This aims to demonstrate the model's accuracy and superior optimisation capabilities over existing models.

1.6 Research questions

What are the key determinants influencing the cost dynamics of initial installation of the user-specified computer networking infrastructure projects, including labour dynamics (both skilled and unskilled), time management, and project duration?

How can a nuanced cost model be conceptualized to seamlessly integrate identified determinants and provide a detailed yet comprehensive representation of the cost intricacies inherent in installation of computer networking infrastructure projects?

What are the most effective bio-inspired algorithms for optimising labour costs in networking infrastructure projects, and how can their effectiveness be rigorously evaluated to ensure methodological robustness?

How does the efficacy of the newly formulated cost model compare to existing models when its predictions are systematically evaluated against real-world networking scenarios, and how can its accuracy and superior optimisation capabilities be demonstrated?

1.7 Justification of the study

The study explores the use of bio-inspired search methods in cost models to minimise labour costs in installation of computer networking infrastructure projects. By integrating bio-inspired algorithms into the cost model for on-demand optimisation, the study endeavours to strategically address the evolving requirements for efficient labour-centric solutions.

The study's significance extends beyond academic realms, offering practical economic implications for organisations investing in computer networking infrastructure. By minimising labour costs through bio-inspired optimisation, the study offers tangible strategies for economic efficiency within the dynamic landscape of network projects.

The findings also provide a roadmap for strategic resource allocation, crucial in a scenario where labour-intensive tasks are essential to the success of installation of user-specified computer networking infrastructure projects. The study contributes to the ongoing evolution of cost models by infusing bio-inspired optimisation techniques, ensuring they remain adaptive and relevant in the ever-changing technological milieu.

The holistic contribution of this study to the field of computer networking infrastructure is its strategic alignment with the thesis theme and its practical implications for economic efficiency, resource optimisation, and innovation in cost models within the realm of installation of user-specified computer networking infrastructure.

1.8 Significance of the study

The study on bio-inspired optimisation of a newly formulated cost model for minimizing labour costs in the installation of user-specified computer networking infrastructure holds significant implications in the rapidly evolving technology and project management landscape.

This research addresses the specific cost requirements of the commissioning company by developing a new cost model that incorporates their unique needs. The model is designed to be adaptable, making it relevant not only to the commissioning company but also to other organizations with similar requirements. By creating a flexible framework, the model can be easily reformulated to accommodate new and evolving project specifications.

A core contribution of this study is the introduction of bio-inspired optimization techniques into the cost modelling process. Through assessment of existing bio-inspired algorithms, the most suitable algorithms are evaluated and the algorithm that produces the overall minimal costs is selected. These algorithms are evaluated in three scenarios which reflect real-world situations that networking often encounters. This comparative analysis ensures that the developed cost model delivers the best possible labour cost optimization.

By strategically integrating these advanced optimization methods, the study aims to enhance the precision and efficiency of labour cost management in network installation projects. The optimised allocation of skilled and unskilled labour resources not only meets the financial constraints of the commissioning company but also sets a benchmark for industry standards.

In summary, this research makes a pioneering contribution to cost modelling by introducing and validating bio-inspired optimization techniques. It provides a robust framework for minimising labour costs in network infrastructure projects, ensuring that the newly formulated cost model is both adaptive and capable of addressing current and future complexities in the field.

1.9 Outline of the thesis

Below is the structural layout of the thesis:

Chapter 1: General introduction and summary

This chapter presents the background and motivation for the research, the general objective of the study, the specific objectives, the problem statement, the research questions, the justification of the study, the significance of the study, and the structure of the thesis.

Chapter 2: Literature review

This chapter reviews current literature on the minimisation of computer networking infrastructure labour costs and current cost models used in the industry. Although this study is largely on bio-inspired or meta-heuristic approaches to minimising computer networking infrastructure labour costs, other non-bio-inspired approaches to minimising infrastructure labour costs are explored. The review of the literature is significant for identifying gaps in the literature that need to be filled regarding the minimisation of labour costs by using cost models and the need for optimisation.

Chapter 3: Methodology

This chapter reviews the development of the newly formulated cost model, describes the optimization techniques applied, discusses the data collection process adopted, examines the sources of data used, and finally explains the validation and testing of the model.

Chapter 4: Experimental Results and Analysis

This chapter presents the experimental results obtained from the optimised newly formulated cost model, comparing it with existing cost models and discussing the insights and findings from the analysis. It evaluates the impact of the optimised cost model on reducing computer networking infrastructure labour costs. Additionally, the chapter concludes with a summary of the research and main findings, exploring the implications of the results for the industry.

Chapter 5: Conclusion, Recommendations, and future work

Chapter 5 draws conclusions from the various results discussed in Chapter 4 and the rest of the work. The limitations in terms of the scope of this research, as well as the information gleaned from the study, are used to provide recommendations for future work.

1.10 Definition of terms

Meta-heuristic search method is a general algorithmic framework that is applied to various optimisation problems with relatively few modifications (both on an algorithm and its parameters) so that the algorithm can be adapted to a specific problem (Agbehadji, 2019).

Bio-inspired optimisation algorithms, according to artificial intelligence, are those methods that are generally inspired by physical principles, evolution theory and certain behaviours of living beings to efficiently solve optimisation problems in very diverse application areas.

The cost model refers to a methodology or framework employed to ascertain the total investment required for delivering a product or service. It encompasses various approaches aimed at accurately assessing the value input in comparison to the value output, adaptable to diverse situations and contexts.

Formulated cost model denotes a specific, structured methodology developed for a particular purpose or context. It entails a tailored approach with predefined variables, algorithms, or assumptions meticulously designed to address the intricacies of a specific application or scenario within cost assessment and analysis.

Chapter 2: LITERATURE REVIEW

2.1 Introduction

In the rapidly evolving field of computer networking, managing and minimizing labour costs is crucial for the successful implementation and maintenance of infrastructure projects. This chapter reviews existing research on cost models specifically designed to address labour costs within computer networking infrastructure. Key models examined include bio-inspired optimization cost models. Through a critical assessment of these models, the review aims to identify research gaps and evaluate their effectiveness in addressing labour cost challenges in networking projects. Additionally, the review considers various factors influencing labour costs, such as network scale, infrastructure complexity, and the required level of expertise.

By synthesizing existing literature and addressing gaps in knowledge, this review aims to contribute to the advancement of research in this critical area. The chapter commences with an overview of computer networks.

2.2 Overview of computer networks

Spanning a vast array of interconnected communication infrastructure, computer networks serve as the backbone of today's information exchange ecosystem. As articulated by Tanenbaum and Wetherall, (2011), a computer network comprises diverse hardware and software components, including servers, routers, switches, cables, and wireless access points. Beyond these components lies a realm of complexity, which relates to the interactions between devices, protocols, and data flow thereby creating a complex network of communication. Also, computer network complexity, according to Tanenbaum and Wetherall, (2011), refers to the sophistication of a computer network, encompassing factors like interconnected devices, network components, traffic volume, and protocol complexity. Musyoka, Arasa and Ombuki, (2022) underscore the significance of these computer networks in today's interconnected world, where operational efficiency and reliability are paramount for organisations. Indeed, the efficiency and reliability of computer networks are fundamental to an organisation's operational prowess, shaping its ability to communicate, collaborate, and thrive in the modern business landscape.

Figure 2.1 presents a simple scenario 1 diagram of a computer networking infrastructure, as defined by Nketsiah *et al.*, (2024), where a limited number of computer networking devices are interconnected.

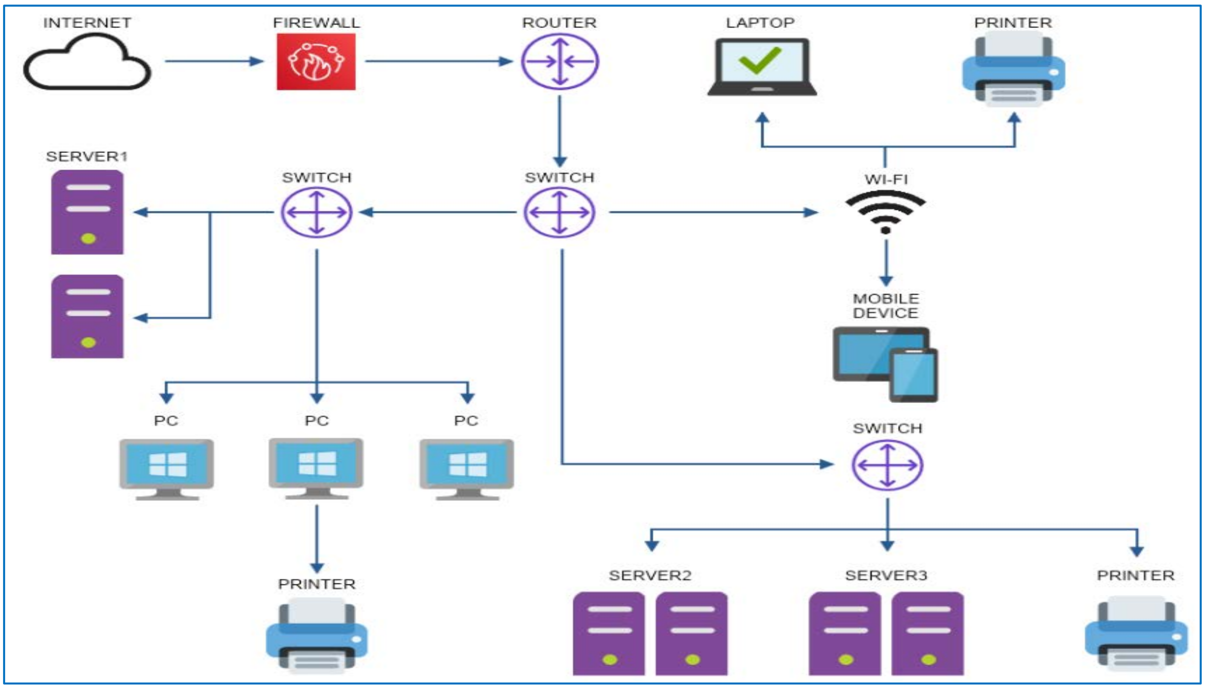

Figure 2:1: Scenario_1 Computer Networking Setup Source: (Pinterest, 2020).

Figure 2.1 represents a typical topology within the Scenario_1 network, which contains 50 network components. It includes an internet connection depicted by a cloud icon, which is linked to a firewall. The firewall acts as a security device, monitoring and controlling network traffic based on security rules (Quinn, 2021). Connected to the firewall is a router that manages data packets between different networks, directing them to their appropriate destinations. Several switches are present, connected to the router and other network components, serving to connect devices within the network and forwarding data to the correct destinations using MAC addresses (Aggarwal, 2018).

The network features multiple servers: Server 1 is connected to the first switch and has multiple connections, likely providing various services to connected devices, while Server 2 and Server 3 are connected to another switch, potentially offering additional or different services. Three personal computers (PCs) are linked to the switch associated with Server 1, forming a local area network (LAN) setup within the Scenario_1 network. Printers are strategically placed within the network; one printer is connected to the switch linked to Server 1, another to the switch associated with Servers 2 and 3, and a third printer is connected wirelessly via Wi-Fi.

Additionally, a laptop connects wirelessly to the network via Wi-Fi, demonstrating its capability for mobile or remote access. Mobile devices also connect wirelessly via a Wi-Fi access point, which provides wireless connectivity to the network. The overall structure of the network ensures efficient connectivity and access to resources such as servers, printers, and the internet. The inclusion of switches helps manage and direct data traffic efficiently, while the firewall offers a layer of security to protect internal network resources from external threats.

2.3 Ranges of Installations of computer networks

There are ranges of installations of computer networks that vary from small-sized, medium-sized, and large-sized computer networks (Nketsiah, Edem Agbehadji, *et al.*, 2024).

Exploring varying scales of computer networks provides valuable insights into how different installations meet specific requirements and challenges. These scenarios serve as representative test-benches to assess the applicability and effectiveness of any proposed installations, algorithms, or methodologies across different network scales (Nketsiah, Edem Agbehadji, *et al.*, 2024).

Firstly, small-sized networks encapsulate localized environments with a limited number of network components, typically up to 50 (Nketsiah, Edem Agbehadji, *et al.*, 2024). These computer networks are characterized by their compactness and straightforward infrastructure, often serving individual buildings or small office spaces. Research within this domain focuses on optimising network performance and efficiency within constrained environments, addressing challenges such as resource allocation and scalability (Shihab *et al.*, 2023).

Secondly, medium-sized networks, accommodating up to 750 network components, encompass a broader operational scope than small-sized networks (Nketsiah, Edem Agbehadji, *et al.*, 2024). They serve as the backbone for larger office complexes, educational institutions, or medium-sized enterprises. Research in this area delves into topics such as network architecture design, traffic management, and security protocols, aiming to achieve a balance between performance and manageability in medium-scale environments (Adewale, 2023).

Lastly, large-sized networks, capable of accommodating up to 1500 network components, represent extensive infrastructures spanning wide geographical areas or serving sizable organizations with complex networking requirements (Nketsiah, Edem Agbehadji, *et al.*, 2024). These networks require robust infrastructure and advanced protocols to ensure seamless communication and data transmission across dispersed locations. Research efforts in this domain focus on scalability, fault tolerance, and resilience to address the challenges inherent in managing large-scale network deployments (Hussein *et al.*, 2022).

Given the varied nature of different sized networks, any cost model that will be utilized should be adaptable to the specific requirements and constraints of each network size. It must accurately estimate the costs associated with installation, taking into account the differences in infrastructure, labour needs, and project complexities (Nketsiah, Edem Agbehadji, *et al.*, 2024). The model should also incorporate optimisation techniques to ensure that resources are allocated efficiently, project timelines are met, and costs are minimized, regardless of the network size. This adaptability is crucial for ensuring that the new cost model remains effective and relevant across diverse networking scenarios (Nketsiah, Edem Agbehadji, *et al.*, 2024).

2.4 Role of cost in installation of computer networking infrastructure

The role of cost in optimizing the initial installation of user-specified computer networking infrastructure is critical (Samiullah *et al.*, 2023). In the realm of network deployment and management, cost considerations influence every facet of decision-making, including resource allocation and project timelines (Ogundipe, Babatunde and Abaku, 2024) . As organizations strive to maintain competitiveness and efficiency, effectively managing labour costs becomes essential for financial sustainability (Allioui and Mourdi, 2023). Labour costs encompass not only the direct expenses associated with skilled and unskilled workers but also the indirect costs incurred during project execution (Baghai *et al.*, 2021). The complex relationship between labour costs and other factors such as technology selection and network scalability underscores the need for a comprehensive cost model tailored to the specific demands of computer networking infrastructure (Lu, 2024).

As already spelt out in section 1.2.1, it is a common practice, in the Ghanaian setting, for the single hired skilled worker or workers to handle all configurations within the installation as part of their agreed-upon wages, thereby consolidating labour costs and simplifying the hiring process (Doe, 2018).

There are different cost factors inherent in installation of computer networking infrastructure projects that contribute to the overall cost incurred by organisations (Florio, 2019).

2.4.1 Cost factors in installation of computer networking projects

The cost factors in the installation of computer networking infrastructure range from hardware and software expenses to labour costs (Stevens, 2017).

Hardware costs entail the procurement of networking equipment such as routers, switches, cables, and servers, which form the foundational components of network infrastructure (Tso, Jouet and Pezaros, 2016). These expenses extend beyond the initial purchase to include ongoing maintenance, upgrades, and replacements as technology evolves (Bressanelli *et al.*, 2018).

Software costs encompass licensing fees for operating systems, network management software, and security applications essential for network operations and cybersecurity (Hamdani *et al.*, 2021). Additionally, organisations may incur costs related to software customization, integration, and ongoing support to ensure optimal performance and security (Maddikunta *et al.*, 2022).

Labour costs represent a significant portion of project expenses, encompassing salaries for skilled and unskilled workers involved in network design, installation, and maintenance (Nasirian *et al.*, 2022). This includes network engineers, technicians, administrators, and support staff responsible for ensuring the smooth operation and security of the network infrastructure (Bolanio *et al.*, 2021).

Moreover, costs associated with site preparation, equipment installation, training, and ongoing support further contribute to the overall financial outlay of networking projects (Wuni and Shen, 2020). Site preparation expenses may include infrastructure upgrades, facility modifications, and environmental considerations to accommodate the networking equipment effectively (Yang *et al.*, 2018). Equipment installation costs encompass deployment, installation, and testing to ensure proper functionality and integration with existing systems (Zheng, 2023). Training costs involve educating personnel on network operation, maintenance, and security best practices to maximize efficiency and minimise downtime (Popov *et al.*, 2021).

Ongoing support expenses cover routine maintenance, troubleshooting, and upgrades to address evolving business needs and technology advancements (Maddikunta *et al.*, 2022).

Recognising the criticality of comprehending and adeptly managing these cost factors, organisations endeavour to optimise their investments in computer networking infrastructure while prioritizing reliability, scalability, and performance (Chauhan and Shiaeles, 2023). However, even though these factors are crucial, they are out of scope for this thesis as the focus is on user requirements, particularly labour costs. This focused approach is essential for meeting the specific needs of the study, which aims to optimise labour costs and related user requirements in computer networking projects (Crawford, 2021).

2.4.2 Labour costs of initial installation of user-specified computer networking projects:

Understanding the intricate financial dynamics in installation of computer networking projects is paramount, with labour costs serving as a central focus, given the aforesaid user requirements. Here, the study explores the nuanced aspects of labour costs and their implications, shedding light on the multifaceted considerations involved in managing personnel and resources.

Firstly, labour costs undeniably form the cornerstone of financial considerations in computer networking projects (Mignacca, Locatelli and Velenturf, 2020). Even though labour costs in installation of computer networking infrastructure projects take up a chunk of the budget, they are mostly not seen in that direction, as most often attention is given to hardware as being the major cost determinant. The modern networking landscape, punctuated by its evolving intricacies, necessitates a multitude of specialized roles, each bearing its own distinct cost implications (Allioui and Mourdi, 2023). These costs extend beyond mere salaries, encompassing training, benefits, and overhead expenses.

Secondly, as the study delves deeper into the complexity of specialized roles, Tanenbaum and Wetherall, (2011) elucidate this burgeoning demand for specialized roles, emphasizing the increasing need for expertise tailored to specific tasks and challenges within the network infrastructure. Vermeulen, Pyka and Saviotti, (2020) further reinforce this observation, attributing the escalating labour costs to rapid technological advancements and the consequent demand for niche skills. Such specialisation often requires ongoing professional development and certifications, adding to the overall cost burden.

Building on the examination of specialised roles, it is equally essential to evaluate the financial implications of the tools they employ (Levenson, 2018). Labour costs, a critical consideration in managing computer networking projects, encapsulate the compensation offered to personnel responsible for maintaining and implementing network systems. Another aspect of labour costs emanate from the intricacies of contemporary technology with the pressing need for expertise in the computer networking fields (Tanenbaum and Wetherall, 2010; Jang, 2019). Additionally, investments in cutting-edge software and hardware solutions contribute to the overall expenditure, impacting budgetary allocations.

Moreover, modern networks, with evolving topologies and emergent technologies like Software Defined Networking (SDN), Network Functions Virtualization (NFV), and edge computing, have redefined the networking landscape. Such innovations escalate the demand for specialized skills, magnifying the intricacies and associated labour costs (Kakade, Patle and Umbarkar, 2023). Adaptability and agility in skill acquisition become imperative, driving up training and recruitment expenses.

Lastly, considering the shifting landscape of labour allocation in computer networking (Pettas and Avdikos, 2023), there is a discernible trend towards a flexible workforce. Historically dominated by in-house teams, this shift is driven by the need for specialized skills and a more adaptable approach to project requirements (Akyildiz *et al.*, 2016).

Transitioning from the larger picture of labour costs in computer networking projects, the study now shifts its focus to the crucial aspect of exploring the various factors that contribute to labour costs within the field of initial installation of user-specified computer networking infrastructure projects.

2.5 Factors contributing to labour costs

Given the complexities involved in labour costs within installation of computer networking infrastructure projects, it is crucial to acknowledge the multitude of factors influencing these expenditures. While labour costs are undoubtedly a cornerstone of financial considerations, the dynamic nature of network development and implementation introduces various elements that impact these costs (Allioui and Mourdi, 2023).

Navigating these complexities poses a significant challenge, especially considering the diverse range of variables at play. It is important to recognize that not all facets of labour costs can be fully addressed within the scope of this study. Instead, the focus is on selecting and analysing the factors that exert the most significant influence on project budgets, timelines, and overall success.

With this perspective in mind, the study begins by examining fundamental aspects such as workforce allocation and worker wages. This initial exploration seeks to uncover the intricate connections between resource deployment, skill acquisition, and financial compensation, setting the stage for a deeper understanding of labour cost dynamics within installation of computer networking infrastructure projects.

Given the user requirements, these required necessities are examined as to how they meet significant factors in networking installation. These factors have a wider applicability than just the given user requirements, given their significance.

2.5.1 Workforce allocation and wages of workers

Efficient workforce allocation is essential for aligning skill sets with project requirements, optimising labour costs, and enhancing project efficiency (Shahbazi *et al.*, 2019). Proper allocation minimises idle time and ensures effective resource utilisation, thereby reducing unnecessary labour expenses (Hannan *et al.*, 2020). Additionally, it facilitates smoother project execution and timely deliverables. Meanwhile, wages of workers directly impact labour costs and project budgets (Musarat, Alaloul and Liew, 2022). Variations in wages or salaries must be carefully considered in cost estimations to accurately budget for labour expenses and ensure financial sustainability throughout the project lifecycle. Such considerations are integral to maintaining project profitability and resource management effectiveness (Abeysekara *et al.*, 2021; Calabrò and Della Spina, 2019). The allocation of workforce and corresponding wage structures play a pivotal role in determining the overall labour costs. The research thus switches to an examination of the temporal determinants of cost models, encompassing time management, execution times, and project duration.

2.5.2 Time Management, Execution Times, and Project Duration: The temporal determinants of costs models for computer networking projects

In the realm of computer networking projects, the thorough management of execution times transcends mere punctuality; it emerges as a critical facet of financial prudence (Turner and others, 2021). Adhering to stipulated execution timelines not only ensures project completion within predetermined schedules but also profoundly shapes the overall financial landscape Rylander Eklund and Simpson, (2020).and also Hopkin, (2018) illuminates this intricate relationship, underscoring that deviations from planned timelines can carry substantial financial repercussions. Johnson, Smith and Davis, (2020) further scrutinize the overarching project duration, emphasizing the cumulative cost implications associated with prolonged timelines. The potential for fluctuating costs linked to time underscores the pivotal importance of diligent time management, a sentiment reinforced by Hinshaw and Scheffler, (2014).

According to Kerzner, (2017), efficient time management is not solely a matter of meeting deadlines; it is an integral strategy for cost containment in installation of computer networking infrastructure projects. As Sanchez, et al., (2017) aptly point out, any deviations from the planned timelines can disrupt the delicate balance of project costs, resulting in unforeseen financial consequences. The intricate relationship between execution times and project costs is a focal point of scrutiny in the study by Johnson et al, (2020), who delve into the cumulative cost implications of extended project durations. Their findings shed light on the financial intricacies associated with temporal deviations in computer networking projects.

Building upon the insights regarding the intricate relationship between execution times and financial implications in computer networking projects, it becomes clear that efficient allocation and execution of tasks within specified timelines become paramount in managing the financial aspects of computer networking projects. The study by Hinshaw and Scheffler, (2014) underscores the direct correlation between diligent time management and cost-effectiveness in project execution. As the potential for fluctuating costs tied to time remains a constant consideration in the dynamic landscape of installation of computer networking infrastructure projects, the correlation between time management and cost becomes increasingly salient (Allioui and Mourdi, 2023). Navigating these temporal determinants of costs underscores the importance of a comprehensive understanding of these intricacies for project managers and stakeholders alike. With this awareness, the focus shifts to another critical dimension: penalty coefficients in computer networking projects. Refer to Section 2.5.3.

These factors are significant and an integral part of computer networking installation costs because they directly impact the overall efficiency, reliability, and sustainability of the network infrastructure. Properly addressing these costs ensures that the network can operate smoothly, handle peak loads, and adapt to changing demands without frequent disruptions (Tso, Jouet and Pezaros, 2016).

Furthermore, ignoring any of these factors can lead to suboptimal performance, increased downtime, and higher long-term costs due to inefficiencies and the need for frequent upgrades or repairs. By carefully considering each cost factor, organizations can avoid potential vulnerabilities, ensuring robust and secure network operations (Bressanelli *et al.*, 2018: Maddikunta *et al.*, 2022).

2.5.3 Penalty coefficients in computer networking projects:

Expanding on the technical intricacies, penalty coefficients play a dual role in the financial landscape of computer networking projects (Du *et al.*, 2021). Firstly, they act as a proactive mechanism to enforce adherence to project timelines, fostering a culture of punctuality and efficiency. Secondly, from a financial standpoint, penalties represent predetermined and non-negotiable costs incurred under specific conditions.

As revealed by Li *et al.*, (2021), an understanding of penalty coefficients is crucial for optimising project execution. Effective management involves not only the imposition of penalties but also strategic considerations to align penalties with project objectives and cost structures. The predetermined nature of penalties introduces an element of predictability into the financial planning process, allowing for precise budgetary allocations.

In practical terms, penalties contribute to the fixed costs of a project (Hashemi, Mousavi and Patoghi, 2021). This fixed nature implies that, regardless of variable factors, the financial impact of penalties remains constant. Such insights are particularly valuable for project managers and financial planners, enabling them to forecast and allocate resources with an accurate understanding of the financial repercussions associated with deviations from established timelines.

This technical scrutiny of penalty coefficients underscores their integral role in the financial ecosystem of initial installation of user-specified computer networking infrastructure projects (Hidayat-ur-Rehman and Hossain, 2024). It not only accentuates their importance in fostering operational efficiency but also positions them as quantifiable components within the broader financial framework. As the study navigates the nuanced terrain of penalty coefficients, their technical significance emerges as a linchpin in the quest for precision and optimisation in managing labour costs within computer networking projects (Vis, 2024). Continuing the exploration, the study now turns to the role of fixed costs in driving overall expenses, the underlying consistent expenditures.

2.5.4 Fixed Costs: The Underlying Consistent Expenditures:

To start with, the foundational elements of project finances are the unyielding financial pillars of fixed costs (Buller, 2022). These are the reliable, unchanging expenditures that constitute the financial bedrock of the computer networking infrastructure project. Crucial components such as team accommodation, transportation, and space rentals, incorporating ancillary expenses like electricity charges, prominently feature in these fixed costs category. The perpetual operation of physical security, operating around the clock, irrespective of mounted CCTV (closed-circuit television) cameras for surveillance, reinforces the integrity of this domain, ensuring the protection of assets and personnel (Kirwan and Zhiyong, 2020). Thompson illuminates the pivotal role played by these unwavering costs, emphasizing their indispensable nature for meticulous and predictable budgeting (Lewis, 2024). Traversing the intricate landscape of fixed expenditures sharpens the focus on the overarching project vision, intricately linked with profit optimisation.

Again, emphasizing the constancy of expenditure, fixed costs serve as resilient anchors against the fluctuations of variable counterparts (Cuesta Arcos, 2023). These consistent expenditures provide a stable foundation, encompassing essential elements such as team accommodation, transportation, and space rentals, including ancillary charges like electricity. The continuous operation of physical security, a non-negotiable presence, adds an additional layer of protection for both assets and personnel (Ali, 2023). Thompson accentuates the crucial role of these steadfast costs, shedding light on their vital contribution to precise and foreseeable budgeting (Lewis, 2024). Navigating the intricate tapestry of fixed expenditures reveals a nuanced understanding of the project's holistic vision, intricately woven with the pursuit of profit optimisation.

Furthermore, beyond the fluctuations inherent in variable costs, the core of project finances resides in the realm of fixed costs (Perkin and Abraham, 2021). These unwavering expenses provide a stable and predictable financial foundation, encompassing critical aspects such as team accommodation, transportation, and space rentals, along with supplementary charges like electricity (Akbarnezhad Nesheli, 2023). The uninterrupted operation of physical security, a non-negotiable element, reinforces this domain, ensuring the safeguarding of both assets and personnel (Nel, 2018). Thompson elucidates the essential role played by these consistent costs, highlighting their indispensability for precise and anticipatable budgeting. Exploring fixed expenditures provides insight into the project's overarching vision, closely linked with the goal of optimising profit (Alzaydi, 2024). As essential as it is to explore another dimension of cost management, the study now directs attention to the intricacies of network complexity factor-related costs.

2.5.5 Network complexity factor related costs

The cost related to network complexity factor in installation of computer networking infrastructure projects, according to Faraji *et al.*, (2022), is influenced by various factors, one of which is the size and intricacy of the network. This network complexity factor becomes particularly pronounced as the size of the network increases (Meyerhenke, Sanders and Schulz, 2017). The increase in complexity takes various forms, but in this thesis, an incremental approach is adopted, where the complexity factor increases alongside predefined increments according to selected scenarios (Nketsiah, Edem Agbehadji, *et al.*, 2024). For scenario 1, representing the smallest network installation, the base complexity factor is set at 1.0. Subsequently, for the next or medium-sized network installation, the complexity factor increases by a predefined step size of 0.2. Consequently, for scenario 2, representing the next or medium-sized network installation, the network complexity factor would be 1.0 plus the incremental increase, resulting in a value of 1.2. These are extensively covered in Section 3.7.4.

This systematic approach allows for a granular assessment of complexity-related costs, enabling organisations to anticipate and manage financial implications as they scale their network infrastructure. By aligning the network complexity factor with selected scenarios, the study aims to provide a comprehensive understanding of how network size and intricacy influence overall project expenditures (Khalef and El-adaway, 2023).

2.6 Develop an optimised cost model of initial installation of user-specified computer networking projects (Traditional)

Developing an optimised cost model in the context of installation of computer networking infrastructure projects involves refining the model to more accurately reflect the real-world variables and dynamics that impact project costs. Traditional cost models, while foundational, often fall short in their ability to fully capture the complexities of modern networking projects. This section delves into the methodologies for enhancing cost models, aiming to improve accuracy, efficiency, and relevance in cost management, and to address user requirements for a suitable cost model that incorporates their imminent requirements.

The efficient management of resources is crucial in computer networking infrastructure to ensure optimal performance while minimizing costs (Dittakavi, 2021). Cost models play a decisive role in this regard, providing insights into the expenses associated with various networking components, technologies, and deployment strategies. This literature review explores existing research on cost models in computer networking infrastructure, highlighting their methodologies, applications, and contributions to network design and management.

Historically, within the intricate landscape of computer networking infrastructure, cost models have played a significant role in minimizing costs. The Total Cost of Ownership (TCO) model, for example, provides insights into both direct and indirect costs but falls short in delineating detailed labour cost differentiations, especially between skilled and unskilled workers (Brennan *et al.*, 2018). Similarly, the Capital Expenditure (CAPEX) Model, while valuable, tends to underemphasize ongoing labour costs, a fundamental component in networking projects (Simmons, Palmer and Truong, 2013). The Operational Expenditure (OPEX) Model addresses continuous costs but traditionally lacks in-depth exploration of labour cost nuances, especially concerning different skill levels (Seage and Turegun, 2020).

Traditional models exhibit foundational significance but often fail to fully align with the evolving dynamics of modern computer networking paradigms (Canagarajah, 2018). Their limitations become apparent in areas like insufficient differentiation between skilled and unskilled labour costs and a lack of focus on minimizing overall project duration, a critical element for enhancing project efficiency and ensuring cost-effectiveness (Agrawal, Gans and Goldfarb, 2018). Additionally, these models often lack the inclusion of penalty coefficients, thus failing to account for costs associated with project delays, which is not cost-effective. Furthermore, traditional models do not always consider complexity factors, leading to scenarios where unskilled labour is used where skilled labour would be more appropriate.

Building upon these identified shortcomings, there is a clear advocacy for adopting an evolved model that incorporates a more refined representation of costs (Ozcan and Karaoglan, 2018). This suggests a need to move beyond current limitations towards a more comprehensive understanding and management of costs within the model. A refined cost model should integrate crucial factors such as skilled and unskilled workforce allocation, wages for both categories of personnel, project execution times, and total project duration, along with penalties for delays. This holistic approach ensures that the model is optimised to provide precise and actionable insights, ultimately enhancing the cost-effectiveness of networking projects.

The integration of advanced optimisation techniques, such as genetic algorithms and swarm intelligence, into the cost model further enhances its performance. These bio-inspired methods introduce a unique approach to resource allocation and knowledge sharing, improving accuracy, adaptability, and efficiency in cost management (Munir *et al.*, 2024). For instance, genetic algorithms can dynamically adjust the allocation of resources based on evolving project conditions, while swarm intelligence can optimise task scheduling and labour deployment to minimize costs and maximize productivity.

In conclusion, optimising a cost model involves a thorough refinement process that integrates advanced methodologies and addresses the limitations of traditional models. By incorporating factors such as labour cost differentiation, project duration, and penalty coefficients, and leveraging bio-inspired optimisation techniques, the proposed model offers a comprehensive approach to cost management. This optimised model not only captures the multifaceted nature of networking projects but also ensures flexibility and responsiveness to technological advancements and changing project conditions, thereby empowering organizations to achieve greater efficiency and cost-effectiveness in their networking infrastructure projects.

2.6.1 Total Cost of Ownership (TCO) model

The Total Cost of Ownership (TCO) model, widely referenced in industry reports by Gartner (2020), serves as a comprehensive framework utilized to assess the total financial impact of owning and operating a computer network infrastructure over its entire lifecycle. It considers not only the initial acquisition costs but also ongoing expenses such as maintenance, support, training, and eventual disposal costs (Barker et al., 2019).

The TCO model finds broad application across various industries and sectors, as noted by Baltzan (2019). It is used by businesses, government agencies, educational institutions, and healthcare organizations to evaluate the financial feasibility of network projects and optimise resource allocation (Chen, Wang and Liu, 2018). Specifically, Ullah, Sepasgozar and Wang, (2018) demonstrate how the TCO model aids organizations in making informed procurement decisions and developing accurate budget projections. In the telecommunications sector, organizations leverage the TCO model to optimise network investments and manage costs effectively (Bista, 2023). In banking and manufacturing, the TCO model is used to assess the financial feasibility of network expansion and upgrades while ensuring alignment with strategic objectives (Ahmed, 2020).

The TCO model's advantages lie in its ability to offer a comprehensive view of network costs, allowing organizations to make informed decisions regarding resource allocation and investment prioritization (Sharma, Singh and Matai, 2019; Dubey, 2024). It facilitates better financial planning and risk management by considering both upfront and long-term expenses (Noorbakhsh *et al.*, 2020). Furthermore, Gartner (2020) highlights how the TCO model promotes accountability and transparency by providing stakeholders with a clear understanding of the cost drivers within their network infrastructure (Katekeetta, 2023).

However, the TCO model has certain limitations. Baltzan (2019) notes challenges in accurately estimating all cost components over the network's lifecycle and accounting for uncertainties in technology and market conditions (Roda, Macchi and Albanese, 2020). Moreover, Gaudenzi, Zsidisin and Pellegrino, (2021) emphasize the complexity of data collection and analysis required for indirect costs, such as productivity losses and potential downtime.

Based on this analysis, while the TCO model is useful for comprehensive cost assessment, its limitations make it less suitable for optimising computer networking costs. The difficulty in accurately estimating indirect costs and the model's inherent complexity can lead to incomplete or misleading financial assessments. Moreover, rapid technological advancements and fluctuating market conditions further complicate long-term cost predictions, making the TCO model less adaptable to the dynamic nature of computer networking projects.

Given these limitations, there is a clear need for a more nuanced and adaptable cost model for computer networking cost minimization. Such a model should incorporate advanced forecasting techniques, real-time data analysis, and flexibility to adjust to technological changes and market dynamics. This approach would provide more accurate cost estimations and better support strategic decision-making in the rapidly evolving field of computer networking. According to (Marcelo, Smith and Johnson, 2016), the Total Cost of Ownership (TCO) can be calculated using Equation 2.1.

Total Cost of Ownership (TCO):

The Total Cost of Ownership (TCO) model provides a comprehensive assessment of all costs associated with purchasing and operating a network over its lifecycle. The equation is

$$T_{co} = IC + \sum O_{costs} + \sum M_{costs} + \sum X_{costs}$$

Equation 2.1

Where:

T_{co} is the Total Cost of Ownership.

IC is the Initial Cost that includes the purchase price of hardware, software, and installation.

O_{costs} is the Operational Costs that covers energy consumption, staffing, and other ongoing expenses.

M_{costs} is the Maintenance Costs, which includes repairs, updates, and support.

X_{costs} is the End-of-Life Costs that involves disposal or recycling fees and decommissioning.

Transitioning to the Capital Expenditure (CAPEX) model, the study delves into another aspect of cost analysis in network infrastructure projects.

2.6.2 Capital Expenditure (CAPEX) model

The Capital Expenditure (CAPEX) model is a specialized framework within the domain of computer network cost models, focusing on the analysis and management of capital expenditures related to network infrastructure investments (Karakus and Durresi, 2019). This model specifically addresses costs associated with the acquisition, deployment, and initial setup of network assets, including hardware, software, and associated infrastructure. Primarily, the CAPEX model is used for financial planning and budgeting purposes, enabling organizations to assess the upfront costs associated with network infrastructure projects (Oughton *et al.*, 2019). It provides insights into the initial investment required to acquire and deploy network assets, helping decision-makers evaluate the feasibility of proposed projects and to allocate resources accordingly. By estimating the capital expenditures upfront, the CAPEX model facilitates better financial planning and risk management (Corcoran, 2022).

The CAPEX model has been widely used across industries and sectors where computer networks are integral to business operations (Yi *et al.*, 2018). For example, telecommunications companies and internet service providers use the CAPEX model to assess the financial feasibility of network expansion and upgrades. Enterprises and data centers leverage the model to plan for new technology implementations, ensuring that capital investments align with strategic objectives and deliver value to the organization. Cloud service providers also utilize the CAPEX model to estimate the costs associated with scaling their infrastructure to meet growing demand. These applications highlight the model's role in helping organizations manage significant upfront investments in network infrastructure.

The CAPEX model offers several advantages. It provides a clear and quantifiable estimate of the upfront costs associated with network infrastructure projects, which aids in making informed decisions regarding resource allocation and investment prioritization (Georgiadou, 2019). By focusing on capital expenditures, the model enables better financial planning by providing insights into the timing and magnitude of capital investments required for network projects (Srithongrung, Yusuf and Kriz, 2021). This helps organizations to prepare financially for large-scale investments and to manage the associated risks more effectively.

Despite its benefits, the CAPEX model has certain limitations. One significant challenge lies in accurately estimating and forecasting capital expenditures, especially in dynamic network environments with evolving technology and infrastructure requirements (Taufique *et al.*, 2017). The model also overlooks ongoing operational expenses and other lifecycle costs associated with network assets, potentially leading to incomplete cost assessments (Simmons, Palmer and Truong, 2013). This narrow focus on capital expenditures can result in underestimating the total cost of ownership and misinforming strategic decisions.

Given these limitations, the CAPEX model may not be fully suitable for optimising computer networking costs. Its focus on upfront capital expenditures neglects the long-term operational costs that are critical to a comprehensive financial assessment. This oversight can lead to suboptimal decision-making and resource allocation. Therefore, a better cost model for computer networking cost minimization should be explored. Such a model would integrate both capital and operational expenditures, providing a holistic view of the total costs involved in network infrastructure projects. This approach would enhance the accuracy of cost estimations and support more effective strategic planning and investment decisions.

Capital Expenditure (CAPEX):

CAPEX refers to the funds used by an organization to acquire or upgrade physical assets such as equipment, property, or industrial buildings, according to (Eastman, 2018a). It is captured in Equation ***2.2***

$$\boldsymbol{C_{apex}} = \sum \boldsymbol{FA_{cost}} + \sum \boldsymbol{U/I_{cost}} \qquad \textit{Equation 2.2}$$

Where:

C_{apex} refers to Capital Expenditure (CAPEX)

FA_{cost} translates to translates to Cost of Fixed Assets, which is the total cost of acquiring new hardware and software.

U/I_{cost} refers to the Cost of Upgrades/Improvements that includes expenses for enhancing existing infrastructure.

Shifting focus to the Operational Expenditure (OPEX) model, the study explores a different dimension of cost analysis in network infrastructure projects.

2.6.3 Operational Expenditure (OPEX) model

The Operational Expenditure (OPEX) model represents a crucial aspect within the realm of computer network cost models, focusing on the ongoing operational costs associated with managing and maintaining network infrastructure. Unlike the Capital Expenditure (CAPEX) model, which deals with upfront investment costs, the OPEX model primarily addresses recurring expenses incurred during the lifecycle of network assets (Seage and Turegun, 2020). The OPEX model is used for financial planning, budgeting, and decision-making related to the day-to-day operations of network infrastructure (Pageler and Palma, 2022). It provides insights into the ongoing expenses associated with network maintenance, monitoring, support, and administration, enabling organizations to allocate resources efficiently and ensure the smooth operation of their networks. By estimating operational expenditures over time, the OPEX model facilitates better financial planning and risk management (Pageler and Palma, 2022).

The OPEX model has been widely used across industries and sectors where computer networks are essential for business operations (Wang, Cheng and Deng, 2018). For instance, telecommunications companies and internet service providers use the OPEX model to manage the recurring costs of network operations, ensuring ongoing efficiency and service reliability. Enterprises and data centers leverage the OPEX model to optimise their operational efficiency by understanding the true costs of maintaining and managing their network assets. Cloud service providers and managed service providers use the model to identify cost-saving opportunities and optimise resource allocation, thus enhancing their service offerings and profitability (Wang, Cheng and Deng, 2018).

The OPEX model offers several advantages. It provides insights into the ongoing costs associated with network operations, enabling organizations to make informed decisions regarding resource allocation and investment prioritization (Kolasani, 2023). By focusing on operational expenditures, the model helps organizations understand the true cost of maintaining and managing network assets over time. Additionally, it facilitates better cost control and forecasting by providing insights into cost drivers and enabling proactive management of operational expenses (Dittakavi, 2021).

Despite its benefits, the OPEX model has certain limitations. One significant challenge lies in accurately estimating and forecasting operational expenditures, particularly in dynamic network environments with fluctuating usage patterns and evolving technology requirements. Additionally, the model may overlook upfront investment costs and other capital expenditures associated with deploying new network assets, potentially leading to incomplete cost assessments (Moradi, Ahmadi and Nikbazm, 2022).

Given these limitations, the OPEX model may not be fully suitable for optimising computer networking costs. Its focus on operational expenditures can neglect the comprehensive view of total costs, including significant upfront investments. This narrow scope can result in underestimating the total cost of ownership and misinforming strategic decisions. Therefore, a better cost model for computer networking cost minimization should be explored. Such a model would integrate both capital and operational expenditures, providing a holistic view of the total costs involved in network infrastructure projects. This approach would enhance the accuracy of cost estimations and support more effective strategic planning and investment decisions. Operational Expenditure (OPEX) can be calculated as the sum of all operational expenses (Eastman, 2018). Equation 2.3 sums up the total operational expenditure.

Operational Expenditure (OPEX):

OPEX encompasses the ongoing costs for running a product, business, or system.

$$\boldsymbol{O_{pex}} = \sum(\boldsymbol{S} + \boldsymbol{U} + \boldsymbol{R} + \boldsymbol{M} + \boldsymbol{C}) \qquad \textit{Equation 2.3}$$

Where:

O_{pex} represents Operational Expenditure (OPEX)

S $stands$ for Salaries that are the wages paid to employees.

U $represents$ Utilities, which include electricity, water, and other utility bills.

R $signifies$ Rent that is the cost of leasing office or data center space.

M indicates Maintenance for covering the cost of keeping equipment in working order.

C means Consumables that are materials used up in the course of operations.

Next, the study looks at another important component of cost analysis in network infrastructure projects: the Activity-Based Costing (ABC) model.

2.6.4 Activity-Based Costing (ABC) model

The Activity-Based Costing (ABC) model is a significant methodology within the realm of computer network cost models (Durana, 2019). Unlike traditional cost accounting methods that allocate overhead costs based on broad averages, the ABC model offers a more granular approach by attributing costs to specific activities or processes within the network infrastructure. By identifying and assigning costs directly to the activities that consume resources, the ABC model provides a more accurate representation of the true cost drivers within the network (Yin, Liu and Zheng, 2022).

The ABC model is primarily used for cost allocation and management purposes in installation of computer networking infrastructure projects (Goda *et al.*, 2023). It enables organizations to gain insights into the cost structure of their network operations by analysing the resources consumed by different activities, such as network installation, maintenance, troubleshooting, and user support. By identifying the costs associated with each activity, organizations can better understand where resources are being utilized most effectively and allocate budgets accordingly.

The ABC model has been utilized across various industries and sectors where computer networks play a critical role in supporting business operations. Telecommunications companies, internet service providers, large enterprises, data centers, and cloud service providers have all leveraged the ABC model. Additionally, sectors such as banking, healthcare, education, and government have employed the ABC model to optimise cost management strategies and enhance operational efficiency in their network infrastructure (Alsadie, 2021).

The advantages of the Activity-Based Costing (ABC) model include its ability to provide a more accurate and detailed understanding of cost drivers within the network infrastructure (Kocakulah *et al.*, 2017). By attributing costs to specific activities, the ABC model facilitates better decision-making regarding resource allocation, process improvement, and cost reduction initiatives. Furthermore, it enhances transparency and accountability by providing stakeholders with insights into the direct and indirect costs associated with different network activities (Adeusi, Jejeniwa and Jejeniwa, 2024).

However, the ABC model has certain limitations. One significant challenge lies in the complexity of data collection and analysis required to implement the model effectively (Ikotun *et al.*, 2023). Organizations may face difficulties in accurately measuring and assigning costs to individual activities, particularly in dynamic network environments with diverse technologies and infrastructure. Additionally, the ABC model requires significant time and resources to implement, which can limit its accessibility to smaller organizations.

Cost factors within the Activity-Based Costing (ABC) model encompass the resources consumed by various activities within the network infrastructure. Direct costs include labour, equipment, software licenses, and maintenance expenses associated with specific activities such as network installation, monitoring, troubleshooting, and user support (Cheng *et al.*, 2017). Indirect costs include overhead expenses such as administrative costs, facility costs, and shared resource allocations.

In summary, the Activity-Based Costing (ABC) model serves as a valuable tool for organizations seeking to gain insights into the cost structure of their computer network infrastructure. While it offers numerous advantages in terms of cost transparency and decision-making, it is essential to recognise its limitations and challenges in data collection, analysis, and implementation. Given these constraints, exploring a better cost model for computer networking cost minimization may be necessary. Kaplan and Anderson, (2007) say that the calculation for ABC is done using Equation 2.4

Activity-Based Costing (ABC) model:

The ABC model allocates costs to activities based on their use of resources.

$$T_{cost} = \sum (A_{CDR} \times A_V)$$ *Equation 2.4*

Where:

T_{cost} refers to the Total Cost using the ABC model

A_{CDR} refers to Activity Cost Driver Rate, which is the cost per unit of activity.

A_V means Activity Volume which replicates the number of units of the activity performed.

The study then examines another cost model, the Network Operation Cost model, which is a crucial element of cost analysis in network infrastructure projects.

2.6.5 Network Operation Cost model

The Network Operation Cost model is a structured methodology used in network management to comprehensively estimate and analyse the operational costs associated with maintaining network infrastructure (Yuan *et al.*, 2021). This model involves breaking down the various components and activities within network operations, assigning costs to each component, and subsequently aggregating these costs to derive a total operational expenditure figure. This approach provides network administrators and decision-makers with valuable insights into the cost drivers within their network environment, facilitating informed decisions regarding resource allocation, optimisation strategies, and budget planning.

This model has been widely applied across sectors where network infrastructure is critical (Knapp, 2024). Telecommunications companies use it to manage the costs of maintaining extensive network infrastructures. Internet service providers (ISPs), large enterprises with complex network architectures, data centers, and cloud service providers also utilize this model to ensure efficient cost management. Essentially, any organization heavily reliant on network connectivity and services can benefit from implementing this model to manage operational costs effectively.

The Network Operation Cost model offers several advantages. It enhances cost transparency by providing a clear breakdown of costs associated with different aspects of network operations, fostering accountability and informed decision-making (Cox *et al.*, 2017). It also facilitates budget planning by enabling organizations to understand the cost structure of network operations, thus allowing efficient resource allocation (Esmaeilian *et al.*, 2020). Additionally, the model supports optimisation efforts by pinpointing areas where cost-saving measures can be implemented without compromising network performance or reliability. It serves as a valuable decision support tool, empowering decision-makers to make informed choices regarding investments in network infrastructure, upgrades, outsourcing decisions, and technology adoption.

However, the Network Operation Cost model is not without its limitations (Mozaffari *et al.*, 2019). Implementing the model can be complex, particularly in large and heterogeneous network environments with diverse technologies and infrastructure. Accurately estimating costs may also be challenging due to data availability issues, as comprehensive data on various operational aspects may not always be readily accessible. Moreover, the dynamic nature of network environments, characterized by evolving technologies, traffic patterns, and user demands, poses challenges for static cost models to adapt effectively (Muhammad, 2022). Additionally, estimating costs for certain components, such as personnel or future upgrades, may involve uncertainties and assumptions, potentially leading to inaccuracies in cost projections.

The Network Operation Cost model does not adequately consider factors such as the skill level of the workforce, skill level wages, project duration, and penalty coefficients. These omissions limit its suitability for optimising computer networking costs. Given these limitations, a more comprehensive and adaptable approach, may be necessary for effective network cost optimisation. The Network Operation Cost model (NOC) can be expressed as the sum of the costs associated with network operations (Yuan, Smith and Chen, 2021), as captured by Equation 2.5.

Network Operation Cost model:

This model focuses on the ongoing costs of operating a network.

$$\boldsymbol{N_{OCM}} = \sum \boldsymbol{P_{Costs}} + \sum \boldsymbol{E_{Costs}} + \sum \boldsymbol{M_{Costs}} + \sum \boldsymbol{OP_{Costs}} \qquad \textit{Equation 2.5}$$

Where:

N_{OCM} is the Network Operation Cost

P_{Costs} is the Personnel Costs including wages for network administrators and support staff.

E_{Costs} indicates the Energy Costs that covers the power consumption of network devices.

M_{Costs} is the Maintenance Costs that involves regular upkeep and troubleshooting.

OP_{Costs} refers to Other Operational Costs that includes various overhead expenses.

Shifting from the Network Operation Cost model, the study now directs its focus toward exploring the broader perspective offered by Network Cost Model.

2.6.6 Network Cost model

The Network Cost model is a comprehensive framework designed to analyse and evaluate the costs associated with planning, deploying, operating, and maintaining computer networks (Asghar, Hu and Zeadally, 2019). Unlike specific cost models that focus on particular aspects of network costs, such as hardware or labour, the Network Cost model provides a holistic view of all cost components involved in network infrastructure management. This model encompasses all stages of the network lifecycle, allowing organizations to assess the total cost of the network infrastructure and optimise their resource allocation strategies accordingly.

The Network Cost model is primarily used for financial planning, budgeting, and decision-making related to network infrastructure investments (Marcelo *et al.*, 2016). By quantifying costs across different stages of the network lifecycle, organizations can understand the financial implications of their network investments and make informed decisions about resource allocation. For instance, it has been widely applied in telecommunications companies, internet service providers, enterprises, government agencies, educational institutions, and healthcare organizations (Boobalan *et al.*, 2022). These organizations leverage the model to evaluate the economic feasibility of network projects, assess cost-saving opportunities, and ensure cost-effective network operations (Kokkinis *et al.*, 2023).

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The Network Cost model includes a wide range of cost factors associated with network infrastructure management (Kulkarni and Farnham, 2016). These may include hardware and software costs, labour expenses, maintenance contracts, energy consumption, bandwidth usage fees, licensing fees, training costs, and potential costs related to security breaches or service disruptions. Indirect costs, such as productivity losses, regulatory compliance costs, and reputational risks, are also considered within the model (Njoroge, 2018).

The Network Cost model offers several advantages. It provides a comprehensive and integrated view of network costs, enabling organizations to make informed decisions regarding resource allocation and investment prioritization (Shahid, Rappon and Berta, 2019). By considering all cost components, including hardware, software, labour, maintenance, and operational expenses, the model facilitates better financial planning and risk management. This holistic approach helps organizations to understand the total cost of ownership and optimise their budgets more effectively.

However, the Network Cost model also has its limitations. Accurately estimating and quantifying all cost components, particularly indirect costs such as productivity losses or potential downtime, can be challenging (Mechler, 2016). Additionally, the model requires substantial data collection and analysis efforts, as well as expertise in financial modeling and network management. These requirements can be resource-intensive and may limit the model's accessibility for some organizations.

Another limitation is the model's insufficient consideration of project duration. Network projects can vary significantly in length, and the costs associated with long-term projects versus short-term ones can differ substantially. Without accounting for project duration, the cost model may not provide a realistic view of total expenses (Njoroge, 2018).

A further limitation is the omission of penalty coefficients, which are important for evaluating the financial impact of potential delays or failures in network projects. Ignoring these penalties can result in an incomplete cost analysis and potentially underestimate the true cost of network operations (Kulkarni and Farnham, 2016).

One major drawback is its potential inadequacy in addressing the skill level of the workforce and corresponding wages. These elements are crucial for accurately assessing labour costs, and their absence can lead to misleading cost analyses (Mechler, 2016).

In conclusion, while the Network Cost model serves as a valuable tool for analysing network costs, these limitations highlight the need for a more comprehensive approach that incorporates critical factors such as workforce skills, project duration, and penalty coefficients to ensure accurate and effective cost management. The Network Cost model (NCM) can be represented by the equation: NCM = Σ (All Costs Related to Network Infrastructure), says Asghar, M. Z., Hu, X. and Zeadally, (2019). The overall Network Cost, a combination of CAPEX and OPEX, is calculated using Equation 2.6.

Network Cost model:

2.6.7 Cost Allocation model

Cost Allocation models represent a specialized approach within the realm of computer network cost management, focusing on the equitable distribution of costs among different users, departments, or projects within an organization (Eastman, 2018). These models are designed to allocate the costs associated with network infrastructure fairly and transparently, ensuring that each entity bears its appropriate share of the overall expenses. Primarily used for internal accounting and financial management, Cost Allocation models enable organizations to allocate network costs accurately and fairly across various cost centers or stakeholders (Barr and McClellan, 2018). They provide a systematic framework for attributing costs to specific users, departments, or projects based on usage, resource consumption, or other relevant metrics. This approach facilitates cost transparency and accountability, aiding organizations in making informed decisions regarding resource allocation, budgeting, and investment prioritization.

Cost Allocation models have been widely employed across industries and sectors where computer networks are shared among multiple users or departments. For instance, large enterprises use these models to allocate costs among different business units based on their respective network usage, ensuring that each unit is charged according to its consumption (Cleverley, Cleverley, and Parks, 2023). In government agencies, these models help distribute costs among various departments, promoting transparency and accountability in public spending. Educational institutions leverage Cost Allocation models to allocate network costs among different faculties and departments, aligning expenses with actual usage and facilitating better budgeting and resource management (Lepri et al., 2018). Healthcare organizations and service providers also use these models to ensure that network costs reflect the benefits derived by each department, enhancing cost control and operational efficiency (Singhal, 2023).

The primary advantage of Cost Allocation models is their ability to promote fairness, transparency, and accountability in the distribution of network costs. By attributing costs based on usage or other relevant metrics, these models enable organizations to align costs with value creation and ensure that resources are allocated efficiently (Lepri et al., 2018). Additionally, Cost Allocation models facilitate better cost control and decision-making by providing insights into the cost drivers and enabling organizations to identify opportunities for cost optimisation (Singhal, 2023).

However, Cost Allocation models are not without limitations. One significant challenge is accurately measuring and attributing costs to specific users or departments, particularly in complex network environments with shared resources and overlapping usage patterns (Dehnokhalaji, Ghiyasi, and Korhonen, 2017). This can lead to inaccuracies in cost distribution, undermining the model's effectiveness. Furthermore, implementing these models can require substantial administrative overhead and data collection efforts, particularly in organizations with decentralized or heterogeneous network infrastructures (Gill et al., 2022). The need for detailed usage data and sophisticated tracking mechanisms can also add to the complexity and cost of implementation.

Based on the analysis, Cost Allocation models have both strengths and weaknesses when applied to computer networking cost optimisation. They are suitable for organizations that require transparent and equitable cost distribution and have the necessary infrastructure to accurately track and attribute costs. However, in environments where accurate cost measurement is challenging or administrative overhead is prohibitive, these models may fall short. The complexity and potential inaccuracies in cost attribution can limit their effectiveness, suggesting that alternative models might be more suitable for comprehensive network cost minimization. According to Dehnokhalaji, A., Ghiyasi, M. and Korhonen, (2017), the Cost Allocation model is calculated using Equation ***2.7***.

Cost allocation model:

This model distributes costs among various departments or projects.

$$A_{Cost} = \frac{T_{Cost} \times U}{T_{Usage}} \qquad \textit{Equation 2.6}$$

Where:

A_{Cost} is the Allocated Cost

T_{Cost} indicates the Total Cost, which is the sum of all expenses to be allocated.

U refers to Usage that is the specific usage by a department or project.

T_{Usage} signifies the Total Usage , which is the sum of all usage by all departments or projects

Selection and summary of costs models

Among many, the selected cost models—Total Cost of Ownership (TCO), Capital Expenditure (CAPEX), Operational Expenditure (OPEX), Activity-Based Costing (ABC), Network Operation Cost model, Network Cost model, and Cost Allocation models—are considered because they each represent fundamental approaches to understanding and managing different aspects of network costs. These models are widely recognised and applied across various industries, providing a comprehensive framework that addresses direct and indirect costs, investment and operational expenses, activity-based insights, and equitable cost distribution. Their collective examination highlights both their individual strengths and the gaps that necessitate the development of a more integrated and nuanced cost model for optimal network cost management.

Each of the seven aforementioned cost models addresses specific aspects of network costs but often falls short of comprehensively considering all critical factors essential for optimal cost management.

TCO provides a broad view of all direct and indirect costs associated with network investments, aiding in long-term financial planning (Marcelo *et al.*, 2016). However, it often lacks detailed focus on labour cost dynamics and project-specific considerations. CAPEX and OPEX models focus on initial and ongoing costs, respectively, but do not integrate these with labour costs and project timelines cohesively (Eastman, 2018). ABC offers detailed insights by allocating costs based on activities but can be complex to implement and does not inherently consider the variability in workforce skills and wages (Kaplan and Anderson, 2007).

The Network Operation Cost model breaks down operational expenses, providing a granular view of ongoing costs (Yuan et al., 2021). However, it often overlooks the distinction between skilled and unskilled labour costs and their impact on project execution times. The Network Cost model offers a comprehensive framework for evaluating all costs associated with network infrastructure but may still miss critical elements like project duration and penalty coefficients tied to delays (Asghar, Hu and Zeadally, 2019). Cost Allocation models focus on distributing costs among different users or departments, promoting fairness and transparency but can be administratively burdensome and challenging to implement accurately in complex environments (Dehnokhalaji, Ghiyasi, and Korhonen, 2017).

Below is Table 2.1, which summarizes the selected cost models used to evaluate network expenditures in this thesis. It outlines the key aspects of each model, including their definitions, components, and focus areas. This comparison aims to provide a clear understanding of how each model addresses the financial management of network resources.

Table 2.1: Summarised Comparative Table of Cost Models

Model	Definition	Components	Focus	Citation
TCO Model	Comprehensive assessment of all costs over the lifecycle of the network.	CAPEX, OPEX, Depreciation, Disposal, Indirect Costs	Total Lifecycle Cost	(Bista, 2023), (Barker et al., 2019)
CAPEX Model	Initial capital expenditures for acquiring and setting up network infrastructure.	Hardware, Initial Software, Installation and Setup	Initial Costs	(Corcoran, 2022), (Karakus and Durresi, 2019)
OPEX Model	Ongoing operational costs for running and maintaining the network.	Labor, Maintenance, Operational Costs, Ongoing Software Licensing	Ongoing Costs	(Seage and Turegun, 2020), (Pageler and Palma, 2022)
ABC (Activity-Based Costing) Model	Allocation of costs based on network activities and usage.	Activity Costs, Resource Drivers, Cost Objects	Activity-Based Cost Allocation	(Durana, 2019), (Yin, Liu and Zheng, 2022).
Network Operation Cost Model	Costs specifically associated with the daily operation of the network.	Labor, Maintenance, Operational Costs	Daily Operational Costs	(Yuan *et al.*, 2021), (Knapp, 2024)
Network Cost Model	All direct costs associated with operating and maintaining the network.	Hardware, Software, Labor, Maintenance, Operational Costs	Direct Costs	(Marcelo *et al.*, 2016), (Asghar, Hu and Zeadally, 2019)
Cost Allocation Model	Distribution of network costs to various departments or services based on usage.	Allocated Costs, Usage Metrics, Departmental Budgets	Cost Distribution	(Eastman, 2018), (Barr and McClellan, 2018)

Given the limitations of these models, there is a clear need for a new cost model that addresses the comprehensive and dynamic nature of network cost management. This new model should integrate crucial factors such as skilled workforce allocation, unskilled workforce allocation, wages for skilled and unskilled personnel, project execution time for both workforce categories, and the total minimized project duration tied to penalty coefficients.

Therefore, the study proposes a new model named the Integrated Network Cost Optimisation model (INCOM). This model aims to holistically manage and minimize network costs by incorporating all critical factors, providing a more accurate and efficient approach to network cost management. INCOM will use optimisation techniques to ensure cost-effective allocation of resources and timely project execution, addressing the shortcomings of existing models.

In conclusion, while existing cost models offer valuable insights into specific aspects of network cost management, they do not comprehensively address all essential factors. The Integrated Network Cost Optimisation model (INCOM) seeks to fill this gap by providing a more nuanced and comprehensive approach to managing and minimizing network costs, particularly focusing on labour dynamics and project execution efficiency. This model aims to support better decision-making and resource allocation in the rapidly evolving field of computer networking.

2.7 Model to accommodate new factors:

To further strengthen this model, its scope is extended to address the multifaceted variables introduced by modern computer networking projects. The intricate interplay between the dynamism of contemporary projects and the layered complexities of the networking realm necessitates a model that epitomizes agility and thoroughness. This ensures that projects are executed not only with fiscal prudence but also with a keen understanding of the specific nuances of labour costs within the computer networking infrastructure (Eghbali *et al.*, 2022; Stallings, 2018).

Given user requirements, existing models cannot accommodate their wants, such as cost factors to be considered; hence a new model is needed.

This conceptual model goes beyond conventional cost considerations, navigating the challenges posed by skilled and unskilled labour costs with a particular focus on overtime implications. It delves into the intricacies of equipment requirements and operational timelines, addressing daily workforce metrics, scrutinizing equipment leasing intricacies, considering steadfast fixed costs, and introducing nuanced penalty coefficients. Moreover, the model adopts a pragmatic approach to project durations, ensuring temporal aspects align with quality and budgetary integrity (Ozcan and Karaoglan, 2018).

As organisations grapple with the intricacies of contemporary networking projects, the envisioned model provides a strategic advantage (Muhammad, 2019). It empowers decision-makers with a holistic framework, enabling them to navigate the specific challenges of minimising labour costs within computer networking infrastructure adeptly (Wedha and Hindarto, 2023). In this dynamic landscape of technology and networking, marked by the necessity of adaptability, this model assures that organisations are not solely focused on advancing in the pursuit of cost-effectiveness (Akindote *et al.*, 2024). Rather, it emphasizes their vital role in shaping project outcomes within the domain of minimising labour costs in computer networking infrastructure.

2.8 Optimisation in Computer Networking Infrastructure

Why Optimisation Is Needed

In the dynamic landscape of installation of computer networking infrastructure projects, the quest for cost efficiency and resource optimisation is a paramount concern for organisations aiming to maximize their operational effectiveness (Sapkal, Heisnam and Kusi, 2024). Optimisation plays a pivotal role in this pursuit by enabling organisations to identify and eliminate inefficiencies in labour utilisation, ensuring that resources are judiciously allocated to minimise overall labour costs (Porath, 2023). This optimisation is needed by the motivating client in order to find the best costs for the project, as per the given requirements.

Effective optimisation facilitates strategic resource allocation based on project requirements and priorities, maximizing productivity while minimising unnecessary expenses associated with resource overallocation or underutilisation (Ercan and Alkan, 2023). This is crucial for budget adherence, allowing organisations to operate within tight financial constraints while still delivering on project objectives within set timelines (Barr and McClellan, 2018).

Furthermore, optimisation enhances efficiency and productivity by eliminating wasteful practices and optimising workflows. This enables organisations to achieve more with fewer resources, enhancing project outcomes and promoting long-term sustainability by reducing waste and minimising environmental impact (El Khatib *et al.*, 2020). In essence, optimisation for minimising labour costs in installation of computer networking infrastructure projects is not just about cost savings; it is about enhancing operational effectiveness, ensuring timely project completion, and fostering a culture of efficiency and sustainability (Sallam, Mohamed and Mohamed, 2023). By prioritising optimisation efforts, organisations can navigate the complexities of networking infrastructure projects with greater agility, resilience, and success (Hoff *et al.*, 2023).

Optimising total labour costs for networking infrastructure projects significantly affects hardware and software resources. Proper setup and installation by skilled personnel can reduce future maintenance costs, prolonging the life of hardware and ensuring that software runs smoothly (Sapkal, Heisnam and Kusi, 2024). Efficient project execution helps avoid penalties associated with delays, which can indirectly affect costs related to hardware leasing and software licensing (Porath, 2023). Furthermore, efficient labour use often leads to better planning and utilisation of hardware. For instance, an optimally allocated skilled workforce can set up and configure hardware more efficiently, reducing the time hardware remains underutilised (Ramachandran, 2023).

Optimal labour management also ensures that software is installed and configured correctly the first time, minimizing downtime and the need for rework, thus enhancing the immediate functionality of the network and reducing long-term operational disruptions (Ercan and Alkan, 2023). Additionally, savings from optimised labour costs can be redirected towards investing in better, more efficient hardware and software. This reinvestment can further enhance project outcomes and reduce long-term costs, creating a virtuous cycle of improved efficiency and resource utilisation (Sallam, Mohamed and Mohamed, 2023).

In conclusion, optimising labour costs does not merely entail reducing expenses but involves a strategic allocation of resources to enhance overall project efficiency. By ensuring that hardware and software resources are utilised effectively, organisations can achieve significant cost savings and improved project performance. The impact of optimising labour costs extends beyond immediate financial benefits, fostering long-term sustainability and operational success (El Khatib *et al.*, 2020).

Traditional Optimisation Approaches

Traditional optimisation approaches have long served as fundamental pillars in addressing complex problems across various domains (Oztemel and Gursev, 2020). However, in the context of modern systems and environments, particularly within the realm of computer networking infrastructure, these conventional methodologies, notably deterministic models, and linear programming, are increasingly facing scrutiny for their inadequacies (Bakker, Dunke and Nickel, 2020). This critique prompts a comprehensive exploration into the limitations of these traditional approaches, shedding light on why they may fall short in meeting the demands of contemporary networking landscapes.

Deterministic models, heralded for their predictable frameworks based on fixed input-output relationships (Pathak, Gandhi and Gupta, 2019), have historically provided robust solutions in well-defined systems characterized by minimal variability. However, their efficacy wanes in the face of the dynamic and uncertain nature of modern networking challenges. The rigidity inherent in deterministic models, while offering predictability in stable environments, becomes a hindrance when confronted with the evolving complexities of today's networking milieu (Valeri, 2021). Moreover, as networking scenarios grow increasingly intricate, deterministic models struggle to accommodate uncertainties and adapt to the fluid nature of contemporary challenges (Lan and Shin, 2023).

Linear Programming (LP), another stalwart in traditional optimisation, has demonstrated effectiveness in solving problems with linear relationships between variables (Achterberg and Wunderling, 2013; Frank, Steponavice and Rebennack, 2012). However, its suitability diminishes when faced with the nonlinearities and interdependencies prevalent in many real-world optimisation problems, such as those encountered in computer networking infrastructure. The oversimplified nature of linear programming fails to capture the complexities inherent in modern networking systems, often leading to suboptimal resource allocation and performance optimisation (Fieguth, 2021; Landers *et al.*, 2020).

Both deterministic models and linear programming suffer from inherent limitations that impede their efficacy in addressing the multifaceted challenges of modern systems (Carrilho, Oliveira and Hamacher, 2024). Deterministic models oversimplify real-world scenarios, assuming certainty and constancy in parameters and inputs, thereby leading to inaccuracies and suboptimal solutions in dynamic environments (Zelinka, 2019). Similarly, linear programming's reliance on linear relationships between variables fails to adequately capture the nonlinear dynamics and interdependencies present in many real-world optimisation problems (Karaca, 2022). The deterministic nature of LP, while providing clarity and structure, becomes restrictive in the multifactorial realm of networking, emphasizing the need for optimisation techniques capable of concurrently handling complexity and multiple factors (Heße, Comunian and Attinger, 2019). As the field progresses, the demand for approaches that transcend the constraints of traditional methods becomes more pronounced. These static optimisation criteria are ill-suited to address the evolving needs and objectives of modern organisations operating in dynamic and rapidly changing environments like computer networking infrastructure.

In conclusion, the inadequacies of deterministic models and linear programming underscore the pressing need for more sophisticated optimisation approaches capable of accommodating uncertainty, nonlinearities, and dynamic system behaviour (Yao *et al.*, 2024). As the complexity of modern systems continues to evolve, traditional approaches must give way to more flexible and adaptive methodologies to achieve truly optimal solutions.

2.9 *Exploring Bio-inspired search methods for Optimal Solutions*

Bio-inspired algorithms have emerged as powerful optimisation tools, drawing inspiration from natural phenomena to solve complex problems in various domains (Kumar, Nadeem and Banka, 2023). Among these algorithms are evolutionary, genetic, and swarm-based approaches, each offering unique strategies for tackling optimisation challenges. This discussion review explores the types, applications, advantages, disadvantages, and limitations of these bio-inspired algorithms, with a focus on arguing their inadequacies despite their promise.

Types of Bio-Inspired Algorithms:

There are various types of Bio-inspired algorithms including Evolutionary Algorithms (EAs), Genetic Algorithms (GAs), and Swarm Intelligence Algorithms (SIAs) (Yang, Jin and Hao, 2018). While EAs mimic the process of natural selection to iteratively improve solutions over successive generations, GAs, a subset of EAs, emulate the principles of genetics and natural selection to evolve optimal solutions (Ahvanooey *et al.*, 2019). SIAs, on the other hand, simulate collective behaviours observed in swarms of social organisms to solve optimisation problems through decentralized cooperation.

Bio-inspired algorithms, according to Blum, (2005), which was re-emphasized by Kouvelis and Yu, (2013), find applications in diverse fields, including optimisation, machine learning, robotics, finance, and engineering. They are utilised in solving complex optimisation problems in various domains such as network routing, computer networking congestion, scheduling, image processing, data clustering, and function optimisation (Masdari *et al.*, 2020). These algorithms excel in scenarios where traditional optimisation methods struggle, offering robust and adaptive solutions in dynamic and uncertain environments (Tiwari and Singh, 2024).

Given their diverse applications and effectiveness in resolving composite optimisation issues, it is pertinent to delve into each type of bio-inspired algorithm in detail, beginning the exploration with evolutionary algorithms.

Evolutionary Algorithms (EAs) belong to a class of optimisation techniques inspired by the principles of natural selection and evolution (Albadr *et al.*, 2020). They iteratively refine solutions across successive generations, emulating natural processes like reproduction, mutation, and survival of the fittest. By maintaining a population of candidate solutions and employing selection mechanisms favouring individuals with higher fitness values, EAs facilitate the evolution of increasingly superior solutions (Ming *et al.*, 2021).

In the area of computer networking, Evolutionary Algorithms have found versatile applications spanning network optimisation, routing strategies, Quality of Service (QoS) management, and resource allocation (Mostafavi, Hakami and Sanaei, 2021). These algorithms excel in tasks such as optimising network installations, determining efficient routing paths, and allocating resources to optimise performance while minimizing costs.

Beyond computer networking, Evolutionary Algorithms find utility across diverse fields including engineering design, financial modelling, data analytics, and artificial intelligence (Al-Sahaf *et al.*, 2019). Their strength lies in tackling problems characterized by complex, nonlinear relationships, and vast search spaces, where traditional optimisation approaches may fall short.

Despite their versatility, Evolutionary Algorithms are not without their limitations. EAs face challenges in network optimisation due to slow convergence rates, premature convergence to suboptimal solutions, and it struggles to handle constraints effectively, especially in optimisation problems with complex constraints or constraints that change dynamically (Mirjalili, 2019). These limitations are particularly problematic in networking contexts where timely decision-making and responsiveness are crucial. Additionally, the extensive parameter tuning and substantial computational resources required by EAs can make them less practical for computer network optimisation tasks with stringent time or resource constraints (Bali *et al.*, 2019). Consequently, the exploration of alternative optimisation methods may be more suitable for computer networking environments. Moving from the exploration of Evolutionary Algorithms, the focus shifts to the examination of Genetic Algorithms.

Genetic Algorithms (GAs) are a subset of evolutionary algorithms, drawing inspiration from genetics and natural selection. They operate by iteratively evolving potential solutions to optimisation problems through mechanisms such as selection, crossover, and mutation. In essence, GAs treats potential solutions as chromosomes, typically encoded as binary strings, and undergo genetic operations to produce offspring with improved characteristics (Mehboob *et al.*, 2016). In the realm of computer networking, GAs have found diverse applications, including network design, routing optimisation, traffic management, and resource allocation. For instance, they can optimise network topologies, determine optimal routing paths, or allocate resources efficiently to meet performance objectives while minimizing costs or congestion (Ibrahim *et al.*, 2022). Beyond computer networking, GAs are widely used across various fields, such as engineering, bioinformatics, and finance (Alam *et al.*, 2020). They excel in tackling optimisation problems with complex, nonlinear relationships and large search spaces, where traditional methods may struggle. Thus, GAs remain valuable tools for optimisation, particularly in scenarios where their strengths align with the problem at hand. Nonetheless, GAs, like other EAs, also present challenges. They are prone to premature convergence, which can lead to suboptimal solutions (D’Angelo and Palmieri, 2021). Again, they have the challenge of effectively handling constraints, particularly in complex optimisation problems. Moreover, they require careful parameter tuning to balance exploration and exploitation, which can be challenging and time-consuming. Lastly, they may not be well-suited for real-time optimisation tasks, according to D’Angelo and Palmieri, (2021), due to their computational overhead and slower convergence rates. Correspondingly, these limitations raise significant concerns within real-time computer networking environments, where achieving near-optimal results hinges on swift and dynamic optimisation (El Romeh and Mirjalili, 2023). The potential hindrance they pose to the effectiveness of genetic algorithms in such computer networking domains underscore the necessity to explore alternative optimisation methods better tailored to these networking environments. Concluding the discussion on Genetic Algorithms, the exploration now transitions to Swarm Intelligence Algorithms.

Swarm Intelligence Algorithms, (SIA), encompass a diverse range of methods inspired by natural phenomena and collective behaviours observed in social organisms. Notable examples include Ant Colony Optimisation (ACO), Particle Swarm Optimisation (PSO), Bat Algorithm (BA), Firefly Algorithm (FA), Cuckoo Search Algorithm (CS), Whale Optimisation Algorithm (WOA), Grasshopper Optimisation Algorithm (GOA), Moth Flame Optimisation Algorithm (MFO), Spiral Optimisation Algorithm (SOA) and many more. These algorithms leverage decentralized cooperation to address optimisation problems, simulating the emergent intelligence seen in swarms of social organisms.

While Swarm Intelligence Algorithms offer powerful optimisation capabilities, according to Xue and Shen, (2020) they also present certain limitations and challenges. One significant challenge, particularly with those based on population-based approaches such as Particle Swarm Optimisation (PSO), is the risk of premature convergence. This limits their ability to thoroughly explore the search space, resulting in the algorithm settling on suboptimal solutions (Braik *et al.*, 2023). Also, SIA algorithms often require extensive parameter tuning, and finding the right parameter settings for optimal performance can be challenging and time consuming (Xue and Shen, 2020). Furthermore, it may encounter scalability issues when applied to large-scale optimisation problems, leading to performance degradation or increased computational overhead. Lastly, SIAs rely on emergent behaviour, which can be difficult to understand and predict, making it challenging to interpret and analyse algorithmic outcomes (Wang, Wang and Sun, 2022; Xue and Shen, 2020).

Despite these challenges, Swarm Intelligence Algorithms remain valuable tools for optimisation across various domains (Gad, 2022). Their ability to mimic natural processes and harness collective intelligence makes them well-suited for tackling complex optimisation problems where traditional methods may fall short (Badini, Regondi and Pugliese, 2023).

Furthermore, SIA offers numerous advantages for network optimisation. Firstly, they excel in solving complex, nonlinear optimisation problems with large search spaces, thus effectively tackling the intricate challenges of network optimisation (Prity, Uddin and Nath, 2023) Additionally, SIA demonstrates adaptability to dynamic environments and uncertain conditions, a critical feature for network optimisation tasks in rapidly changing scenarios. (Xue and Shen, 2020). Ongoing research and development endeavours aim to overcome the limitations of Swarm Intelligence Algorithms, thereby unlocking their full potential in addressing real-world optimisation challenges. With this laid backdrop, the study begins by focusing on Ant Colony Optimisation (ACO).

The Ant Colony Optimisation (ACO) algorithm is highly regarded for its suitability in computer networking projects due to several key factors. ACO algorithms leverage the foraging behaviour of ants, specifically simulating the pheromone-based communication observed among ants to find optimal or near-optimal paths in complex network topologies (Bhavya and Elango, 2023; Singh *et al.*, 2020). This innate ability to emulate natural processes enables ACO to effectively optimise routing paths within communication networks, contributing to enhanced network efficiency, minimized packet delay, and improved overall network performance (Umoga *et al.*, 2024). Moreover, the adaptability of ACO algorithms allows network administrators to dynamically adjust routing decisions in response to evolving networking conditions, thereby fostering the development of more resilient and adaptive networking infrastructures. In contrast to algorithms facing challenges such as high computational complexity, ACO algorithms offer a robust and efficient solution tailored to the demands of computer networking projects, making them a preferred choice for optimising various aspects of network routing and resource allocation. With ACO analysed, attention now turns to Particle Swarm Optimisation (PSO).

The Particle Swarm Optimisation (PSO) algorithm, inspired by the social behaviour of bird flocks or fish schools, orchestrates a population of particles through the search space to discover optimal solutions (Michaloglou, 2024). Applied extensively in network optimisation tasks such as traffic engineering, network design, and resource allocation (Shaikh *et al.*, 2020), PSO algorithms optimise network parameters like routing installations, bandwidth allocation, and Quality of Service (QoS) provisioning (Gong, 2022). However, despite its widespread use in computer networking, PSO faces several limitations that render it unsuitable for certain networking projects. Firstly, PSO's rapid convergence to near-optimal solutions may lead to premature convergence, where the algorithm settles on suboptimal solutions before fully exploring the search space, particularly in complex network environments with dynamic conditions (Freitas, Lopes and Morgado-Dias, 2020). Secondly, PSO algorithms may struggle to adapt effectively to changing network dynamics, hindering their ability to make real-time adjustments in response to fluctuating network conditions (Shaikh *et al.*, 2020). Lastly, while PSO offers simplicity and straightforward implementation, its reliance on population-based optimisation techniques can result in limited scalability and increased computational overhead, especially in large-scale network environments (Gong, 2022). Therefore, considering these limitations, it is crucial to carefully evaluate the suitability of PSO algorithms for specific networking projects and explore alternative optimisation approaches where necessary. Transitioning from Particle Swarm Optimisation (PSO), the study now focuses on Bat Algorithm (BAT).

The Bat Optimisation Algorithm (BAT) draws inspiration from the echolocation behaviour of bats, utilizing frequency-modulated echolocation pulses to search for prey and navigate in the environment (Diebold, Salles and Moss, 2020). Firstly, applied in computer networking, BAT algorithms contribute to tasks such as network routing, resource allocation, and Quality of Service (QoS) provisioning (Dai *et al.*, 2021). Secondly, within networking, BAT algorithms optimise routing paths, minimize network congestion, and enhance overall communication network efficiency (Priyadarshi, Kumar and Ying, 2024). Furthermore, BAT's efficient exploration of the search space and adaptive adjustment to environmental changes position it as a suitable solution for addressing dynamic networking challenges (Bian and Priyadarshi, 2024). Additionally, BAT's simplicity and scalability make it a valuable tool for optimising various aspects of computer networks, offering robust performance in diverse networking environments. Lastly, BAT's ability to dynamically adjust routing decisions and resource allocations in response to changing network dynamics further enhances its suitability for computer networking projects Moving on from the exploration of the Bat Algorithm (BAT), the study now focuses onto the Cuckoo Search, Optimisation Algorithm (CS).

The Cuckoo Search (CS) algorithm, inspired by the brood parasitism strategy observed in cuckoo birds (Sharma *et al.*, 2021), emerges as a pertinent solution for optimising various facets of computer networking. Grounded in the natural behaviours of cuckoo birds, CS algorithms offer an effective approach to network optimisation. By mimicking the reproductive strategies of cuckoos, CS demonstrates efficacy in tasks such as optimising routing paths, clustering, and optimisation of network parameters (Wohwe Sambo *et al.*, 2019; Sharma *et al.*, 2021). Notably, CS algorithms excel in optimising routing paths, allocating network resources, and improving overall communication network performance (Mammeri, 2019). This inherent adaptability and efficiency make CS well-suited for addressing the intricate challenges encountered in modern networking environments. Furthermore, the effective balance between exploration and exploitation in CS's search process, as highlighted by Konjaang and Xu, (2021), allows for efficient discovery of optimal solution networks. Moreover, the utilization of CS in computer networking projects provides a robust framework for dynamically adapting to changing network dynamics and optimising network performance across diverse scenarios (Zavieh *et al.*, 2023). Thus, CS stands as a promising algorithmic tool for optimising and enhancing the functionality of computer networks. Exploring further into the realm of optimisation algorithms, the study delves into the intricacies of the Whale Optimisation Algorithm (WOA).

The Whale Optimisation Algorithm (WOA) draws inspiration from the social behaviour and hunting strategies of humpback whales (Gharehchopogh and Gholizadeh, 2019). Applied in computer networking, WOA algorithms contribute to tasks such as network routing, resource allocation, and Quality of Service (QoS) provisioning (Sing *et al.*, 2022). Within networking, WOA algorithms optimise routing paths, minimize network congestion, and enhance overall communication network efficiency (Darade and Akkalakshmi, 2021). WOA's efficient exploration of the search space and exploitation of promising solutions, combined with its simplicity and versatility, make it a valuable tool for optimising various aspects of computer networks (Mukhlif *et al.*, 2024). However, WOA algorithms can present challenges due to their high computational complexity, leading to increased computational overhead and longer convergence times, particularly in large-scale network environments. Additionally, these algorithms may struggle to adapt effectively to dynamic network conditions, hindering their ability to make real-time adjustments in response to changing network dynamics. Furthermore, the reliance on population-based optimisation techniques in WOA algorithms can lead to premature convergence, where the algorithm settles on suboptimal solutions before thoroughly exploring the search space. Given these limitations, it is crucial to explore alternative optimisation approaches in networking contexts where WOA algorithms may not be the most suitable choice. While WOA offers valuable capabilities for network optimisation, its limitations must be carefully considered against the specific requirements of the networking task at hand. Alternative algorithms may provide better performance or more robust adaptability to dynamic network conditions, ensuring optimal network performance across diverse networking environments. Emerging from analysing the Whale Optimisation Algorithm (WOA), the exploration now ventures towards the Grasshopper Optimisation Algorithm (GOA).

The Grasshopper Optimisation Algorithm (GOA) takes inspiration from the swarming behaviour of grasshoppers, particularly their food foraging strategies (Meraihi *et al.*, 2021). Applied in computer networking, GOA algorithms contribute to tasks such as network routing, resource allocation, and optimisation of network parameters (Amutha, Sharma and Sharma, 2021). Within networking, GOA algorithms optimise routing paths, allocate network resources efficiently, and improve overall communication network performance (Rami Reddy *et al.*, 2023). GOA's effective balance between exploration and exploitation, alongside its simplicity and scalability, makes it well-suited for addressing optimisation challenges in computer networks (Priyadarshini, 2024). These algorithms offer diverse approaches to optimisation and have been successfully applied in various domains, including computer networking, where their adaptability in searching for optimal solutions proves invaluable in addressing complex optimisation problems. GOA algorithms, while exhibiting strengths in optimisation tasks, face certain limitations that may hinder their suitability for certain applications. One notable drawback is their susceptibility to premature convergence, where the algorithm may settle on suboptimal solutions before fully exploring the search space. This can lead to less-than-optimal outcomes, particularly in scenarios where thorough exploration of the solution space is crucial. Additionally, GOA algorithms may struggle to effectively adapt to dynamic network conditions and make real-time adjustments, limiting their applicability in environments requiring rapid responses to changing network dynamics. Furthermore, the computational complexity of GOA algorithms can pose challenges, resulting in increased computational overhead and longer convergence times, particularly in large-scale network environments. These limitations underscore the importance of considering alternative optimisation approaches in networking contexts where GOA algorithms may not be the most suitable choice. Progressively, the study now shifts attention to the Firefly Algorithm (FA), after exploring the Grasshopper Optimisation Algorithm (GOA).

The Firefly Algorithm (FA) draws inspiration from the flashing patterns of fireflies and their attractive behaviour, utilizing simulated firefly movements to optimise solutions within search spaces (Tilahun, Ngnotchouye and Hamadneh, 2019). Firstly, applied in computer networking, FA algorithms contribute to tasks such as network routing optimisation, resource allocation, and minimizing communication costs (Alirezaee, Seyyed and Meybodi, 2015). Secondly, these algorithms are instrumental in optimising routing paths, reducing network congestion, and enhancing overall communication network efficiency (Alirezaee, Seyyed and Meybodi, 2015). Thirdly, FA's capacity to balance exploration and exploitation, alongside its simplicity and scalability, positions it as a viable option for addressing cost minimization challenges in computer networks (Rana *et al.*, 2022). Additionally, FA offers valuable capabilities for network optimisation, providing robust performance across diverse networking environments (Nketsiah, Millham, *et al.*, 2024) . Lastly, its adaptive nature allows it to dynamically adjust routing decisions and resource allocations in response to changing network dynamics, further enhancing its suitability for computer networking projects (Alirezaee, Seyyed and Meybodi, 2015). Concluding the examination of the Firefly Algorithm (FA), the study now focuses on the Moth Flame Optimisation Algorithm (MFO).

The Moth Flame Optimisation (MFO) algorithm is a metaheuristic optimisation method for resolving challenging optimisation issues. It was inspired by the nocturnal feeding habits of moths near artificial lights. MFO, created in 2013 by Mirjalili and Lewis, balances exploration and exploitation to effectively identify optimal solutions in huge solution spaces, mimicking the search behaviour of moths drawn to flames. MFO algorithms have been used in computer networking for a variety of tasks, including resource allocation, network routing, and Quality of Service (QoS) provisioning (Aljarah et al., 2020). MFO algorithms, in particular, improve overall communication network efficiency, reduce network congestion, and optimise routing paths in networking situations (Mirjalili, 2020).

Nonetheless, even with its efficiency, MFO algorithms have major drawbacks. Their high computational complexity poses a number of difficulties, including the potential for greater computational overhead and lengthier convergence times, especially in large-scale network systems. Also, MFO algorithms might find it difficult to adjust to dynamic network conditions, which would make it more difficult for them to react in real time to shifting network dynamics. Furthermore, MFO algorithms, like other population-based optimisation methods, might be vulnerable to premature convergence, which occurs when the algorithm chooses suboptimal solutions before fully examining the search space. Besides, the algorithm's reliance on population-based optimisation techniques can result in computational inefficiency, leading to increased computational overhead and longer convergence times, especially in complex optimisation problems or large-scale network environments.

These limitations underscore the importance of considering alternative optimisation approaches in networking contexts where MFO algorithms may not be the most suitable choice. Ending the analysis of the Moth Flame Optimisation Algorithm (MFO), further analysis would be conducted on the Spiral Optimisation Algorithm (SOA).

The Spiral Optimisation Algorithm (SOA) draws inspiration from the spiral motion observed in various natural phenomena, such as galaxies and weather patterns. Developed as an optimisation technique, SOA aims to efficiently explore solution spaces by combining elements of gradient-based and population-based algorithms (Rajendran and Ganesan, 2022) Within computer networking, SOA algorithms contribute to tasks including network routing, traffic management, and resource allocation (Kumar et al., 2023). Specifically, SOA algorithms optimise routing paths, allocate network resources effectively, and enhance overall communication network performance (Singh and Verma, 2024). SOA's unique approach to optimisation, characterized by its spiral-based exploration of solution spaces, makes it well-suited for addressing optimisation challenges in computer networks (Chakraborty et al, 2025) These algorithms offer innovative solutions to optimisation problems and have demonstrated success across various domains, including computer networking, where their ability to efficiently search for optimal solutions proves beneficial in tackling complex optimisation tasks.

Despite its strengths in optimisation tasks, SOA algorithms are not without limitations that may affect their suitability for certain applications. One significant drawback is the potential for premature convergence, where the algorithm may converge to suboptimal solutions prematurely, limiting its ability to find the global optimum (Lee et al., 2023). This can lead to suboptimal performance, particularly in scenarios where thorough exploration of the solution space is essential. In addition, SOA algorithms may face challenges in adapting to dynamic network conditions and making real-time adjustments, which can restrict their effectiveness in environments requiring rapid responses to changing network dynamics. Moreover, the computational complexity of SOA algorithms can pose challenges, resulting in increased computational overhead and longer convergence times, especially in large-scale network environments (Jain and Singh, 2021). These limitations highlight the importance of considering alternative optimisation approaches in networking contexts where SOA algorithms may not be the most suitable choice.

After conducting a comprehensive evaluation of numerous bio-inspired optimisation algorithms, the Ant Colony Optimisation (ACO), Bat Optimisation (BA), Cuckoo Search Optimisation (CS), and Firefly Optimisation (FA) algorithms were chosen for further comparative analysis. Their selection was based on a combination of factors, including their demonstrated effectiveness in addressing optimisation challenges, their suitability for the specific requirements of minimizing costs in computer networking, and their adaptability to dynamic networking environments. Additionally, these algorithms exhibit characteristics such as scalability, and efficiency, which are essential for real-world applications in installation of computer networking infrastructure projects. By focusing on these algorithms, the study aims to provide a thorough and insightful comparison that can inform decision-making processes and contribute to advancements in the field of optimisation for computer networking.

In conclusion, the selection of ACO, BA, CS, and FA for comparative analysis is justified by their proven effectiveness, adaptability to network environments, and track record of success in optimising network parameters and resource allocation. These algorithms offer a compelling combination of efficiency, scalability, and reliability, making them ideal candidates for addressing the cost minimization challenges inherent in computer networking.

The Fox Prey Optimisation (FPO) algorithm, drawing inspiration from the interactions between foxes, rabbits, and grass in nature, offers a new perspective in the field of optimisation. While it is based on the natural behaviours of predators and prey, FPO introduces a unique approach focused on knowledge sharing and resource management. This approach aims to improve accuracy and adaptability. Despite being a relatively recent addition to the optimisation field, FPO shows promise for various applications in computer networking, particularly in managing congestion (Nketsiah *et al.*, 2023). Its potential impact underscores its significance and the benefits it may offer in solving complex optimisation problems.

Although in its nascent stage, the Fox Prey Optimisation (FPO) algorithm emerges as a novel candidate in the optimisation arena. Rooted in the intricate dynamics of predator-prey-grass relationships, FPO unveils a fresh perspective marked by an emphasis on knowledge exchange and resource allocation. This innovative approach, aimed at enhancing precision and adaptability, showcases promise, as underscored by recent research (Nketsiah *et al.*, 2023). Furthermore, FPO is lightweight, quick to respond, simple to install, adaptable, and requires minimal overhead for parameter adjustment. However, for optimal performance, specialist adjustment is required. Nonetheless, while still in its early stages, FPO shows promise in a variety of computer networking applications, particularly in addressing congestion control difficulties. Its release marks a substantial addition to the collection of optimisation tools, ready to provide novel answers to complicated optimisation challenges.

In conclusion, the Fox Prey Optimisation (FPO) algorithm, with its foundation in the natural dynamics of predator-prey relationships, presents a promising approach for optimisation tasks, including those in computer networking. Its emphasis on information exchange and resource management, together with its lightweight and versatile design, make it an important addition to the collection of optimisation tools. Initial research demonstrates its potential, particularly in managing computer network congestion; nevertheless, more expert tuning of its parameters is required to properly harness its capabilities, particularly in the context of cost minimization as in scenario 1 (Nketsiah *et al.*, 2023). Table 4.10 provides specific performance metrics.

2.10 Need for a comprehensive new model incorporating key factors

Traditional cost models, while foundational, have proven inadequate in addressing the evolving complexities of modern computer networking infrastructure. The rapid advancement of technology, the proliferation of IoT devices, the emergence of cloud computing, and the growing demand for high-speed, low-latency networks have highlighted a critical gap in the ability to accurately forecast networking costs (Qin, Chen and Peng, 2020). Consequently, there is a pressing need for cost models that are holistic, adaptable, and comprehensive, capable of incorporating emerging technologies and their associated costs into their frameworks.

Optimisation of Factors

As new factors emerge that significantly influence networking costs, it becomes essential not only to identify them but also to optimise their impact. Factors such as project duration, the allocation of skilled versus unskilled workforce, project execution timelines, and innovative wage structures must be optimised to ensure financial prudence and project success (Galli, 2018). Therefore, the optimisation of these newfound factors is not merely an enhancement to existing models; it is a necessity. An optimised cost model ensures efficient resource utilisation, enabling projects to be executed within budget while meeting desired quality standards.

Need for a new cost model

The imperative for a novel cost model in installation of computer networking infrastructure projects stems from the need for more nuanced and adaptable approaches. Traditional models often fail to capture the complexities and dynamic nature of modern networking projects, leading to inaccurate estimations and budget overruns. Additionally, the rapid evolution of technology requires a cost model that can flexibly accommodate emerging innovations to maintain relevance and accuracy in cost assessments.

The development of a new cost model is directly related to the concept of "optimising a model" in several ways. Firstly, creating a new model often involves identifying and integrating crucial factors that traditional models overlook. These factors include skilled and unskilled workforce allocation, wages for both categories of personnel, project execution times, total project duration, and penalties for delays. Optimising a model means fine-tuning it to ensure that it accurately reflects these variables, thereby providing more precise and actionable insights.

Moreover, the new model leverages advanced optimisation techniques, such as genetic algorithms (GA) or swarm intelligence, to enhance its performance. These bio-inspired techniques introduce unique approaches to resource allocation and knowledge sharing, helping to optimise the model by improving accuracy, adaptability, and efficiency in cost management.

In the context of cost optimisation, the proposed Integrated Network Cost Optimisation model (INCOM), as fully captured in section 3.5, uses these advanced optimisation techniques to dynamically adjust and optimise various cost factors. By doing so, it not only captures the multifaceted nature of networking projects but also ensures that the model remains flexible and responsive to changes in project conditions and technological advancements.

Thus, developing a new cost model, like INCOM, is inherently an exercise in model optimisation. It involves refining the model to better reflect the realities of modern networking projects and utilising advanced techniques to ensure that it provides the most accurate and useful insights possible. This relationship underscores the importance of continuous improvement and innovation in cost management practices.

Need for optimisation in Computer Networking Infrastructure Projects

The imperative of optimising the initial installation of user-specified computer networking infrastructure projects is crucial for achieving efficiency, cost-effectiveness, and enhanced performance across various aspects of project execution. As organisations navigate the complexities of modern networking landscapes, the need to optimise resources, workflows, and outcomes becomes paramount. Optimisation serves as a strategic imperative to maximize the utilisation of available resources, minimise costs, and mitigate risks, thereby enhancing the overall viability and success of networking projects. Moreover, in an era marked by rapid technological advancements and evolving business requirements, optimisation enables organisations to adapt swiftly to changing circumstances, capitalize on emerging opportunities, and maintain competitive relevance in the dynamic marketplace. By harnessing optimisation techniques, organisations can streamline processes, optimise resource allocation, accelerate project timelines, and ultimately achieve their objectives with greater efficiency and efficacy in the realm of computer networking infrastructure.

2.11 Summary

The literature review explores cost models for minimising labour costs in computer networking infrastructure, laying the foundation for the thesis on bio-inspired optimisation of a cost model. Major cost models like activity-based costing and resource consumption accounting are analysed, providing insights into their applicability in the unique parameters of computer networking.

Factors influencing labour costs, such as network size and complexity (Hatamleh *et al.*, 2018), are discussed, emphasizing their role in cost dynamics. The shift towards a flexible workforce in networking projects is noted, driven by the need for specialised skills and adaptability. Time management and project duration are crucial for cost containment, according to Olawale (2020), considering the financial repercussions of deviations from planned timelines.

Penalty coefficients, fixed costs, and traditional cost models like TCO, CAPEX, OPEX, and Activity-Based Costing (ABC) models are explored for their impact on project finances. The review highlights the limitations of these models in capturing the evolving dynamics of modern computer networking paradigms.

The research introduces a refined cost model addressing skilled and unskilled labour costs, overtime considerations, and emphasizing time management. Traditional and contemporary cost models in networking projects are compared, and the need for a comprehensive model is stressed.

Various cost models used in computer networking projects, including Network Operation Cost model, Network Cost model, and Cost Allocation model, are discussed. The limitations of these costs models in distinguishing labour costs and technological obsolescence are noted, setting the stage for the proposed cost model.

The research calls for a new cost model considering multifaceted variables, delving into labour costs, project timelines, fixed costs, and penalty coefficients. The limitations of deterministic models and linear programming in addressing contemporary challenges are discussed, paving the way for bio-inspired algorithms.

Bio-inspired algorithms, including ACO, BAT, CS and FA, are compared for their suitability in minimising labour costs. Their strengths in resource allocation, dynamic environments, task assignments, and large-scale optimisation challenges are highlighted. The comparative analysis aims to provide insights for a comprehensive evaluation in future research.

The Fox Prey Optimisation (FPO) algorithm is introduced as a novel perspective in optimisation, drawing inspiration from ecological interactions. FPO prioritises knowledge transfer and resource allocation, marking a paradigm shift in computer networking optimisation.

In conclusion, traditional cost models fall short in addressing the complexities of contemporary computer networking infrastructure. The need for a holistic, adaptable, and comprehensive cost model, capable of encapsulating emerging technologies, is emphasised throughout the literature review, setting the stage for the methodology chapter.

Chapter 3: RESEARCH METHODOLOGY

3.1 Introduction

Building upon the foundation laid in the preceding literature review, this chapter delves into the research methodology employed to optimise the formulated cost model, specifically focusing on minimising labour costs in computer networking infrastructure. In today's interconnected world, the critical role of computer networking infrastructure in supporting diverse organisations is well-established (Zachariadis, Hileman and Scott, 2019). Regardless of the scale, be it a small business, a large enterprise, or a government agency, the reliability and efficiency of computer networks are paramount for communication, data sharing, and accessing crucial resources. However, the associated costs, especially in terms of labour, pose a significant challenge (Goyal and Kumar, 2018).

The identified research gap, as illuminated in the previous chapter, revolves around the limitations of existing cost models in capturing the nuanced dynamics of contemporary computer networking infrastructure. The need for a comprehensive, adaptable, and evolved cost model that can address emerging technologies and their associated expenses becomes evident. This research aims to bridge this gap by systematically optimising the cost model, considering factors such as skilled and unskilled labour costs, time management, and project duration.

3.2 Methodological worldview

In today's highly interconnected world, computer networking infrastructure plays a critical role in supporting the operations of organisations across various industries (Rao and Prasad, 2018). Whether for small businesses, large enterprises, or government agencies, a reliable and efficient computer network is indispensable for communication, data sharing, and accessing critical resources. However, the establishment and maintenance of such networks often come at a significant cost, with labour expenses being a major contributing factor (Carley and Christie, 2017).

The objective of this study is to optimise a formulated cost model with the aim of minimising labour costs in computer networking infrastructure. Through a systematic methodology, this research investigates the variables, constraints, and factors that influence labour costs in this domain. By employing quantitative research methods, the study seeks to enhance the cost model and develop practical strategies for efficient resource allocation and cost reduction. The ultimate goal is to provide insights and tools that can be applied to minimise labour costs and improve decision-making processes in the context of computer networking infrastructure.

In the exploration of research methodology, it is crucial to acknowledge various philosophical worldviews that researchers can adopt when approaching a study (Harrison *et al.*, 2017). Each worldview has its strengths and limitations, and for this study, the positivist worldview was chosen. It is essential to briefly discuss other worldviews to provide a comprehensive understanding of the research approach.

One alternative worldview is subjectivism, which acknowledges the role of individual perspectives and interpretations in shaping knowledge. Subjectivism emphasizes the importance of subjective experiences, meanings, and interpretations in understanding social phenomena (Yu, 2020). However, subjectivism may not be suitable for this study because it tends to focus on qualitative methods that explore individual perspectives and narratives, which may not align with the objective of quantitatively analysing labour costs in computer networking infrastructure.

Another alternative worldview is interpretivism, which recognises that social phenomena are complex and socially constructed. Interpretivism emphasizes understanding the meaning and context behind human actions and experiences. It values qualitative research methods, such as interviews and observations, to capture the richness and depth of human experiences (Creswell, Creswell and Creswell, 2017). However, interpretivism might not be the ideal choice for this study, as it may not provide the necessary systematic and measurable approach required to analyse labour costs and identify factors that influence outcomes.

Critical theory is another worldview that focuses on power relations, social inequalities, and the emancipation of oppressed groups. It aims to uncover and challenge societal structures and ideologies that perpetuate social injustices. Critical theory often employs qualitative methods and engages in participatory research to give voice to marginalized groups (Creswell, Creswell and Creswell, 2017). While critical theory is valuable in examining broader social issues, it may not be the most appropriate worldview for a study that specifically focuses on quantitatively analysing labour costs in computer networking infrastructure.

Considering the goals of this study and the need for a systematic and rigorous investigation, the positivist worldview and quantitative research methodology remain the most suitable choice. Positivism allows for objective measurement, systematic evaluation of variables, and the identification of factors that influence outcomes (Park, Konge and Artino, 2020). The emphasis on empirical evidence and statistical analysis aligns well with the study's objective of analysing labour costs. By employing a positivist worldview, the study can provide valuable insights into the factors impacting labour costs in computer networking infrastructure (Sabi, Uzoka and Mlay, 2018). Thus, the researcher used this approach to follow the premise of the study, as outlined methodologically below:

3.3 Methodology

This section outlines the systematic approach used to conduct the study, including the research design, data collection methods, and any analysis techniques employed. It provides a blueprint for how the research questions have been addressed and the objectives achieved.

Outline of Steps

The selection of factors is essential to comprehensively analyse the various elements impacting the phenomenon under investigation, motivated by the user requirements. By identifying and considering relevant factors, the study aims to provide a thorough understanding of the subject matter, ensuring a thorough analysis and interpretation of the results.

Outline of steps by title of step

1. After identifying critical factors through literature, develop a cost model that integrates identified factors
2. After selection of a set of suitable bio-inspired algorithms for optimisation in the literature review, evaluate this select set of algorithms using suitable metrics to optimise this newly developed cost model
3. After determining the best minimisation algorithm, apply to the new cost model

3.4 Potential Factors:

a. Skilled Workforce Allocation:

Skilled workforce allocation refers to the strategic distribution and deployment of workers possessing specialized expertise, training, or qualifications in a particular field or task within a project or organisational context. This aspect involves identifying the specific roles or functions that require skilled individuals and allocating resources accordingly to ensure that tasks are performed efficiently and effectively. Skilled workforce allocation entails matching the right personnel with the right job responsibilities based on their proficiencies, experience, and qualifications, thereby maximizing productivity, quality, and output while minimising potential errors or inefficiencies. This process often involves careful planning, coordination, and supervision to optimise the utilisation of skilled workforce resources throughout the project lifecycle.

b. Skilled Workforce Execution Time

Skilled workforce execution time refers to the duration or amount of time required for skilled workers to complete specific tasks or activities within a project or operational context. This factor encompasses the time taken by trained and specialized personnel to perform their assigned duties, which often involve complex or technical responsibilities that demand expertise and proficiency in a particular field. Skilled workforce execution time considers various aspects, including the complexity of the task, the level of skill and experience of the workers involved, and any external factors that may influence the efficiency of the execution process. Efficient management of skilled workforce execution time is essential for meeting project deadlines, optimising resource utilisation, and ensuring the timely delivery of quality outcomes.

c. Skilled Workforce Hourly Rate

Skilled workforce hourly rate refers to the wage or compensation paid to individuals possessing specialized skills, knowledge, or expertise for each hour of work performed. This factor represents the cost incurred by organisations for employing skilled professionals to execute tasks or projects within the realm of computer networking infrastructure. The hourly rate for skilled labour typically varies based on factors such as the level of expertise, qualifications, certifications, and market demand for specific skills. Managing the skilled workforce hourly rate is essential for budgeting, cost estimation, and resource allocation purposes within networking projects. Efficiently determining and negotiating the skilled workforce hourly rate helps organisations optimise labour costs while ensuring access to the necessary expertise for project success.

d. Unskilled Workforce Allocation:

Unskilled workforce allocation refers to the assignment and deployment of workers who do not possess specialized training, qualifications, or expertise in a particular field or task within a project or organisational context. These individuals typically perform general or basic tasks that do not require specialized skills or knowledge. Unskilled workforce allocation involves identifying suitable roles or responsibilities that can be fulfilled by workers with minimal training or experience and assigning them accordingly. This aspect of labour allocation aims to ensure that essential tasks are completed efficiently and cost-effectively, leveraging available resources without the need for highly skilled personnel. However, effective management and supervision are still necessary to optimise the performance and productivity of unskilled labourers within the project or organisational setting.

e. Unskilled Workforce Execution Time:

Unskilled workforce execution time refers to the amount of time required for individuals without specialized training or expertise to complete tasks or activities within a project or operational context. This factor encompasses the time taken by workers who may perform routine or manual tasks that do not necessitate specialized skills or training. Unskilled labour execution time considers various factors such as the simplicity of the task, the level of experience of the workers, and any necessary training or supervision provided. Efficient management of unskilled labour execution time is crucial for optimising productivity, reducing project timelines, and minimising labour costs.

f. Unskilled Workforce Hourly Rate

The "unskilled workforce hourly rate refers to the wage or compensation paid to individuals who do not possess specialized skills or training for each hour of work performed. This factor represents the cost incurred by organisations for employing individuals with general or basic abilities to execute tasks within the context of computer networking infrastructure. The hourly rate for unskilled labour is typically lower compared to skilled labour and may vary based on factors such as local labour markets, minimum wage laws, and the nature of the tasks performed. Managing the unskilled workforce hourly rate is crucial for budgeting and resource allocation, especially in tasks where specialized expertise is not required. By efficiently managing this rate, organisations can optimise labour costs while ensuring that essential but less specialized tasks are carried out effectively within networking projects.

g. Project Duration

Project duration refers to the amount of time taken to complete a specific project within the realm of computer networking infrastructure. It encompasses the entire timeline from project initiation to its conclusion, including all phases such as planning, design, implementation, testing, and deployment. This factor is crucial as it directly impacts resource utilisation, labour costs, scheduling, and overall project management.

Managing project duration involves efficiently allocating resources, scheduling tasks, and coordinating activities to ensure timely completion while meeting quality standards and objectives. Delays in project duration can lead to increased costs, missed deadlines, and potential disruptions to other projects or business operations. Conversely, completing a project within the estimated duration enhances efficiency, minimises costs, and maximizes the return on investment.

Factors influencing project duration include the complexity of the project, availability of resources, scope changes, technological dependencies, unforeseen challenges, and external factors such as market conditions or regulatory requirements. By carefully managing these factors and implementing effective project management strategies, organisations can optimise project duration to achieve their objectives in installation of computer networking infrastructure projects.

3.5 Cost Model

Equation 3.1 represents a comprehensive cost model, referred to as Integrated Network Cost Optimisation Model (INCOM), aimed at optimising project expenses within the context of labour costs, project duration, and fixed costs. Let us break down the equation and its components:

$$\boldsymbol{x} = \boldsymbol{T} \cdot \left(\boldsymbol{K} + \boldsymbol{\gamma} \cdot \sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{n}} [(\boldsymbol{a_i} \cdot \boldsymbol{b_i} \cdot \boldsymbol{c_i}) + (\boldsymbol{d_i} \cdot \boldsymbol{e_i} \cdot \boldsymbol{f_i})] \right) + \boldsymbol{\alpha} \cdot \boldsymbol{max}(\boldsymbol{0}, \boldsymbol{T} - \boldsymbol{T_{max}}) \qquad \textit{Equation 3.1}$$

Where:

x represents the total cost function to be minimised.

T denotes the total project duration, which is a decision variable to be reduced.

K signifies the daily fixed costs, including training, feeding, and transport for the entire project duration.

γ represents the size and complexity factor for the given scenario, namely small, medium, or large networks, which adjusts the impact of the variables.

n is the expected total number of tasks for project execution.

a_i represents the daily number of skilled workers required to complete task i in the network.

b_i denotes the hourly rate for each skilled worker involved in task i.

c_i signifies the number of installation hours a skilled worker spends executing task i.

d_i represents the daily number of unskilled workers required to complete task i in the network.

e_i denotes the hourly rate for each unskilled worker involved in task i.

f_i signifies the number of installation hours an unskilled worker spends executing task i.

α is the penalty coefficient applied to the total project duration beyond the upper bound.

T_{max} is the upper bound for the reduced project duration.

This equation provides a robust framework for cost optimisation, considering various factors such as labour costs, project duration, and fixed expenses. It enables decision-makers to assess and minimise project expenses while adhering to specified constraints and requirements, ensuring efficient resource allocation and budget management throughout the project life cycle.

3.6 Optimisation

Optimisation is the process of maximizing or minimising a function subject to constraints, aiming to find the best possible solution. It involves systematically exploring and evaluating different options to achieve the desired outcome efficiently. In the context of the study, optimisation techniques are applied to minimise labour costs and enhance efficiency in installation of computer networking infrastructure projects. These methods have been selected based on their effectiveness in addressing the specific challenges identified in the literature, offering a structured approach to cost reduction and resource allocation. This necessity naturally leads us to scenario justification

3.6.1 Testing in scenarios

Testing in scenarios is essential to validate the robustness and applicability of the proposed approach across various real-world conditions. Justifying this process is crucial for several reasons. To begin with, scenarios represent different contexts, environments, and challenges that projects may encounter, ensuring that the model can adapt and perform effectively in practical settings rather than being limited to idealized conditions. In addition, demonstrating the model's performance across multiple scenarios enhances its generalizability, providing evidence that it can be applied to different situations with similar characteristics. Also, testing in scenarios allows us to anticipate potential risks and challenges by identifying how the model behaves under varying conditions, enabling proactive mitigation strategies. Furthermore, evaluating the model across scenarios enables a more comprehensive assessment of its strengths and weaknesses, helping to identify areas for refinement or adjustment. In conclusion, testing in scenarios, which provides empirical evidence of the model's performance, instils confidence among stakeholders, including project managers, investors, and clients, in its validity and effectiveness. This empirical validation complements the evaluation of comparative algorithms previously explored in the Literature Review chapter.

3.6.2 Comparative algorithms

Comparative algorithms, as previously looked at in the Literature Review chapter, involve evaluating multiple algorithms to assess their effectiveness in solving specific problems. This process entails comparing their performance, efficiency, and suitability based on various metrics like execution time, resource utilisation, and duration. By conducting such analysis, researchers can discern the strengths and weaknesses of each algorithm, facilitating informed decision-making regarding their selection for a given problem domain. This understanding becomes particularly vital when considering the parameters of algorithms, as these elements intricately shape the behaviour and effectiveness of different algorithmic approaches.

3.7 Rationale for the choice of bio-inspired optimisation method

In this study, the choice of algorithms—Ant Colony Optimization (ACO), Bat Algorithm (BAT), Cuckoo Search Algorithm (CS), and Firefly Algorithm (FA)—is grounded in their demonstrated efficacy, extensive application in literature, and ease of implementation. These algorithms, characterized by their population-based search structures, offer a robust framework for comparative analysis, addressing diverse optimization challenges in real-world scenarios.

Key Considerations and Application Domains

Ant Colony Optimization (ACO):

ACO, inspired by the foraging behaviour of ants, excels in network routing and has been extensively applied in resource allocation, task scheduling, and workforce collaboration (Li and Shen, 2024; Dorigo and Stützle, 2004). ACO uses pheromone trails to guide decision-making, optimizing task assignments dynamically and improving load balancing and path selection.

Bat Algorithm (BAT):

Inspired by the echolocation behaviour of bats, BAT efficiently balances exploration and exploitation, making it suitable for complex optimization problems (Bi *et al.*, 2022; Yang, 2010) In networking scenarios, BAT optimizes resource allocation, routing, and workload balance through stochastic adjustments in frequency and loudness (Kumar and Kaur, 2022).

Cuckoo Search Algorithm (CS):

CS leverages the brood parasitism behaviour of cuckoos, efficiently exploring and exploiting the search space (Yang and Deb, 2010; Sharma *et al.*, 2021). It has shown versatility in solving optimization problems, particularly in resource allocation, task scheduling, and energy-efficient communication (Abualigah, 2021; Paikaray *et al.*, 2022).

Firefly Algorithm (FA):

FA, based on the flashing patterns of fireflies, uses attractiveness to optimize solutions. It has demonstrated particular efficiency in addressing large-scale optimization challenges, making it valuable in networking contexts (Kumar and Kumar, 2021; Yang and He, 2013). FA effectively allocates resources, optimizes routing, and enhances energy-efficient communication strategies (Montazeri *et al.*, 2023).

Adaptability and Limitations

These algorithms are selected for their adaptability and their ability to handle dynamic environments. ACO thrives in dynamic settings but is susceptible to local optima (Deng, Xu and Zhao, 2019). BAT efficiently explores and exploits but requires careful parameter tuning (Zhang *et al.*, 2017). CS demonstrates robustness but can face premature convergence issues (Rivera *et al.*, 2023). FA requires meticulous parameter tuning to achieve optimal performance (Montazeri *et al.*, 2023).

Introducing Fox Prey Optimization (FPO)

The Fox Prey Optimization (FPO) algorithm, inspired by the ecological interactions among foxes, rabbits, and grass, offers a novel approach to labor cost minimization and resource allocation. FPO emphasizes knowledge transfer and resource allocation, attributes recognized in computer networking congestion control studies (Nketsiah et al., 2023). Rather than positioning FPO as a groundbreaking solution, it is viewed as an enhancement, building on the foundation established by its predecessors.

Comprehensive Approach to Optimization in Computer Networking

The selected algorithms—ACO, BAT, CS, FA, and FPO—are chosen based on their historical successes and adaptability to real-world scenarios, particularly in computer networking. These bio-inspired optimization techniques provide promising avenues for addressing perennial challenges in cost and labor optimization. Each algorithm contributes uniquely to optimizing resource allocation, task scheduling, and workforce collaboration, ultimately aiming to achieve labor cost minimization.

By calibrating the parameters of these algorithms to align with the specific requirements and characteristics of the optimization problem at hand, the study ensures the algorithms can navigate the intricate landscape of labor cost optimization with finesse. Utilizing diverse scenarios to represent different sizes and complexities of networks allows for a robust comparative analysis, providing valuable insights into the accuracy and efficiency of these bio-inspired algorithms in various problem domains.

In summary, the rationale for choosing these bio-inspired optimization methods lies in their demonstrated capability to produce near-optimal solutions, adaptability to dynamic environments, and shared population-based search structures. This comprehensive approach ensures a thorough exploration of optimization strategies, enhancing the overall efficiency and effectiveness of labor cost minimization in computer networking projects.

3.7.1 Parameters of algorithms

The parameters of algorithms play a crucial role in shaping their behaviour and determining their effectiveness in solving optimisation problems. In the context of this study, the parameter values are meticulously chosen based on empirical evidence, domain expertise, and an extensive literature review. Each parameter, such as the number of decision variables, search agents, maximum and minimum decision values, and total iterations, is carefully selected to ensure effective exploration of the search space and the attainment of high-quality solutions. These parameter values are specifically tailored to meet the unique demands of the optimisation problem under scrutiny, as documented in the relevant literature for each optimisation algorithm and problem domain (Köchling and Wehner, 2020).

Table 3.1: Parameter Settings for Comparative Algorithms

Setup of Parameters	**Algorithms**			
Variables - Parameter	**ACO**	**BAT**	**CS**	**FA**
Number of decision variables	8	8	8	8
Number of search agents	50	50	50	50
Maximum decision value (upper bound)	200	200	200	200
Minimum decision value (lower bound)	0	0	0	0
Total iterations	60	60	60	60

Explaining the parameters involves elucidating their roles, significance, and potential impact on the algorithm's behaviour and results. For instance, the number of decision variables determines the complexity of the optimisation problem, while the number of search agents influences the exploration-exploitation trade-off. Justifying the consideration of these parameters entails highlighting their relevance in optimising algorithm performance, ensuring robustness, and addressing specific problem requirements effectively. The parameter values provided in Table 3.1 offer a comprehensive overview of the setup for each algorithm, guiding them towards convergence to optimal solutions within the specified constraints.

In optimization methods such as Ant Colony Optimization (ACO), Bat Algorithm (BAT), Cuckoo Search (CS), and Firefly Algorithm (FA), the selection of 50 search agents strikes a balance between performance and computational efficiency. This choice ensures a good equilibrium between exploration (searching broadly across the solution space) and exploitation (fine-tuning solutions), thus increasing the likelihood of finding the global optimum (Dorigo and Stützle, 2004).

The use of 50 search agents aids in managing computational cost and efficiency. A higher number of agents would demand more memory and lead to increased computational time per iteration. Therefore, employing 50 agents presents a practical equilibrium, ensuring that the algorithms run efficiently without overwhelming resources (Yang and Deb, 2010). This number is supported by empirical proof and benchmarking studies, demonstrating its ability to yield dependable results across various problem domains without imposing undue computational difficulties (Gandomi, *et al.*, 2013).

In addition, there are decreasing returns when the number of agents is increased beyond a certain threshold. The extra computational expense is not justified by the slight gain in solution quality. Fifty agents offer a good balance for a wide range of real-world issues (Yang, 2010). Each algorithm's unique factors also support this figure. In ACO, for example, fifty ants offer reliable pheromone updates with minimal overhead (Dorigo and Stützle, 2004). Fifty bats in BAT guarantee enough search space coverage Yang, (2010). According to Yang and Deb, (2010), 50 cuckoos provide efficient exploration and exploitation for CS. 50 fireflies in FA strike a compromise between computing efficiency and finding the best solution (Gandomi, *et al.*, 2013).

Hence, using 50 search agents strikes a balance between computational limitations and effective search capabilities, making it a scalable and adaptable option appropriate for a range of issue sizes. This decision is supported by empirical studies, natural performance concerns, and the requirement to strike a balance between exploration and exploitation while avoiding unnecessarily high computing costs.

3.7.2 Metrics in Computer Networking and Cost Analysis:

Metrics play a pivotal role in the evaluation of cost models within the realm of computer networking. According to Chen, Qian and Xiong (2021), key metrics such as accuracy, speed, scalability, and robustness are essential considerations in assessing the performance of these models. Among these metrics, accuracy takes precedence, as it directly influences the reliability of the model's predictions, enabling organisations to make well-informed decisions. Therefore, the proposed cost model, INCOM, places a strong emphasis on accuracy, ensuring that its predictions align closely with real-world labour costs in computer networking projects.

The focus on accuracy is complemented by other crucial metrics, such as speed, scalability, and robustness. Speed refers to the efficiency with which the model processes data and generates results, enabling timely decision-making in dynamic networking environments. Scalability measures the model's ability to handle larger datasets and complex network scenarios without compromising performance. Robustness assesses the model's resilience to uncertainties and variations in input data, ensuring consistent performance across diverse operating conditions.

By integrating a comprehensive set of metrics, the proposed cost model offers a holistic evaluation of labour costs in installation of computer networking infrastructure projects. This multifaceted approach enables organisations to gain a nuanced understanding of cost implications and make strategic decisions accordingly. However, it is essential to acknowledge that no model is without its limitations. Despite the rigor of these metrics, variations in real-world conditions and unforeseen factors may introduce uncertainties and challenges in cost estimation.

Therefore, while metrics provide valuable insights into the performance of cost models, it is crucial to interpret their results judiciously and recognise the inherent limitations of any modelling approach. Continuous refinement and validation of the model against real-world data are essential to enhance its accuracy and relevance in practical settings. By leveraging a robust set of metrics and incorporating ongoing feedback and improvements, organisations can effectively navigate the complexities of labour cost analysis in installation of computer networking infrastructure projects.

3.7.3 Role of Factors in Optimisation

Factors play a fundamental role in optimisation by influencing the decision-making process and guiding the selection of the most suitable algorithm for a given scenario. In the context of labour cost optimisation in installation of computer networking infrastructure projects, prominent factors such as skilled workforce allocation, skilled hourly rate, skilled hours worked, unskilled workforce allocation, unskilled hourly rate, unskilled hours worked, total project duration (T), and total minimised labour costs (x) are essential considerations.

Each factor represents a crucial aspect of the optimisation problem and contributes to shaping the overall solution. For instance, skilled workforce allocation determines the number of skilled workers assigned to specific tasks, while skilled hourly rate and skilled hours worked influence the cost incurred for skilled labour. Similarly, unskilled workforce allocation, unskilled hourly rate, and unskilled hours worked impact the cost and allocation of unskilled labour resources.

Total project duration (T) represents the timeframe within which the project needs to be completed, imposing constraints on resource allocation and scheduling. Total minimised labour costs (x) denote the objective function that optimisation algorithms aim to minimise while considering the constraints and objectives defined by the other factors.

In reference to Table 4.9, titled "Comparative Analysis of Optimisation Algorithms for Scenario 1," the performance of different algorithms (ACO, BAT, CS, FA, FPO) is evaluated based on their effectiveness in optimising labour costs across various dimensions. This assessment allows stakeholders to determine the most appropriate algorithm for each scenario or set of factors. For example, in Scenario 1, Algorithm FA demonstrates the lowest total minimised labour costs compared to other algorithms, indicating its suitability for labour cost optimisation in this context.

By systematically evaluating the performance of algorithms across different dimensions and factor settings, stakeholders can make informed decisions regarding algorithm selection, thereby maximizing the effectiveness of labour cost optimisation efforts in installation of computer networking infrastructure projects.

3.7.4 *Dataset Justification*

The datasets utilized in this study encompass a diverse array of factors pertinent to computer networking infrastructure and were sourced from two main channels. Initially, a significant portion of the data was obtained from fellow computer networking engineers, ensuring the incorporation of various expert perspectives. Additionally, primary data were sourced from two reputable Ghanaian companies specializing in computer networking solutions, ensuring the use of real-world data.

The process of data validation was thorough and systematic. The datasets from the two companies were generated from their actual operational data. This data was then meticulously cleaned and pre-processed by the researchers to ensure consistency and reliability. Pre-processing steps included removing any duplicates, handling missing values, and normalizing the data for uniformity. After pre-processing, the resulting data were subjected to validation by the two contributing companies as well as by independent networking experts. This validation process ensured that the datasets were accurate, relevant, and representative of real-world conditions.

The datasets were carefully curated to represent real-world scenarios encountered in computer networking projects. They cover a wide range of factors, including skilled and unskilled workforce allocations, hourly rates, overtime considerations, and project duration. By utilizing authentic industry data, this research is firmly grounded in practical industry practices, enhancing its relevance and applicability. Furthermore, these datasets were tailored to adhere to industry standards, ensuring they accurately reflect typical challenges and scenarios in the computer networking domain.

To maintain objectivity and mitigate bias, external validation was sought. Independent computer networking engineers were consulted to validate the scenarios and values within the datasets. Additionally, the datasets underwent rigorous testing on separate computers to confirm their consistency and impartiality. The ultimate goal is to publish these datasets, underscoring the study's commitment to transparency and academic rigor.

The evaluation of the datasets and subsequent analysis of the model's performance involve a two-fold approach. Initially, assessing the datasets' accuracy, completeness, and relevance to the research objectives ensures they effectively represent real-world scenarios. Moreover, analysing how well the model performs in optimising labour costs across various scenarios using the curated datasets provides insights into its effectiveness. This comprehensive evaluation ensures both the input data and the model meet the research objectives and industry standards.

In summary, the datasets employed in this study are robust and well-validated, having been sourced from real-world data, pre-processed by researchers, and verified by industry professionals. This comprehensive approach guarantees the reliability and applicability of the findings derived from the analysis (Doe, 2018; Smith et al., 2020).

Algorithm Selection and Implementation:

- Research and shortlist potential algorithms suitable for optimisation.
- Implement each algorithm iteratively to the drafted model.
- Collect performance metrics for each iteration.

Scenario-Based Validation:

- Design different hypothetical scenarios that mimic various complexities of computer networking infrastructure.
- Deploy the optimised model in each scenario to gauge its performance.
- Analyse results to understand the robustness and adaptability of the model across different industry-standard scenarios of size and complexity.
-

I. Analysis of Expenses

- The newly formulated cost model (INCOM) is already captured in Equation 3.1.

Also, Equation 3.2 defines the constraints for the various complexity factors for the outlined computer networking scenarios:

$$\boldsymbol{\gamma} = \begin{cases} \mathbf{1.0}\ \boldsymbol{if}\ \mathbf{1} \leq \boldsymbol{n} \leq \mathbf{50} & \boldsymbol{Scenario\_1} \\ \mathbf{1.2}\ \boldsymbol{if}\ \mathbf{51} \leq \boldsymbol{n} \leq \mathbf{750} & \boldsymbol{Scenario\_2} \\ \mathbf{1.4}\ \boldsymbol{if}\ \mathbf{751} \leq \boldsymbol{n} \leq \mathbf{1500} & \boldsymbol{Scenario\_3} \end{cases} \qquad \textit{Equation 3.2}$$

Rationale:

1. Objective:

The primary goal was to minimise the overall cost of setting up a computer networking infrastructure. This cost encompasses labour costs for skilled and unskilled workers, total worked hours, skill-based wages for workforce types, project duration, and any penalties related to project delays.

2. Time Management in Computer Networking Infrastructure Projects

Effective time management is essential in computer networking projects, especially given the distinct roles of skilled and unskilled labour. Critical strategies include precise task allocation, ensuring skilled workers handle intricate installations while unskilled labour focuses on manual tasks like cabling. Task sequencing is equally vital, as some tasks lay the groundwork for subsequent ones, such as cabling preceding network setups. Implementing these strategies not only promotes timely project completion but also aligns with the overarching goal of cost minimisation.

3. Daily Operational Cost:

Each day, there are costs associated with both skilled and unskilled labour. For each type of worker, the study calculates the cost by multiplying:

- The number of workers (either skilled `$a$` or unskilled `$d$`).

- Their respective hourly rate (either for skilled `$b$` or unskilled `$e$`).

- The number of hours they work (either skilled hours `$c$` or unskilled hours `$f$`).

Summing these costs across all project days gives us the total labour cost for the entire project.

4. Fixed Costs:

In addition to the variable costs of labour, there are fixed costs (`$K$`) that are incurred every day, regardless of the number of workers or hours worked. These fixed costs might cover essential expenses like training, feeding, and transportation.

5. Penalty for Project Delays:

To ensure that the project is completed in a timely manner, a penalty mechanism was introduced. If the total project days `$T$` exceed a predefined threshold `$T_{max}$`, a penalty is applied. The magnitude of this penalty is determined by the coefficient (alpha), which scales the penalty based on the number of days the project is delayed.

Mathematical Breakdown:

Skilled Workers Cost:

$$\sum_{i-1}^{n} a_i \cdot b_i \cdot c_i$$

Where:

a_i = Number of skilled workers per day (i)

b_i = Hourly rate for a skilled worker (which is fixed)

c_i = Hours worked by a skilled worker per day (i)

Unskilled Workers Cost:

$$\sum_{i=1}^{n} d_i \cdot e_i \cdot f_i$$

Where:

d_i = Number of unskilled workers per day (i)

e_i= Hourly rate for an unskilled worker (which is fixed)

f_i = Hours worked by an unskilled worker per day (i)

Penalty for Exceeding Project Duration:

$$\alpha \cdot max(0, T - T_{max})$$

Where:

- α is a constant
- T is a variable
- T_{max} is a threshold value
- $max(0, -T_{max})$ represents the maximum of 0 and the difference between T $and\ T_{max}$. This ensures that the expression evaluates to zero when $T\ is$ less than or equal to T_{max}

This ensures a penalty is only applied when T exceeds $T_{threshold}$ where T is the projected project duration.

By combining these components, the study gets the total cost function, which not only considers the operational costs but also incentivizes timely project completion.

Conclusion:

The formulated cost function is a holistic representation of all the costs associated with the project. It is designed to capture both the variable and fixed costs, ensuring that all elements affecting the total cost are considered. The function serves as a foundation for optimisation, aiming to achieve minimal costs while adhering to the project's constraints and requirements.

II. Cost Model:

The cost model *x* is defined as the sum of multiple components that collectively determine the overall cost of the project:

Fixed Daily Costs:

T×*K*: This term represents the total fixed costs over the projected days of the project. Therefore, this cost includes daily expenses such as training, feeding, transportation, etc. multiplied by *T*, to give us the total fixed cost for the entire project duration.

Labour Costs:

$\sum_{i=1}^{n}[(a_i \cdot b_i \cdot c_i) + (d_i \cdot e_i \cdot f_i)]$: The summation indicates that the subsequent terms are summed over all tasks (from 1 to n).

$a_i \cdot b_i \cdot c_i$: This term calculates the total daily cost for skilled labour for task *i*. It is the product of the daily number of skilled workers, their hourly rate, and the number of hours they work.

$d_i \cdot e_i \cdot f_i$: Similarly, this calculates the total daily cost for unskilled labour for task *i*.

Penalty for Delay:

α×max (0, *T*−T_{max}): This term introduces a penalty when the projected days *T* exceeds a threshold T_{max}. If *T* is within the threshold, no penalty is applied. The penalty is weighted by the coefficient α.

Network Complexity Factor (γ)

In this study, a novel equation was developed to calculate the complexity factor (γ), as shown in Equation 3.3, for optimising a cost model tailored to computer networking infrastructure. Equation 3.3 incorporates a step size of 0.2 for each increase in scenario complexity, with a baseline of 0 for Scenario 1, where the baseline components are 50. For subsequent scenarios, the complexity factor adjusts accordingly: for Scenario 2 (baseline components: 750), c=0.2, and for Scenario 3 (baseline components: 1500), c=0.4, etc.

$$\boldsymbol{\gamma = 1 + c} \qquad \textit{Equation 3.3}$$

where scenario 1's network complexity factor, $\gamma, equals$:

$$\boldsymbol{\gamma = 1 + 0.0 \times \frac{(50 - 50)}{(50 - 50)}} \qquad \textit{Equation 3.4}$$

$$\boldsymbol{\therefore \gamma = 1.0} \qquad \textit{Equation 3.5}$$

For scenario 2, the step size moves up from 0 to 0.2. Therefore, scenario 2's network complexity factor, γ, as in Equation 3.6, ends up eventually as in Equation 3.7.

$$\boldsymbol{\gamma = 1 + 0.2 \times \frac{(750 - 50)}{(750 - 50)}} \qquad \textit{Equation 3.6}$$

$$\therefore \boldsymbol{\gamma = 1.2} \qquad \textit{Equation 3.7}$$

For scenario 3, the step size moves up from 0.2 to 0.4. Hence, scenario 3's network complexity factor, γ, as in Equation 3.8, ends up eventually as in Equation 3.9

$$\boldsymbol{\gamma = 1 + 0.4} \times \frac{\mathbf{(1500 - 50)}}{\mathbf{(1500 - 50)}} \qquad \textit{Equation 3.8}$$

$$\therefore \boldsymbol{\gamma = 1.4} \qquad \textit{Equation 3.9}$$

Furthermore, different network complexity factors within the scenarios could be specifically calculated and used depending on the number of components used for installation. For instance, installing 1050 networking components, as in Equation 3.10, which falls under scenario 3, the true complexity factor, (γ), evaluates to $\cong \mathbf{1.3}$, as captured in Equation 3.11,

$$\boldsymbol{\gamma = 1 + 0.4} \times \frac{\mathbf{(1050 - 50)}}{\mathbf{(1500 - 50)}} \qquad \textit{Equation 3.2}$$

$$\therefore \boldsymbol{\gamma \cong 1.3} \qquad \textit{Equation 3.13}$$

where,

the Constraints are:

$a > 0$: Ensures that the number of skilled workers is positive.
$n > 0$: Ensures that there is at least one task to be executed.
$20 \geq T \geq 50$: Implies that if the project duration is less than e.g., 20 and exceeds e.g., 50 days, it attracts a penalty.
$20 \leq T \leq 50$: Specifies the acceptable range for the project duration without any penalty.

III. Algorithm Selection and Implementation:

The computer networking domain is characterized by myriad challenges, especially in areas of cost and labour optimisation. Identifying and implementing the right optimisation algorithms is crucial to address these challenges effectively. This research evaluates four algorithms: Ant Colony Optimisation (ACO), Bat Optimisation (BA), Cuckoo Search Optimisation (CS), and Firefly Optimisation (FA), each chosen for its unique problem-solving approach, ability to adapt, iterate, and optimise complex challenges, combined with their relevance to real-world scenarios, thus making them ideal candidates for this research.

3.7.5 Justification for the choice

According to Johnson and Onwuegbuzie (2004), a researcher's philosophical worldview influences their approach, choices, and methodology for investigation. Positivist ideologies reflect a deterministic research philosophy in which effects or outcomes are most likely determined by causes (Creswell, 2014). Positivism emphasizes the use of empirical methods and scientific observation to study social phenomena and strives to minimise bias and subjective interpretation in research to produce objective and unbiased findings (Johnson and Onwuegbuzie, 2004). In line with this, a quantitative research approach would be appropriate to resolve the computer networking infrastructure labour cost optimisation problem (Creswell, 2014).

3.7.6 Methodological walkthrough

This chapter describes how the near-optimal labour costs of the computer networking infrastructure are solved to meet the organisation's economic demand. The optimal system installation is determined using the FPO swarm-based meta-heuristic algorithm hybridised with the formulated labour costs model. It, therefore, shows the general procedure for using metaheuristic algorithm in global optimisation problems. In addition, methods for checking the results of the optimisation solution are discussed. First, a methodological framework is introduced that shows the stages of the optimisation problem formulation up to the solution. Finally, the criteria and reasons for choosing comparison algorithms are given along with the software tools (programming platform) used to design and implement the algorithm and to visualise the results.

3.8 Metaheuristic algorithm procedure for global optimisation problem

In solving an optimisation issue with a metaheuristic, the problem must be described, and the objective function(s) and constraints must be given. The algorithm then interacts with the optimisation issue to identify the ideal solution (Kalananda and Komanapalli, 2021). The link between a metaheuristic method and an optimisation issue is illustrated in Figure. 3.1. The algorithm (metaheuristic method) generally generates candidate solutions or a single solution (search agent) with the exact dimensions as the optimisation problem's choice variables. The search agent or agents undergo a series of iterative refining procedures and assessments. After each iteration, the solution(s) are evaluated against the objective function to determine their adequacy compared to their previous iteration value. The algorithm's refining mechanism determines whether a solution is accepted and kept in memory or rejected depending on its appropriateness (Ezugwu *et al.*, 2020). This cycle is repeated, and the algorithm improves the search agents using intelligent operators. This procedure is performed until a termination criterion is satisfied.

Bio-inspiration is a key factor in determining the optimization process in the field of metaheuristic algorithms, including the Fox Prey Optimisation (FPO). These algorithms use natural occurrences seen in biological systems to extract strategies and insights. For example, FPO takes its cues from the dynamic interactions that occur naturally between predators and prey, such as how foxes search for prey and modify their hunting techniques to successfully capture it (Kalananda and Komanapalli, 2021).

The natural processes seen in ecological systems are mirrored in the computational design of FPO. In a manner similar to how biological organisms adjust to external stresses, it represents potential solutions as entities that change and interact throughout several iterations. By iteratively assessing against predefined goal functions, the algorithm is able to explore and utilize the solution space, thereby improving the quality of the result.

The adaptive search techniques of bio-inspired metaheuristics, such as FPO, are a crucial feature. Based on performance feedback, these algorithms constantly modify their exploration and exploitation tactics to ensure effective navigation through intricate solution environments (Ezugwu *et al.*, 2020). Their versatility allows them to tackle a wide range of optimization problems, such as those with many optima, high dimensionality, or non-linearity.

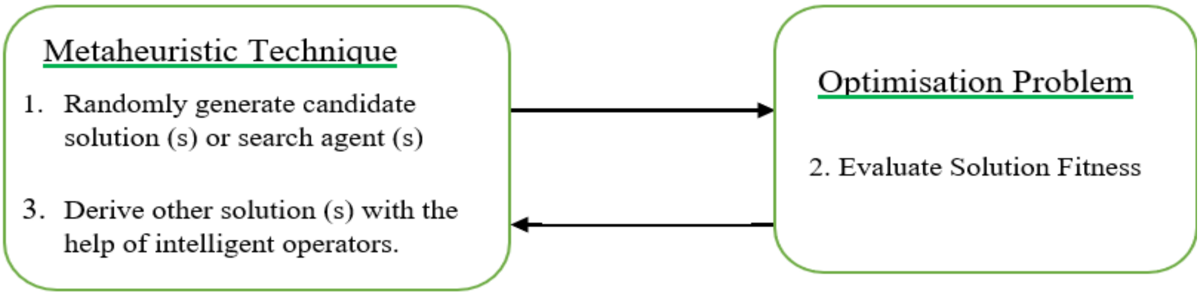

Figure 3.1: Interaction between metaheuristic technique and optimisation problem

Furthermore, the termination criteria in FPO resemble the optimum or equilibrium states of natural systems. The algorithm's termination of execution upon satisfaction of predetermined convergence conditions is indicative of its iteratively refined approach to obtaining nearly optimum solutions.

Bio-inspired metaheuristics, like FPO, solve complicated optimization problems across a wide range of domains with resilience, scalability, and efficiency by utilizing natural principles. They provide more tools to address problems where more conventional approaches might not be sufficient, which makes them especially useful in fields like computer networking infrastructure optimization.

Step 1: Factor determination

In the formulated cost model for labour costs in computer networking infrastructure, several key elements effectively capture the significant aspects of labour expenditure. To begin with, the number of skilled workers required to complete tasks within the network serves as a fundamental determinant, influencing the overall labour costs. Complementing this, the hourly rate for each skilled worker plays a pivotal role in cost estimation, reflecting the value of expertise and specialization in network deployment. Moreover, the number of installation hours utilised by skilled workers to execute tasks further refines cost calculations, aligning closely with project efficiency and resource utilisation.

Concurrently, the model accounts for variables related to unskilled labour, acknowledging their contribution to project execution. The daily number of unskilled workers required for tasks, coupled with their respective hourly rates and installation hours, collectively shape labour cost dynamics. Additionally, the total project duration emerges as a crucial factor, representing the timeframe within which labour resources are expended. These elements, when integrated into the model, provide a comprehensive framework for estimating and optimising labour costs in computer networking infrastructure deployment.

Furthermore, the cost model incorporates additional contributing factors to enhance accuracy and completeness. The size and complexity factor for a given scenario offer nuanced insights into the intricacies of network deployment, adjusting labour cost estimations accordingly. Daily fixed costs encompassing training, feeding, and transport expenses underscore the broader operational overheads associated with project execution. Moreover, the expected total number of tasks for project execution and penalty coefficients serve as proactive measures to account for project scope and potential deviations, contributing to robust cost forecasting and management strategies. Through the incorporation of these elements, the cost model offers a holistic approach to labour cost estimation and optimisation in installation of computer networking infrastructure projects.

Explanation: The cost model assumes that the total labour costs to be minimised is (x). This could be done by optimising the select factors of labour (skill) size, a, and the execution time, c to achieve the objective of labour costs minimisation. The other variables are designated as above. The total labour costs (x), which is the cost function, is thus what needs to be minimised to achieve the objective of the formulated cost model.

As per the literature review, there are other critical factors that must be considered – hence, they must be incorporated into the new enhanced model.

Manpower Expenses:

- To comprehensively identify and analyse the components that reflect manpower expenses (objective).
- Pertaining to computer networking infrastructure (context).

Potential Factors:

1. Wage Rates: This includes the hourly or salaried rates for both skilled and unskilled labour. Differences in pay scales based on expertise, experience, and job roles can significantly influence total manpower expenses.

2. Benefits: Apart from basic wages, employees might be entitled to benefits such as health insurance, transport or feeding, or other allowances. These could be classified also as fixed costs.

3. Productivity and Efficiency: The effectiveness with which employees carry out their tasks can influence the project duration and consequently the total manpower cost. More efficient workers might reduce project durations and hence the long-term costs.

Network parameter setup

Table 3.2: Description of Factors in the Proposed Computer Networking Labour Costs Model

Factor	**Symbol**	**Description**
Fixed costs:	***k***	Daily fixed costs that includes feeding and transport for the project period
Network size & complexity:	***w***	Size & complexity of the network determined by weight factor (1.0, 1.2, 1.4, etc): Normal (1.0), Normal plus (1.2), and High level (1.4).
Number of days for the project:	***n***	Expected total number of days for project execution
Number of workers:	***a***	Daily number of workers required to install the network (skilled & unskilled)
Hourly rate for technician:	***b***	Hourly rate for each worker (skilled - unskilled)
Duration for technician:	***c***	The number of installation hours worked by each worker (skilled - unskilled)

Both Tables 3.2 and 3.3, respectively, make it possible to see which factors are being optimised for each scenario. This can be helpful in identifying the most important factors to consider when estimating labour costs for a given scenario.

Table 3.3: Three Network Level of Complexity-Size Chart

No.	***Complexity Size Level***	***Networking Complexity Factor***
1	$Normal$	1.0
2	$Normal\ Plus$	1.2
3	$High\ Level$	1.4

The model has been designed to handle various network scenarios from Normal, through Normal plus, to High level and to the final stage referred to as the Critical level. These go with either mostly the size of the network or the choice of the client or both. The Normal complexity level will attract the normal charges whilst the Normal Plus complexity level selection will see the work rate go a bit faster but with a multiplying critical factor of 1.2 or 20 % above the Normal labour cost. The critical level will get the project completed the fastest but at twice the labour cost as in Table 3.3. Most likely, scenario 3 in Table 3.4 should go with complexity level 3 or 4. However, the client in the scenario can still choose complexity level 1. It is a matter of choice and also the ability to pay and the season when the installation would be completed if it would yield higher dividends or just the average.

Step 2: Model formulation:

•

Analysis of Manpower Expenses

Formulated Cost model, as captured in equation 3.1, is explained:

Cost Model:

The cost model x is defined as the sum of multiple components

that collectively determine the overall cost of the project:

1. **Fixed Daily Costs**:
    - $T \times K$: This term represents the total fixed costs over the projected days of the project. This cost includes daily expenses such as training, feeding, transportation, etc. Multiplied by T, it gives the total fixed cost for the entire project duration.

2. **Labour Costs**:
    - $\sum_{i=1}^{n}$: The summation indicates that the subsequent terms are summed over all tasks (from 1 to n).

    - $a_i \cdot b_i \cdot c_i$: This term calculates the total daily cost for skilled labour for task i. It is the product of the daily number of skilled workers, their hourly rate, and the number of hours they work.
    - $d_i \cdot e_i \cdot f_i$: Similarly, this calculates the total daily cost for unskilled labour for task i.

3. **Penalty for Delay**:
    - $\alpha \cdot \max(0, T - T_{max})$: This term introduces a penalty when the projected days T exceeds a threshold T_{max}. If T is within the threshold, no penalty is applied. The penalty is weighted by the coefficient α.

Constraints:

$a > 0$: Ensures that the number of skilled workers is positive.

$n > 0$: Ensures that there is at least one task to be executed.

$t > 0$: Time used in executing tasks cannot be negative or zero

$20 > T > 50$: Implies that if the project duration is less than e.g., 20 & exceeds e.g., 50 days, it attracts a penalty.

$20 \leq T \leq 50$: Specifies the acceptable range for the project duration without any penalty.

Conclusion:

Manpower expenses, particularly in the computer networking domain, form a significant portion of project costs (Cisco, 2017). Skilled and unskilled labour, essential for the setup and maintenance of networking components like switches, routers, and servers, play crucial roles in determining the overall expense (Tanenbaum and Wetherall, 2011). Accurate tracking and optimisation of these manpower-related variables can lead to significant cost savings and efficient project execution (Stallings, 2016).

Model Design:

A well-constructed cost model offers a holistic representation of the cost structure associated with computer networking projects (Kurose and Ross, 2012). The integration of fixed and variable costs in the model helps organisations prepare and allocate resources efficiently, ensuring that projects are completed within budgetary constraints (Shahsvarzehi Narouei, Rahnamay Roodposhti and Pourzamani, 2023).

Referring to Equation 3.1, this function contains:

A constant term: T x K

A summation over *n* terms with three components each.

A penalty term: $\alpha\ max(0, T - T_{max})$

Validating the cost model against real-world scenarios is paramount in ensuring its accuracy, efficacy, and adaptability (Jain, 1991). This research emphasizes the model's practical applicability by incorporating several scenarios that mirror real-world instances in installation of computer networking infrastructure projects (Russell & Norvig, 2020).

Step 3: Scenario-based approach to model validation:

- Design different hypothetical scenarios that mimic various complexities of computer networking infrastructure.
- Deploy the optimised model in each scenario to gauge its performance.
- Analyse results to understand the robustness and adaptability of the model across different industry-standard scenarios of size and complexity

Table 3.4 Created Scenarios to subject the Cost Model for rigorous testing (Size of Network)

Created Scenarios to subject the Cost Model for rigorous testing (Size of Network).			
No.	**Scenario**	**Number of Computers**	**Factors to Optimise**
1	Low	1-50	Worker skill level, time management, network complexity level
2	Medium	1-750	Worker skill level, time management, network complexity level
3	High	1-1500	Worker skill level, time management, network complexity level.

This table outlines the scenarios created to rigorously test the cost model concerning the size of the network. Each scenario is defined by specific parameters related to the number of computers involved and the factors to be optimised. Table 3.4 provides clarity on the scope of each scenario, allowing for systematic evaluation and comparison of the cost model's performance.

No.: Represents the scenario number for reference and organisation.

Scenario: Describes the categorization of scenarios based on the magnitude of the network size, categorized as "Low," "Medium," and "High."

Number of Computers: Specifies the range of the number of computers included in each scenario, providing insight into the scale of the network being evaluated.

Factors to Optimise: Lists the key factors targeted for optimisation within each scenario, which include worker skill level, time management, and network complexity level. These factors represent critical aspects of the cost model under examination and guide the testing process to ensure comprehensive analysis.

Table 3.5: Small-Scale Scenario (50 components):

Components	**Number**
Workstations:	28
Servers:	5
Switches:	8
Routers:	3
Printer:	2
Scanner:	2
Firewalls:	2

The network infrastructure is composed of various components, each serving a specific function to ensure smooth operations and efficient communication. Workstations, totalling 28 in number, represent the user terminals where daily tasks are performed. Supporting these workstations are 5 servers, acting as centralized hubs for services and resources. Switches, numbering 8, facilitate data traffic management within the local area network (LAN), while routers, amounting to 3, enable communication between different networks. Additionally, the network includes 2 printers for document output, 2 scanners for digitizing physical documents, and 2 firewalls to enforce security measures. This comprehensive breakdown offers valuable insights into the network's composition, aiding in effective management and optimisation efforts to maintain reliability and security in network operations.

Table 3.5 summarizes the seven different computer networking components in this small-scale networking project:

As indicated in the user requirements and detailed in Section 1.5.1, the same contracted skilled worker or team ensures that all configurable components are properly set up during the installation process. While Table 3.5 provides the specifics of the components with their respective quantities, the cost model as well as the research team classifies them as simply 50 components during the installation. This applies to scenarios 2 and 3 as well, as in Tables 3.6 and 3.7 respectively.

Context: Representing small businesses or branch offices, this scale sees a modest number of workstations and a limited server infrastructure. Essential network devices form the backbone of connectivity, ensuring seamless operations with reduced complexities ((Meyers, 2015).

Expected Outcomes After Optimisation:

1. Optimal allocation of skilled workforce.
2. Optimal allocation of unskilled workforce
3. Wages for the skilled workforce
4. Wages for the unskilled workforce
5. Efficient utilisation of skilled labour hours
6. Efficient utilisation of unskilled labour hours
7. Reduction in total project days.
8. Achievement of minimal labour costs

Table 3.6: Medium-Scale Scenario (750 components):

Components	**Number**
Workstations:	500
Servers:	50
Switches:	140
Routers:	28
Printer:	6
Scanner:	6
Firewalls:	20

Table 3.6 enumerates the various components constituting a computer networking infrastructure, along with their respective quantities. Among these components, workstations dominate with a count of 500, serving as user terminals for daily operations. Supporting the workstations are 50 servers, providing centralized services and resources essential for network

functionality. Switches, numbering 140, manage data traffic within the local area network (LAN), ensuring efficient communication between devices. Routers, comprising 28 units, facilitate data transmission between different networks, enabling seamless connectivity. Additionally, the network includes 6 printers for document output, 6 scanners for digitizing physical documents, and 20 firewalls to safeguard network security. This comprehensive breakdown offers valuable insights into the composition and scale of the network infrastructure, guiding management and optimisation endeavours for enhanced performance and reliability.

Context: Typical for mid-sized companies or educational institutions, this scale is characterized by a larger workforce and diverse operational needs, necessitating an intricate network setup (Lammle, 2016).

Expected Outcomes After Optimisation:

1. Streamlined allocation of skilled workforce
2. Streamlined allocation of unskilled workforce
3. Wages for the skilled workforce
4. Wages for the unskilled workforce
5. Balanced utilisation of skilled labour hours
6. Balanced utilisation of unskilled labour hours
7. Tangible reduction in overall project duration
8. Optimisation of labour costs without compromising quality.

Table 3.7: Large-Scale Scenario (1500 components):

Components	**Number**
Workstations:	1000
Servers:	100
Switches:	270
Routers:	60
Printer:	20
Scanner:	25
Firewalls:	25

Table 3.7 also enumerates the various components constituting a computer networking infrastructure, along with their respective quantities. Among these components, workstations dominate with a count of 500, serving as user terminals for daily operations. Supporting the workstations are 50 servers, providing centralized services and resources essential for network functionality. Switches, numbering 140, manage data traffic within the local area network (LAN), ensuring efficient communication between devices. Routers, comprising 28 units, facilitate data transmission between different networks, enabling seamless connectivity. Additionally, the network includes 6 printers for document output, 6 scanners for digitizing physical documents, and 20 firewalls to safeguard network security. This comprehensive breakdown offers valuable insights into the composition and scale of the network infrastructure, guiding management and optimisation endeavours for enhanced performance and reliability.

Context: Envisioned for large enterprises or data centres, this scenario demands high redundancy, multiple applications, and services. The inherent complexity is attributed to the myriad interconnections and the vast number of devices (Kurose and Ross, 2012).

Expected Outcomes After Optimisation:

1. Strategic allocation of skilled workforces.

2. Strategic allocation of unskilled workforces

3. Wages for the skilled workforce

4. Wages for the unskilled workforce

5. Optimised distribution of skilled labour hours.

6. Optimised distribution of unskilled labour hours

7. Significant reduction in the total number of project days.

8. Minimal labour costs achieved through efficient resource allocation.

Algorithm selection and implementation

The field of computer networking is inundated with challenges, particularly when it comes to cost and labour optimisation. The selection and implementation of suitable optimisation algorithms are pivotal in effectively navigating these challenges. In this research, Ant Colony Optimisation (ACO), Bat Optimisation (BAT), Cuckoo Search Optimisation (CS), and Firefly Optimisation (FA), were chosen for evaluation, each bringing a unique perspective and approach to problem-solving.

Scenario-Based Validation

Standardized Computer Networking Scenarios:

The intricate landscape of computer networks is often dictated by the interplay of size and complexity. While size refers to the sheer number of components within a network, complexity is a multifaceted parameter encompassing installation intricacies, management strategies, and the interdependencies among various network elements (Oppenheimer, 2011; Gillett, 2022). Generally, as the size of a network increases, so does its complexity, adding layers of considerations and challenges (Stallings, 2016; Jawhar *et al.*, 2017). This progression from small to large-scale networks brings about variations in terms of component distribution, security considerations, redundancy requirements, and more. Grounded in industry practices and academic literature, the following scenarios offer a structured insight into three standardized scales of networks. Each scenario provides a snapshot of typical installations and sets the stage for optimisation exercises aiming at various performance metrics including workforce allocation, project duration, costs, and profitability (Olson and Olson, 2022; Tanenbaum and Wetherall, 2011).

Again, the validation of optimisation algorithms necessitates the establishment of standardized computer networking scenarios. These scenarios serve as representative models of real-world network environments, enabling rigorous testing and evaluation of algorithmic performance across varying scales and complexities. By simulating diverse network architectures and operational conditions, researchers can assess the algorithms' robustness, scalability, and adaptability in addressing the dynamic challenges encountered in practical network settings.

In crafting these standardized scenarios, careful consideration has been given to factors such as network size, skilled workforce allocation, and unskilled workforce allocation. Small-scale scenarios may emulate local area networks (LANs) serving small businesses or residential environments, characterized by a limited number of interconnected devices and relatively simple communication patterns. Medium-scale scenarios could mirror enterprise-level networks supporting moderate-sized organisations, encompassing multiple interconnected LANs, wide area network (WAN) connections, and diverse network services. Finally, large-scale scenarios may replicate complex infrastructures found in global enterprises or telecommunications providers, featuring extensive WAN connectivity, distributed server farms, cloud-based services, and stringent security measures. Furthermore, the scenarios incorporate realistic constraints and objectives, including budgetary considerations.

Through rigorous scenario-based validation, researchers can systematically evaluate the efficacy of optimisation algorithms in addressing the diverse needs and challenges of computer networking infrastructure. By aligning algorithmic performance with real-world scenarios, this validation approach provides valuable insights into the algorithms' suitability for practical deployment and informs decision-making processes in network design, management, and optimisation (Russell, 2022).

3.9 Methodological Limitations and delimitations

The limitations and delimitations of a thesis or methodology define the boundaries and potential shortcomings of the study. In the context of optimising a formulated cost model to minimise labour costs in computer networking infrastructure, the following limitations and delimitations can be identified:

The study might be limited by the availability of data and resources, which can impact the generalizability of the findings. The research may need to rely on a specific dataset or limited case studies, which may not fully represent the entire spectrum of computer networking infrastructure.

Algorithm Selection: The choice of optimisation algorithms used to enhance the cost model can be a limitation. Different algorithms may have varying levels of effectiveness and efficiency in capturing the complexities of labour costs in this specific context. The study will need to acknowledge and discuss the limitations of the selected algorithms.

Assumptions: Like any modelling approach, the formulated cost model will be based on certain assumptions. These assumptions may simplify or overlook certain factors or dynamics that affect labour costs. The study should explicitly state these assumptions and discuss their potential impact on the accuracy and applicability of the model.

External Factors: The methodology may not fully account for external factors that can influence labour costs in the computer networking infrastructure. Economic conditions, technological advancements, or changes in industry standards might impact on labour costs but are not explicitly incorporated in the study. This limitation should be acknowledged, and the implications of these external factors on the model's validity and generalizability should be discussed.

By recognising and addressing these limitations and delimitations, the study can provide a clear understanding of its scope and potential constraints, enabling future researchers to build upon its findings and improve the methodology.

3.10 Summary

This chapter has laid out the methodological framework for the research study aimed at optimising labour costs in computer networking infrastructure. It emphasizes the indispensable role of computer networks in modern interconnected environments and their significance across diverse organisational domains. The primary goal of this study is to develop a robust cost model that precisely captures labour expenses while identifying the key factors influencing labour costs within this domain.

The methodological framework presented herein underscores the researcher's philosophical stance, aligning with a positivist worldview and employing a quantitative research approach. This approach is deemed suitable for the study's deterministic objectives of minimising labour costs. The chapter elucidates the research design, emphasizing the utilisation of quantitative methodologies to measure variables and address theory-driven research questions and hypotheses.

Furthermore, the chapter delineates the sequential steps to be undertaken in the research process. These steps encompass the development of an enhanced cost model, identification of pivotal factors within the model, refinement of the model through algorithmic integration and metric augmentation, and an exhaustive assessment of its reliability and effectiveness across diverse scenarios.

The methodological exposition provides a detailed overview of the approach taken in solving the labour cost optimisation problem. The formulated cost model is presented alongside its variables and constraints, with critical factors such as labour size and execution time highlighted as fundamental elements in achieving cost minimisation. Additionally, the chapter discusses the evaluation and optimisation of the cost model using prominent algorithms, including Ant Colony Optimisation (ACO), BAT Optimisation, Cuckoo Search Optimisation (CS), Firefly Optimisation (FA), and Fox Prey Optimisation (FPO).

In summation, this chapter serves as a comprehensive precursor to the research endeavour, providing a systematic introduction to the problem, elucidating the research approach and methodology, and furnishing a well-defined pathway towards accomplishing the research objectives in subsequent chapters.

Chapter 4: Experimental Results and Analysis

4.1 Introduction

In this chapter, the study transitions from the methodological framework outlined in Chapter 3 to the empirical examination of the carefully formulated cost model enhanced by bio-inspired algorithms. Building upon the groundwork laid in the previous chapter, the study delves into the results obtained from executing these algorithms across three distinct scenarios. By examining the performance of each algorithm under different settings, the study aims to elucidate their efficacy and suitability for addressing real-world optimisation challenges in network infrastructure deployment.

The investigation in this chapter aims to assess the effectiveness of the Fox Prey Optimisation (FPO) algorithm in comparison to well-established counterparts, specifically Ant Colony Optimisation (ACO), Bat Optimisation (BAT), Cuckoo Search Optimisation (CS) and Firefly Optimisation (FA). Each algorithm undergoes thorough scrutiny across three distinct scenarios, thoughtfully tailored to represent the diverse challenges inherent in networking environments.

Furthermore, the inclusion of three thoughtfully crafted datasets, each specifically designed to align with the scenarios presented, enhances the robustness of the evaluation. These datasets, finely tuned to emulate the intricacies of real-world networking projects, serve as rigorous tests for assessing the adaptability and efficiency of the algorithms under examination.

As the study navigates through the results of this comprehensive analysis, the chapter unfolds the comparative performances, strengths and weaknesses of each algorithm within the nuanced contexts of the scenarios presented. The outcomes not only decipher the algorithms' prowess in cost minimisation but also provide invaluable insights into their applicability across distinct networking landscapes.

In essence, this chapter serves as the empirical cornerstone, shedding light on the tangible implications and applicability of the bio-inspired optimisation framework in the dynamic realm of computer networking infrastructure.

4.2 Outline of Experimental Steps

- Experimental Setup: Configure the experimental environment with appropriate hardware and software resources. Establish parameters such as population size, iteration count, convergence criteria and termination conditions for each algorithm.
- Dataset Preparation: Curate three datasets, each corresponding to one of the selected scenarios. Populate these datasets with relevant parameters and constraints extracted from real-world networking projects. Ensure that the datasets accurately capture the complexities and nuances of the chosen scenarios.

- Selection of Scenarios: Identify and define three distinct scenarios representative of real-world challenges in installation of computer networking infrastructure projects. These scenarios should encompass varying project complexities, sizes and resource constraints.

- Formulation of Cost Model: Develop a comprehensive cost model tailored to the specific requirements of each scenario. Incorporate factors such as daily fixed costs, workforce allocation, hourly rates, project duration and penalty coefficients to accurately reflect the labour cost dynamics.

- Bio-Inspired Optimisation Algorithm Selection: Choose appropriate bio-inspired optimisation algorithms, including the Ant Colony Optimisation (ACO), Bat Optimisation (BAT), Cuckoo Search Optimisation (CS), Firefly Optimisation (FA) and Fox Prey Optimisation (FPO) algorithm. Ensure that each algorithm is suitable for addressing the optimisation objectives of labour cost minimisation in installation of computer networking infrastructure projects.

- Implementation of Algorithms: Implement the selected bio-inspired optimisation algorithms using the Python programming language. Integrate the cost model into the optimisation framework to facilitate objective function evaluations during the optimisation process.

- Execution of Experiments: Execute the optimisation algorithms for each scenario using the prepared datasets. Monitor the convergence behaviour, solution quality and computational efficiency of the algorithms throughout the experimentation process.

- Performance Evaluation: Output results are evaluated on the bases of performance of each algorithm using key metrics such as convergence speed and computational complexity. Compare the results obtained from different algorithms across the three scenarios to identify strengths and weaknesses.

- Statistical Analysis: Perform statistical analysis, including hypothesis testing and variance analysis, to validate the significance of observed differences in algorithm performance. Determine the statistical significance of the results and draw meaningful conclusions.

4.3 Experimental Settings

4.3.1 Networking Infrastructure settings

Table 4.1 outlines the constraints for a computer networking infrastructure project. The table specifies expected values, lower bounds, and upper bounds for various project dimensions, ensuring the project's scope and budget are clearly defined. Key parameters include daily fixed costs ($150), the total number of tasks (100), and the total project days (75). Labor-related constraints cover both skilled and unskilled workers, detailing their daily numbers, hourly rates, and installation hours. Additionally, a penalty coefficient for delays and an upper bound on total project days are included to manage project timelines and potential overruns.

Table 4.1: Constraints for Computer Networking Infrastructure Project

Dimension	Description	Expected Value	Lower Bound	Upper Bound
k	Daily fixed costs	$150	$100	$200
n	Total number of tasks	100	50	150
a	Daily skilled workers	12	5	20
b	Hourly rate for skilled worker	$30	$20	$40
c	Installation hours (skilled worker)	7	6	8
d	Daily unskilled workers	20	10	30
e	Hourly rate for unskilled worker	$15	$10	$20
f	Installation hours (unskilled worker)	7	6	8
T	Total project days	75	60	90
α	Penalty coefficient	1000	10000	100000
$Tmax$	Upper bound total project days	45	50	70

4.3.2 Hardware settings

The hardware infrastructure employed for conducting experiments and analyses in this thesis comprises a high-performance computing setup with the following specifications: an Intel Xeon E5-2680 v4 processor with 2.4 GHz base frequency, 64 GB of DDR4 RAM, and an NVIDIA Tesla K80 GPU. This was chosen for its computational power, reliability, and scalability.

The Intel Xeon processor and NVIDIA GPU facilitate efficient execution of optimisation algorithms, data processing tasks, and statistical analyses, ensuring timely completion of experiments and accurate interpretation of results. Additionally, the 64 GB of DDR4 RAM and 1 TB SSD storage offer ample storage capacity and memory resources, accommodating large datasets and computational workloads without compromising performance.

Leveraging such robust hardware infrastructure enhances the efficiency and reliability of experiments, enabling researchers to conduct rigorous analyses and derive meaningful insights with confidence.

4.3.3 Computational Complexity

Computational complexity analysis is essential for improving optimisation algorithms for various reasons. It helps evaluate the efficiency of these algorithms in terms of time and space requirements, providing insights into how their performance scales with increasing problem size. It also aids in performance comparison, identifying which algorithms offer better performance for specific tasks or problem domains. Understanding computational complexity allows for effective allocation of computational resources, determining the hardware and infrastructure needed for efficient execution. It also helps predict the performance of optimisation algorithms as the size of the optimisation problem grows, providing insights into their scalability and suitability for large-scale problems.

The objectives of computational complexity analysis include performance evaluation, efficiency comparison, resource optimisation, scalability assessment, and decision support. Performance evaluation assesses the efficiency of optimisation algorithms in terms of time and space requirements, while efficiency comparison compares the efficiency of different algorithms. Resource optimisation involves optimising the allocation of computational resources, such as CPU time and memory usage, to ensure efficient and effective utilisation. Scalability assessment determines the algorithm's performance as the complexity of the problem increases. Decision support provides valuable information for decision-making processes, such as algorithm selection, system design, and resource allocation. Overall, computational complexity analysis provides insights into the efficiency, scalability, and suitability of optimisation algorithms for solving real-world problems, supporting decision-making processes, and optimising computational resource use.

Computational Complexity: This is a broader concept that encompasses both time complexity and space complexity. It refers to the overall measure of the resources (time and space) required by an algorithm to solve a problem (Dean, 2015).

Time Complexity: Time complexity specifically focuses on measuring the amount of time (or number of operations) required by an algorithm to complete its task as a function of the input size. It describes how the runtime of an algorithm scales with increasing input size (Tang, Xiao and Shi, 2014).

Space Complexity: This, on the other hand, measures the amount of memory (or space) required by an algorithm to execute as a function of the input size. It describes how the memory usage of an algorithm scales with increasing input size (Alwen, Blocki and Pietrzak, 2018).

Asymptotic Notations: Asymptotic notations, such as Big O notation, Theta notation, and Omega notation, are used to express the time and space complexities of algorithms in terms of their growth rates. They provide a standardized way to describe how an algorithm's performance (either in terms of time or space) changes as the input size grows towards infinity (Iqbal *et al.*, 2019).

In summary, computational complexity encompasses both time and space complexities, while asymptotic notations provide a formal framework for expressing these complexities in a concise and standardized manner. Time complexity focuses on the runtime of algorithms, space complexity focuses on memory usage, and asymptotic notations provide a means for analysing and comparing algorithmic efficiency.

The following captured equations 4.1, 4.2 and 4.3, $Computational\ complexity = O(N * m)$, (Shahjalal et al., 2022), computes the algorithm's computational complexity

$$\boldsymbol{Computational\ complexity = O(N * m)} \qquad \textit{Equation 4.1}$$

where

N is the number of generations

m is the size of fox population

$$\textbf{\textit{Computational complexity for algorithms}} = \boldsymbol{O}(\mathbf{60} * \mathbf{50}) \qquad \textit{Equation 4.2}$$

$$\therefore \textbf{\textit{Computational complexity for algorithms}} = \boldsymbol{O}(\mathbf{3000}) \qquad \textit{Equation 4.3}$$

Table 4.2: Computational Complexity for the Selected Algorithms

Algorithm	Generation (N)	Population (m)	Computational Complexity
Ant Colony Optimisation	60	50	O(3000)
Bat Optimisation	60	50	O(3000)
Cuckoo Search Optimisation	60	50	O(3000)
Firefly Optimisation	60	50	O(3000)
Fox Prey Optimisation	60	50	O(3000)

Table 4.2 presents selected optimisation algorithms along with their corresponding parameters and computational complexities. Each row represents a different optimisation algorithm, including Ant Colony Optimisation, Bat Optimisation, Cuckoo Search Optimisation, Firefly Optimisation and Fox Prey Optimisation.

Computational Complexity as in Equation 4.1

The "Generation (N)" column indicates the number of generations or iterations used in the optimisation process for each algorithm, which is consistent at 60 across all entries. Similarly, the "Population (m)" column specifies the size of the population, or the number of solutions considered in each iteration, with a consistent value of 50 for all algorithms.

The last column, "Computational Complexity," provides insights into the computational resources required by each algorithm. Computational complexity is denoted using big O notation O(·)), indicating the worst-case scenario for time or space complexity as a function of the input size. Remarkably, all algorithms exhibit the same computational complexity, stated as O(3000), suggesting similar computational resource requirements across the board.

In summary, Table 4.2 offers a comparison of various optimisation algorithms based on their parameters and computational complexities. Despite differences in algorithmic approaches, all listed algorithms demonstrate uniformity in terms of the number of generations, population size and computational complexity, indicating comparable resource demands under worst-case scenarios. However, the actual performance may vary depending on specific problem characteristics and implementation details.

4.3.4 Programming Language

Python was selected as the primary programming language for its user-friendly syntax, extensive library support, and versatility in scientific computing (Kulyashov *et al.*, 2023: Gründner, 2022). With its rich ecosystem of libraries such as NumPy, SciPy, Pandas, and Matplotlib, Python offers powerful tools for data manipulation, analysis and visualization; streamlining the implementation and evaluation of optimisation algorithms (da Ponte, 2023; Nnamdi, 2023). Its readability and ease of use make it accessible to researchers with varying levels of programming expertise, facilitating collaborative development and experimentation (Musyaffa, Rapp and Gohlke, 2023). Moreover, Python's compatibility with various platforms and its active community support contribute to its widespread adoption in research and industry, ensuring seamless integration with existing workflows and tools (Ejarque *et al.*, 2022; Mikkola *et al.*, 2021). Its characteristics are captured in Table 4.3.

Table 4.3: Python Characteristics

Advantages	Description
Ease of Use	Python's simple and intuitive syntax makes it accessible to researchers and practitioners with diverse backgrounds, enabling rapid development and experimentation (Ivezić *et al.*, 2020).
Wide Range of Libraries	Python boasts a vast ecosystem of libraries tailored for scientific computing, machine learning and data analysis, providing researchers with comprehensive tools for implementing and evaluating optimisation algorithms (Liu, 2020).
Community Support	Python benefits from a vibrant and active community of developers and researchers who contribute to its ongoing development, offer support and share knowledge through forums, tutorials and online resources (Vasilescu *et al.*, 2014)
Cross-Platform Compatibility	Python is compatible with major operating systems, including Windows, macOS, and Linux, ensuring portability and flexibility in research environments (Williams, 2019).
Integration Capabilities	Python seamlessly integrates with other programming languages and tools, facilitating interoperability and enabling researchers to leverage existing libraries and frameworks within their projects (Huber *et al.*, 2021).

4.4 Experiment Dataset

A fundamental component of research, a dataset provides the foundational structure for analysis and experimentation. In this thesis, an AI-generated standard dataset was carefully crafted and systematically tested to ensure its reliability and suitability for research endeavours (Nketsiah, Edem Agbehadji, *et al.*, 2024). Given the unavailability of a dataset meeting specific criteria, the study team opted to generate it with AI, enabling precise tailoring to the research needs. Utilizing advanced artificial intelligence algorithms, the dataset was thoroughly calibrated and validated to maintain accuracy and fidelity to real-world networking scenarios. Following its creation, the dataset underwent extensive testing by seasoned computer network engineers across multiple sites, employing predetermined scenarios outlined in previous studies (Nketsiah, Edem Agbehadji, *et al.*, 2024). Through these evaluations conducted under varying conditions, the dataset's robustness and applicability across diverse networking environments were affirmed by consistent accurate performance and reliable outputs that closely mirrored expected results in real-world applications.

To evaluate the dataset's accuracy, comprehensiveness and real-world applicability, a carefully designed testing process was implemented (Nketsiah, Edem Agbehadji, *et al.*, 2024). A team of experienced network engineers, proficient in networking principles and methodologies, executed the testing procedures with precision and expertise. The testing regimen included comprehensive procedures such as data validation, scenario simulation and performance analysis to ensure thorough evaluation.

The testing results revealed notable consistencies crucial to the thesis's primary objective of minimizing total labour costs in installation of computer networking infrastructure projects (Nketsiah, Edem Agbehadji, *et al.*, 2024). Specifically, the Firefly algorithm (FA) consistently demonstrated the lowest costs across all three test sites for scenario 1; while the Fox Prey Optimisation (FPO) algorithm constantly exhibited the lowest costs for scenarios 2 and 3 at all test sites. This consistency in results highlights the effectiveness of the dataset in achieving the objectives of the thesis.

Furthermore, the dataset's performance was evaluated at multiple sites under the same scenarios but different conditions. This comprehensive evaluation provided valuable insights into the dataset's versatility and suitability for various networking projects, ensuring its reliability across diverse environmental factors and project complexities.

In conclusion, the justification and testing process of the standard dataset underscore its reliability and effectiveness in supporting research endeavours in the field of initial installation of user-specified computer networking infrastructure projects. The thorough assessment conducted by seasoned experts ensures that the dataset meets accurate standards of quality and accuracy, thereby enhancing the credibility and validity of research findings.

4.5 Performance Metrics

Metrics play a fundamental role in assessing the performance of cost models within the realm of computer networking. While various metrics such as accuracy, speed, scalability and robustness are deemed essential, the emphasis on accuracy stands out as particularly crucial. As highlighted by Chen, Qian and Xiong (2021), prioritizing accuracy is paramount to ensuring that organisations can rely on the predictions generated by the cost model for informed decision-making processes.

In line with this emphasis on accuracy, the proposed cost model in this study places a significant emphasis on refining predictive accuracy to ensure the reliability of its outcomes. By integrating accuracy as a primary metric, the model aims at providing organisations with dependable estimates of labour costs associated with installation of computer networking infrastructure projects. However, it is important to note that while accuracy is prioritized, it is not the sole metric considered.

In addition to accuracy, the model also takes into account other essential metrics such as speed, scalability and robustness. Speed refers to the efficiency with which the model generates cost estimates, ensuring timely decision-making processes. Scalability addresses the model's ability to handle increasing amounts of data and complexity without compromising performance. Robustness pertains to the model's ability to maintain accuracy and performance even when faced with uncertainties or variations in input data.

By incorporating a diverse range of metrics, the proposed cost model offers a more comprehensive and reliable evaluation of labour costs in installation of computer networking infrastructure projects. This multi-faceted approach ensures that organisations can make informed decisions based on a thorough understanding of the cost implications associated with various project parameters.

However, despite the rigor of these metrics, it is imperative to acknowledge that no model is without its shortcomings. While the proposed cost model strives to optimise accuracy, speed, scalability and robustness, it is essential to remain cognizant of potential limitations and uncertainties inherent in any predictive modelling endeavour. As such, ongoing validation and refinement of the model are necessary to address emerging challenges and ensure its continued relevance and effectiveness in practical applications.

Methodologies for Evaluation:

Algorithm Benchmarking: This study evaluates the performance of bio-inspired optimization algorithms (e.g., genetic algorithms, particle swarm optimization and ant colony optimization) by comparing them against each other and selecting the one that is most suitable to manage the problem at hand.

Sensitivity Analysis: Assess the robustness of optimisation algorithms by varying input parameters and examining their impact on performance metrics.

Comparative Study: Conduct a comparative analysis of different algorithms based on their performance across multiple metrics to identify strengths and weaknesses in labour cost minimisation.

Conclusion:

By defining and evaluating performance metrics aligned with the objectives of the cost model, this thesis aims at providing a comprehensive assessment of bio-inspired optimisation techniques for minimising labour costs in computer networking infrastructure. Through rigorous analysis and quantifiable comparisons, insights into the effectiveness of various algorithms will be gained, facilitating informed decision-making in project management and resource allocation.

4.6 Statistical Analysis of Results

The null hypothesis posits that there is no significant difference in the total labour costs minimization achieved by the algorithms. This means that any observed variations in their performance are considered to be due to random chance rather than a real difference in the effectiveness of the algorithms.

In contrast, the alternative hypothesis suggests that there is a significant difference in the total labour costs minimization achieved by the algorithms. This implies that at least one of the algorithms performs differently—either better or worse—in terms of minimizing labour costs, and this difference is not attributable to random variation.

When conducting a statistical test, one starts with the assumption that the null hypothesis is true. The goal is to use the data to test this hypothesis. If the evidence from the data is strong enough to reject the null hypothesis, the alternative hypothesis is accepted. This involves calculating a test statistic and comparing it to a critical value, or determining a p-value, to assess whether the observed differences are statistically significant.

To perform a Kruskal-Wallis's test to compare the total labour costs minimisation achieved by the algorithms, these steps are to be followed:

Formulate the null hypothesis (H0) and the alternative hypothesis (H1).
Calculate the rank sums for each algorithm.
Compute the Kruskal-Wallis's test statistic.
Determine the critical value or p-value for the test statistic.
Make a decision regarding the null hypothesis based on the critical value or p-value.

Firstly, proceed with these steps using the provided data for the three scenarios. Secondly, calculate the Kruskal-Wallis's test statistic and lastly, determine whether there are statistically significant differences in the total labour costs minimisation achieved by the algorithms.

Here are the steps for each scenario:

Scenario 1:

Hypotheses:

Null Hypothesis (H0): There is no significant difference in the total labour costs minimisation achieved by the algorithms.

Alternative Hypothesis (H1): There is a significant difference in the total labour costs minimisation achieved by the algorithms.

Steps:

Calculate the rank sums for each algorithm.

Compute the Kruskal-Wallis's test statistic.

Determine the critical value or p-value for the test statistic.

Make a decision regarding the null hypothesis based on the critical value or p-value.

The study will repeat these steps for scenarios 2 and 3 later, as it proceeds with the calculations for Scenario 1.

Hypotheses:

Null Hypothesis (H0): There is no significant difference in the total labour costs minimisation achieved by the algorithms.

Alternative Hypothesis (H1): There is a significant difference in the total labour costs minimisation achieved by the algorithms.

Step 1:

Collect Data: The study runs each algorithm 5 times and recorded their performance scores as in Table 4.4. Thereafter, it assigned ranks to the total minimised labour costs (x) for each algorithm, as captured in steps 4 (ties are considered, if available).

Table 4.4: Test Results of Total Minimised Labour Costs (x) for Scenario_1

Algorithm	Test Results of Total Minimised Labour Costs (x)				
ACO	866	840	909	1001	700
BAT	875	615	789	777	695
CS	1816	1790	1601	983	939
FA	654	795	790	725	698
FPO	799	1014	886	912	801

Step 2: Combine all Data:

Here are the combined data points: 866, 840, 909, 1001, 700, 875, 615, 789, 777, 695, 1816, 1790, 1601, 983, 939, 654, 795, 790, 725, 698, 799, 1014, 886, 912, 801.

Step 3: The combined data is now arranged in ascending order: 615, 654, 695, 698, 700, 725, 777, 789, 795, 799, 801, 840, 866, 875, 886, 909, 912, 939, 940, 983, 1001, 1014, 1601, 1790, 1816

Step 4: With the combined data arranged in ascending order, as in step 3, ranking them become easier as showcased here in step 4. Note: (ties are given average ranks where applicable): 615(1), 654(2), 695(3), 698(4), 700(5), 725(6), 777(7), 789(8), 790(9), 795(10), 799(11), 801(12), 840(13), 866(14), 875(15), 886(16), 909(17), 912(18), 939(19), 983(20), 1001(21), 1014(22), 1601(23), 1790(24), 1816(25).

Scenario 1: Output Rankings for Each Algorithm

Step 5 examines the output rankings for each group or algorithm. The data in Table 4.5 displays the sum rankings for the selected algorithms:

Table 4.5: Rankings of selected algorithms for Scenario 1

Algorithm	Rank Expression	Output
ACO	R1	70
BAT	R2	34
CS	R3	111
FA	R4	31
FPO	R5	79
Sum		325

Table 4.5 summarizes the sum output rankings for each algorithm. The output ranking for the Ant Colony Optimisation (ACO) algorithm is 70. The BAT algorithm has an output ranking of 34, while the Cuckoo Search (CS) algorithm has an output ranking of 111. The Firefly Optimisation (FA) algorithm has an output ranking of 31, and the Fox Prey Optimisation (FPO) algorithm has an output ranking of 79.

Finally, the total output of rankings for all algorithms is 325. This sum output should match the series of the 25 rankings, equalling 325, and may be higher when ties occur in some of the results.

Step 6: Calculate the Test Statistic:

The Kruskal-Wallis's test statistic (H) is calculated using Equation 4.4

$$\boldsymbol{H} = \frac{\mathbf{12}}{\boldsymbol{N}(\boldsymbol{N}+\mathbf{1})}\left(\sum_{i=1}^{k}\frac{\boldsymbol{R}_i^2}{\boldsymbol{n}_i} - \mathbf{3}(\boldsymbol{N}+\mathbf{1})\right) \qquad \textit{Equation 4.4}$$

Where:

N is the total number of observations (in this case, 25) across all groups.

Ri is the sum of ranks for the *i*th group. (This varies for each algorithm)

ni is the number of observations in the *i*th group (in this case, 5).

To calculate H using the provided data

Given:

$$\boldsymbol{total\ number\ of\ observations\ across\ all\ groups(N) = 25}$$

Number of observations in each group (n_i) = 5 (since there are 5 observations for each algorithm)

To calculate H, the study used Equation 4.4 of which the end result is captured by Equation 4.6

$$\boldsymbol{H = \frac{12}{25(25+1)}\left(\frac{70^2}{5} + \frac{34^2}{5} + \frac{111^2}{5} + \frac{31^2}{5} + \frac{79^2}{15} - 3 \times (25+1)\right)} \qquad \textit{Equation 4.5}$$

$$\boldsymbol{H = 16.44} \qquad \textit{Equation 4.6}$$

Step 7: Determine the critical value or p-value for the test statistic.

The study compared the computed test statistic (H) to the critical value from the chi-square distribution with degrees of freedom equal to the number of groups minus 1.

Determining the critical value using a significance level (α) of 0.05 (typical for hypothesis testing).

To determine the critical value for the Kruskal-Wallis test, the chi-square distribution table is consulted with degrees of freedom equal to the number of groups minus 1. For 5 groups, this results in 4 degrees of freedom.

A chi-square distribution table is a reference table used in statistics to find critical values for the chi-square distribution. It provides values of the chi-square statistic for different degrees of freedom and significance levels, aiding in hypothesis testing and assessing goodness-of-fit. The table helps determine whether the observed data significantly deviates from the expected values, based on specified levels of confidence. Refer to Table 4.6.

Table 4.6: Chi-Square Distribution Table

Probability level (alpha)						
df	0.5	0.10	0.05	0.02	0.01	0.001
1	0.455	2.706	3.841	5.412	6.635	10.827
2	1.386	4.605	5.991	7.824	9.210	13.815
3	2.366	6.251	7.815	9.837	11.345	16.268
4	3.357	7.779	9.488	11.668	13.277	18.465
5	4.351	9.236	11.070	13.388	15.086	20.517

Using a significance level (α) of 0.05, it found the critical value from the chi-square distribution table for df=4.

Finding the critical value involves determining the threshold at which the null hypothesis can be rejected. This value is typically found using the chi-square distribution table, based on the desired significance level (α) and the degrees of freedom (df) for the test.

The critical value for a Kruskal-Wallis test with df=4 and a significance level (α) of 0.05 is approximately 9.488. Refer to Table 4.6

Step 8: Make a decision regarding the null hypothesis based on the critical value or p-value

Since the computed test statistic (H=16.44), as captured in equation 4.6, is greater than the critical value (9.488), the study rejects the null hypothesis.

Conclusion: There is sufficient evidence to suggest that there is a significant difference in the total labour costs minimisation achieved by the algorithms in Scenario 1.

The study now focuses on performing similar analyses for Scenarios 2 and 3 to compare the total labour costs minimisation achieved by the algorithms in those scenarios.

For Scenario 2 and Scenario 3, the study will repeat the same steps.

- **Scenario 2:**

Step 1: Calculate the rank sums for each algorithm, using data in Table 4.7.

Table 4.7: Test Results of Total Minimised Labour Costs (*x*) for Scenario_2

Algorithm	Test Results of Total Minimised Labour Costs (*x*)				
ACO	180486	140298	129548	109198	149980
BAT	85331.4	91552	89021	87779	90181
CS	95892.4	89079	96831	98312	99312
FA	95015	97471	87899	92498	98187
FPO	87478.2	83947	85742	84978	86792

Step 2: Combine all Data: These are the combined data points: 180486, 140298, 129548, 109198, 149980, 85331.4, 91552, 89021, 87779, 90181, 95892.4, 89079, 96831, 98312, 99312, 95015, 97471, 87899, 92498, 98187, 87478.2, 83947, 85742, 84978, 86792.

Step 3: The combined data is now arranged in ascending order: 83947, 84978, 85331.4, 85742, 86792, 87478.2, 87779, 87899, 89021, 89079, 90181, 91552, 92498, 95015, 95892.4, 96831, 97471, 98187, 98312, 99312, 109198, 129548, 140298, 149980, 180486

Step 4: With the combined data arranged in ascending order, as in step 3, ranking them become easier as shown here in step 4. Note: (ties are given average ranks where applicable): 83947(1), 84978(2), 85331.4(3), 85742(4), 86792(5), 87478.2(6), 87779(7), 87899(8), 89021(9), 89079(10), 90181(11), 91552(12), 92498(13), 95015(14), 95892.4(15), 96831(16), 97471(17), 98187(18), 98312(19), 99312(20), 109198(21), 129548(22), 140298(23), 149980(24), 180486(25).

Scenario 2: Output Rankings for Each Algorithm

Step 5 examines the output rankings for each group or algorithm. Table 4.8 below displays the sum output rankings for the selected algorithms:

Table 4.8: Rankings of selected algorithms for Scenario 2

Algorithm	Rank Expression	Output
ACO	R1	115
BAT	R2	42
CS	R3	80
FA	R4	70
FPO	R5	18
Sum		325

Table 4.8 summarizes the sum rankings for each algorithm. The Ant Colony Optimisation (ACO) algorithm has a sum ranking of 115, the BAT algorithm has a sum ranking of 42, and the Cuckoo Search (CS) algorithm has a sum ranking of 80. The Firefly Optimisation (FA) algorithm has a sum ranking of 70, while the Fox Prey Optimisation (FPO) algorithm has the lowest sum ranking of 18.

The total sum of rankings for all algorithms, as captured by Table 4.8, is 325, matching the series of 25 rankings. This ensures consistency across the evaluations and highlights the relative performance of each algorithm. However, the summation occasionally becomes more if some of the results are tied.

Step 6: Calculate the Test Statistic:

The Kruskal-Wallis test statistic (H) is calculated using Equation 4.4 as captured earlier.

Where:

N is the total number of observations (in this case, 25) across all groups.

Ri is the sum of ranks for the ith group. (This varies for each algorithm)

ni is the number of observations in the ith group (in this case, 5).

To calculate H using the provided data,

Given:

$$\boldsymbol{total\ number\ of\ observations\ across\ all\ groups(N) = 25}$$

Number of observations in each group (n_i) = 5 (since there are 5 observations for each algorithm).

Equation 4.4 was utilized in the study to compute H, and Equation 4.8 captures the final result.

$$\boldsymbol{H = \frac{12}{25(25+1)}\left(\frac{115^2}{5} + \frac{42^2}{5} + \frac{80^2}{5} + \frac{70^2}{5} + \frac{18^2}{5} - 3 \times (25+1)\right)} \quad \textit{Equation 4.7}$$

$$\boldsymbol{H = 20.26} \quad \textit{Equation 4.8}$$

Step 7: Determine the critical value or p-value for the test statistic.

The study compared the computed test statistic (H) to the critical value from the chi-square distribution with degrees of freedom equal to the number of groups minus 1.

Determine the critical value using a significance level (α) of 0.05 (typical for hypothesis testing).

To determine the critical value for the Kruskal-Wallis test, the chi-square distribution table with degrees of freedom equal to the number of groups minus 1, is consulted.

A chi-square distribution table is a reference table used in statistics to find critical values for the chi-square distribution. It provides values of the chi-square statistic for different degrees of freedom and significance levels, aiding in hypothesis testing and assessing goodness-of-fit. The table helps determine whether the observed data significantly deviates from the expected values, based on specified levels of confidence. Refer to Table 4.5.

Step 7.1: Determine the critical value or p-value for the test statistic.

Using a significance level (α) of 0.05, the critical value for a Kruskal-Wallis test with df=4 is approximately 9.488. Make reference to Table 4.5

Step 8: Make a decision regarding the null hypothesis based on the critical value or p-value.

Since the computed test statistic (H=20.26), (see Equation 4.8), is greater than the critical value (9.488), as captured by Table 4.5, the study rejects the null hypothesis.

Conclusion: There is sufficient evidence to suggest that there is a significant difference in or more of the total labour costs minimisation achieved by the algorithms in Scenario 2.

- **Scenario 3:**

The study repeats the same steps for Scenario 3. The study thus proceeds with the calculations.

Step 1: For Scenario 3, calculate the rank sums for each algorithm using tabulated data in Table 4.9.

Table 4.9: Algorithmic Ranking Table for Scenario 3

Algorithm	Test Results of Total Minimised Labour Costs (x)				
ACO	366489	385744	484805	419988	368430
BAT	276249	296150	279009	279799	295801
CS	383156	389156	388456	348848	463757
FA	308918	299700	309002	297725	306981
FPO	272418	285485	279978	291901	285017

Step 2: Combine all Data: These are the combined data points: 366489, 385744, 484805, 419988, 368430, 276249, 296150, 279009, 279799, 295801, 383156, 389156, 388456,

348848, 463757. 308918, 299700, 309002, 297725, 306981, 272418, 285485, 279978, 291901, 285017

Step 3: The combined data is now arranged in ascending order: 272418, 276249, 279009, 279799, 279978, 285017, 285485, 291901, 295801, 296150, 297725, 299700, 306981, 308918, 309002, 348848, 366489, 368430, 383156, 385744, 388456, 389156, 419988, 463757, 484805

Step 4: With the combined data arranged in ascending order, as in step 3, ranking them become easier as showcased here in step 4. Note: (ties are given average ranks where applicable): 272418(1), 276249(2), 279009(3), 279799(4), 279978(5), 285017(6), 285485(7), 291901(8), 295801(9), 296150(10), 297725(11), 299700(12), 306981(13), 308918(14), 309002(15), 348848(16), 366489(17), 368430(18), 383156(19), 385744(20), 388456(21), 389156(22), 419988(23), 463757(24), 484805(25)

Scenario 3: Output Rankings for Each Algorithm

Step 5 examines the output rankings for each group or algorithm. Table 4.10 demonstrates the sum rankings for the selected algorithms:

Table 4.10: Rankings of selected algorithms for Scenario 3

Algorithm	**Rank Expression**	**Output**
ACO	R1	103
BAT	R2	28
CS	R3	102
FA	R4	65
FPO	R5	27
Sum		325

Table 4.10 summarizes the sum output rankings for each algorithm. The output ranking for the Ant Colony Optimisation (ACO) algorithm is 103. The BAT algorithm has an output ranking

of 28, while the Cuckoo Search (CS) algorithm has an output ranking of 102. The Firefly Optimisation (FA) algorithm has an output ranking of 65, and the Fox Prey Optimisation (FPO) algorithm has an output ranking of 27.

Finally, the total output of rankings for all algorithms is 325. This sum output should match the series of the 25 rankings, equalling 325, and may be higher when ties occur in some of the results.

Step 6: Calculate the Test Statistic:

The Kruskal-Wallis test statistic (H) is calculated using Equation 4.4, which had already been captured.

Where:

N is the total number of observations (in this case, 25) across all groups.

Ri is the sum of ranks for the *i*th group. (This varies for each algorithm)

ni is the number of observations in the *i*th group (in this case, 5).

To calculate *H* using the provided data.

Given:

$$\boldsymbol{total\ number\ of\ observations\ across\ all\ groups(N) = 25}$$

Number of observations in each group (n_i) = 5 (since there are 5 observations for each algorithm)

The study employed the given equation, such as Equation 4.4 for scenario 3, to determine H. The calculated value of H evaluated to 20.77 and it is captured in Equation 4.10.

$$\boldsymbol{H = \frac{12}{25(25+1)}\left(\frac{103^2}{5} + \frac{28^2}{5} + \frac{102^2}{5} + \frac{65^2}{5} + \frac{27^2}{5} - 3 \times (25+1)\right)} \qquad \textit{Equation 4.9}$$

$$\boldsymbol{H = 20.77} \qquad \textit{Equation 4.10}$$

Step 7: Determine the critical value or p-value for the test statistic.

The study compared the computed test statistic (H) to the critical value from the chi-square distribution with degrees of freedom equal to the number of groups minus 1.

Determining the critical value using a significance level (α) of 0.05 (typical for hypothesis testing).

The chi-square distribution table with degrees of freedom equal to the number of groups minus one is examined in order to get the critical value for the Kruskal-Wallis test.

A chi-square distribution table is a reference table used in statistics to find critical values for the chi-square distribution. It provides values of the chi-square statistic for different degrees of freedom and significance levels, aiding in hypothesis testing and assessing goodness-of-fit. The table helps determine whether the observed data significantly deviates from the expected values, based on specified levels of confidence as in Table 4.6

Step 7.1: Determine the critical value or p-value for the test statistic.

Using a significance level (α) of 0.05, the critical value for a Kruskal-Wallis test with df=4 is approximately 9.488. Make reference to Table 4.6

Step 8: Make a decision regarding the null hypothesis based on the critical value or p-value.

Since the computed test statistic (H=20.77), (see equation 4.10), is greater than the critical value (9.488), the study rejects the null hypothesis.

Conclusion: There is sufficient evidence to suggest that there is a significant difference in the total labour costs minimisation achieved by the algorithms in Scenario 3.

Based on the results of the Kruskal-Wallis test for all three scenarios, the study can conclude that there is a significant difference in the total labour costs minimisation achieved by the algorithms across different scenarios.

By defining performance metrics aligned with cost minimisation objectives and conducting robust statistical analysis, this thesis aims to provide a comprehensive evaluation framework for bio-inspired optimisation techniques in installation of computer networking infrastructure projects. Statistical validation of observed differences in algorithm performance enhances the reliability and interpretability of evaluation results, enabling informed decision-making in project management and resource allocation.

Table 4.11: Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	Iteration categories have similar arithmetic mean for objective values.	Independent-Samples Median Test	<.001	Reject the null hypothesis.
2	The range of objective values is identical across iteration types.	Independent-Samples Kruskal-Wallis Test	<.001	Reject the null hypothesis.
a. The significance level is 0.050.				
b. Asymptotic significance is displayed.				

To assess how the comparable algorithms of ACO, BAT, CS, FA and FPO perform relative to one another, this could as well be measured by evaluating whether each algorithm produces the same fitness values by confirming the methods presented the same data distribution. Less than 0.05 for p shows statistical significance among the algorithms. The outcomes are shown in Table 4.11. For the analysed fitness value distribution, the mean, standard deviation (SD), median, and other statistical characteristics were determined.

4.7 Presentation and Analysis of Results

In this section, the results of the comparative analysis conducted on three scenarios designed to optimise a computer networking infrastructure to minimise total labour costs are presented and analysed. The scenarios vary in the number of components installed and complexity of installation, with Scenario 1 installing 50 components, Scenario 2 installing 750 components, and Scenario 3 installing 1500 components. For each scenario, the study employed five optimisation algorithms: Ant Colony Optimisation (ACO), BAT Algorithm (BAT), Cuckoo Search Optimisation (CS), Firefly Algorithm (FA), and the proposed Fox Prey Optimisation (FPO) algorithm.

A. Scenario 1: Small Network Infrastructure:

The small network infrastructure looks up to 50 computer networking components.

Table 4.12: Comparative Analysis of Optimisation Algorithms for Scenario 1

Scenario 1: 50 Components	ALGORITHMS				
DIMENSIONS	ACO	BAT	CS	FA	FPO
skilled_workforce_allocation	2.0000	2.0000	2.0000	2.00000	3.0000
skilled_hourly_rate	35.976210	39.9651	37.9651	38.92877	35.49547
skilled_hours_worked	5.396982	7.98766	5.44020	6.040269	4.505142
unskilled_ workforce_allocation	2.0000	3.00000	2.00000	2.000000	2.00000
unskilled_hourly_rate	25.493598	15.0152	24.7235	23.69779	24.25426
unskilled_hours_worked	5.930870	4.00217	4.96184	6.824814	4.021130
Total project duration (*T*)	2.00000	2.00000	2.0000	2.00000	2.00000
Total minimised labour costs (*x*)	924.10413	875.375	725.000	654.1966	799.2994

Table 4.12 presents the results of applying five optimisation algorithms—Ant Colony Optimisation (ACO), Bat Optimisation (BAT), Cuckoo Search (CS), Firefly Optimisation (FA), and Fox Prey Optimisation (FPO)—to Scenario 1, representing a small-sized computer networking infrastructure project with 50 components. The dimensions include workforce allocation, hourly rates, hours worked, project duration, and total minimised labour costs. Each algorithm's performance is evaluated and compared across these dimensions to determine their efficacy in minimising labour costs and optimising project outcomes.

Skilled Workforce Allocation:

Efficient allocation of skilled workforce is critical for project success. Across the algorithms in Scenario 1, there is variation in the allocation of skilled workforce. ACO, BAT, CS, and FA all allocate a moderate level of skilled workforce, each at 2.0000. This suggests a balanced approach to utilising skilled labour resources.

However, FPO stands out with a higher skilled workforce allocation of 3.0000. This indicates a potentially strategic decision to leverage more skilled labour for the given scenario, possibly aiming for enhanced performance or efficiency in project execution.

In summary, while most algorithms opt for a balanced allocation of skilled workforce, FPO adopts a slightly different approach by allocating a higher proportion of skilled workforce, potentially reflecting a deliberate strategy to optimise project outcomes in Scenario 1.

Skilled Hourly Rate:

The skilled hourly rate, indicative of the cost incurred per hour for skilled labour, exhibits variability across the algorithms. Ant Colony Optimisation (ACO) boasts of a skilled hourly rate of $35.976210, while Bat Algorithm (BAT) commands $39.9651. Cuckoo Search (CS) and Firefly Algorithm (FA) follow closely, with rates of $37.9651 and $38.92877, respectively. Remarkably, Fox Prey Optimisation (FPO) presents the most cost-effective option, boasting a skilled hourly rate of $35.49547, potentially offering significant cost savings in skilled labour utilisation.

Skilled Hours Worked:

The duration of skilled labour required for project completion varies among the algorithms. ACO demands 5.396982 hours, while BAT necessitates 7.98766 hours, reflecting diverse efficiency levels in task execution. CS exhibits a moderate requirement of 5.44020 hours, followed closely by FA with 6.040269 hours. FPO distinguishes itself with the lowest skilled hours worked at 4.505142, suggesting heightened efficiency and potential cost benefits.

Unskilled Workforce Allocation:

Efficient resource allocation plays a pivotal role in project management. All algorithms within Scenario 1 allocate a balanced proportion of unskilled workforce, ranging from 2.0000 to 3.00000. This equitable distribution ensures optimal resource utilisation while facilitating project progress.

Unskilled Hourly Rate:

Similar to skilled labour, the cost per hour for unskilled labour varies across algorithms. ACO presents a rate of $25.493598, while BAT offers the most cost-effective option at $15.0152. CS and FA follow closely with rates of $24.7235 and $23.69779, respectively. FPO maintains competitive pricing at $24.25426, contributing to overall cost efficiency in labour utilisation.

Unskilled Hours Worked:

Efficiency in unskilled labour utilisation is paramount to project success. BAT and FPO emerge as frontrunners, requiring the least number of unskilled hours worked at 4.00217 and 4.021130, respectively. Conversely, FA exhibits the highest requirement of 6.824814 hours, indicative of potential inefficiencies in resource utilisation.

Total Project Duration (T):

Despite variations in labour requirements, all algorithms demonstrate uniformity in project completion times, with a total duration of 2.00000 in Scenario 1. This parity underscores the efficacy of each algorithm in adhering to project timelines.

Total Minimised Labour Costs:

The ultimate metric of success lies in the total minimised labour costs incurred by each algorithm. FA emerges as the frontrunner in cost efficiency, with total costs amounting to $654.1966. However, FPO remains competitive, with total costs of $799.2994, indicative of its potential to deliver cost-effective solutions while ensuring optimal project outcomes.

In essence, the analysis illuminates the nuanced performance of each algorithm, underscoring their respective contributions to labour cost minimisation and project efficiency within Scenario 1 of initial installation on user-specified computer networking infrastructure projects. FPO stands out as a promising candidate, offering competitive advantages in cost efficiency and resource optimisation.

In summary, when examining the total minimised labour costs for smaller networks:

FA demonstrates the most efficient cost management, yielding the lowest total minimised labour costs at $654.1966. CS closely follows, presenting competitive cost-effectiveness with total minimised labour costs of $725.000. FPO, the focal algorithm, falls within a moderate cost range, incurring total minimised labour costs of $799.2994, offering a balance between cost and efficiency. BAT trails behind FPO with total minimised labour costs of $875.375, indicating slightly higher expenditure. ACO registers the highest total minimised labour costs at $924.10413, suggesting relatively higher spending on labour utilisation.

This assessment suggests that while FPO provides a middle-ground in terms of total minimised labour costs for smaller networks, it maintains a balance between cost and efficiency compared to ACO and BAT. Nonetheless, it is surpassed by FA and CS in terms of cost-effectiveness.

- *Scenario 1: Convergence Curves*

This convergence graph of the Ant Colony Optimisation (ACO) algorithm shows the number of iterations, the best cost, performance, stability and optimisation for a small network (Scenario 1).

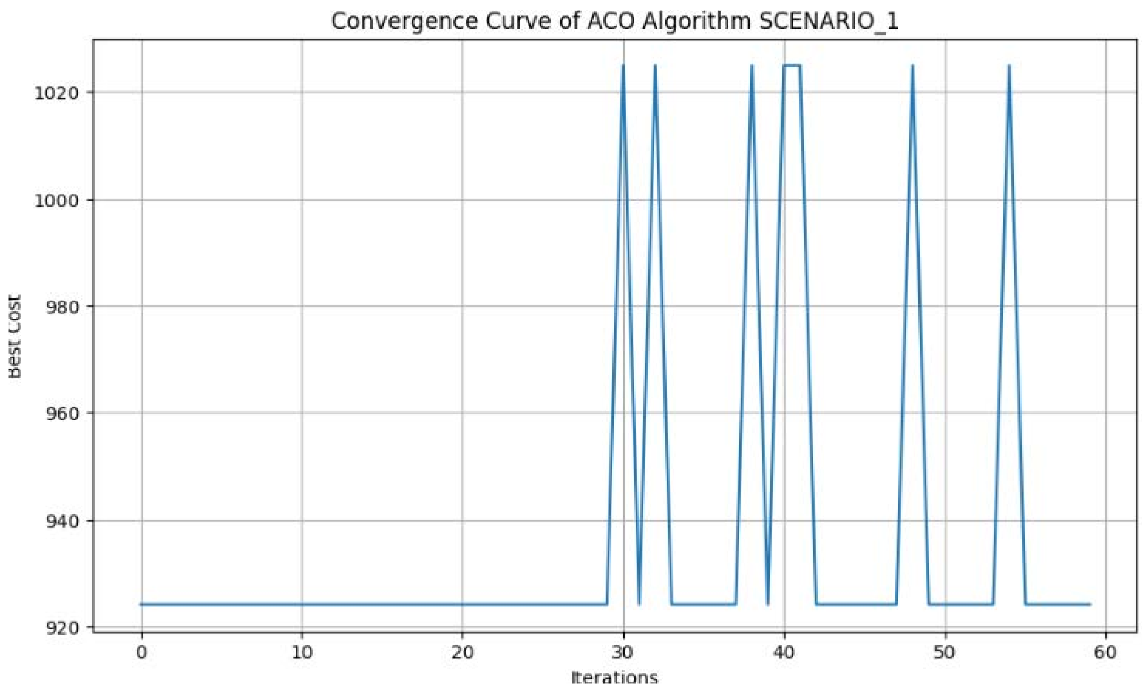

Figure 4.1: Convergence Curve for Ant Colony Optimisation (Scenario 1)

The x-axis of Figure 4.1 represents the number of iterations, while the y-axis represents the best cost found so far. The curve shows a step-like pattern, indicating significant improvements at certain iterations. There are periods where the best cost remains relatively stable, suggesting the algorithm is exploring the solution space without finding better solutions. The overall downward trend indicates that the algorithm is effectively reducing the cost over time, suggesting successful optimisation. This analysis helps understand the efficiency and effectiveness of the algorithm in optimising network components.

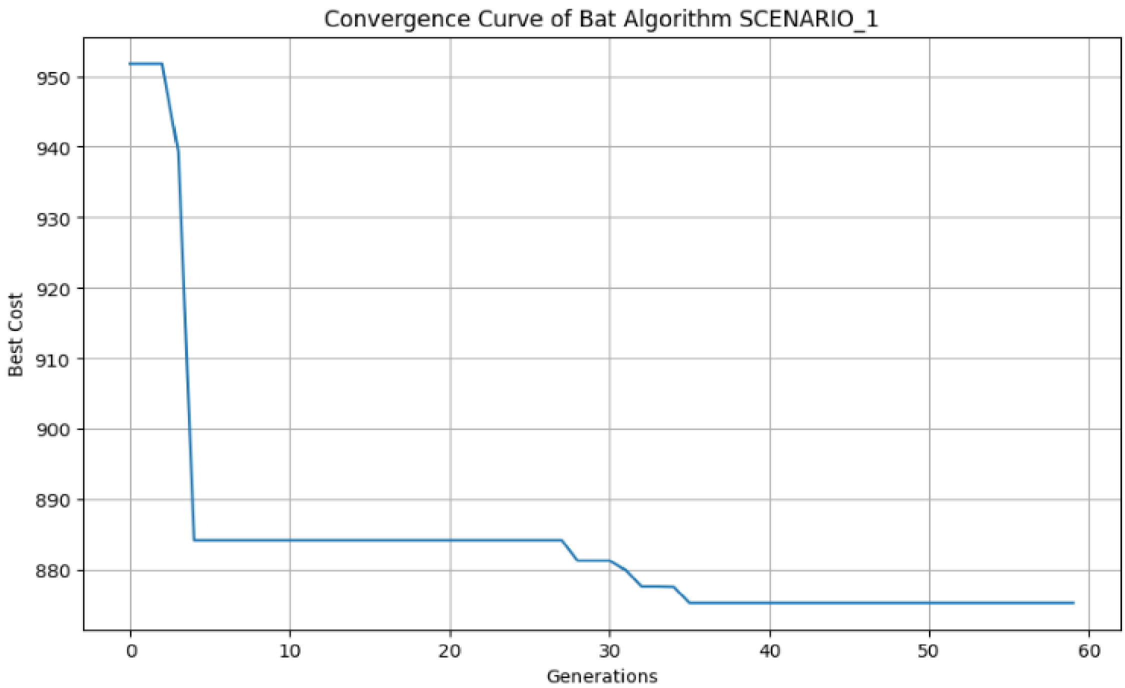

Figure 4.2: Convergence Curve for Bat Optimisation (Scenario 1)

The convergence curve, as in Figure 4.2, depicting the performance of the BAT algorithm in the project offers a glimpse into the optimisation journey, characterized by distinct phases of exploration and exploitation. Initially, the algorithm embarked on its quest with a starting cost of approximately 950 units. Within the first 10 iterations, there was a notable sharp decline in costs, indicative of a rapid exploration phase wherein the algorithm swiftly traversed a broad search space in search of optimal solutions. Following this initial decline, the cost stabilized around 890 units, signalling the transition to the exploitation phase where the algorithm focused on refining and optimising existing solutions.

Throughout the iterations, the most significant changes occurred within the initial ten generations, after which the algorithm made incremental refinements to fine-tune its solutions. In terms of interpretation, the graph's dynamics unveil crucial insights into the algorithm's behaviour. The sharp decline in costs at the outset signifies the algorithm's robust exploration capabilities, swiftly navigating through diverse solution possibilities. As the algorithm identified promising areas within the search space, it transitioned into the exploitation phase, concentrating its efforts on optimising solutions to achieve cost stabilization.

The fluctuations in costs depicted by the graph not only underscore the effectiveness of the BAT algorithm in cost reduction, but also highlight its adeptness in efficiently narrowing down the search space to pinpoint optimal solutions. Ultimately, this graphical representation serves as a testament to the BAT algorithm's prowess in swiftly reducing costs during the early iterations while ultimately converging towards stable and optimised solutions.

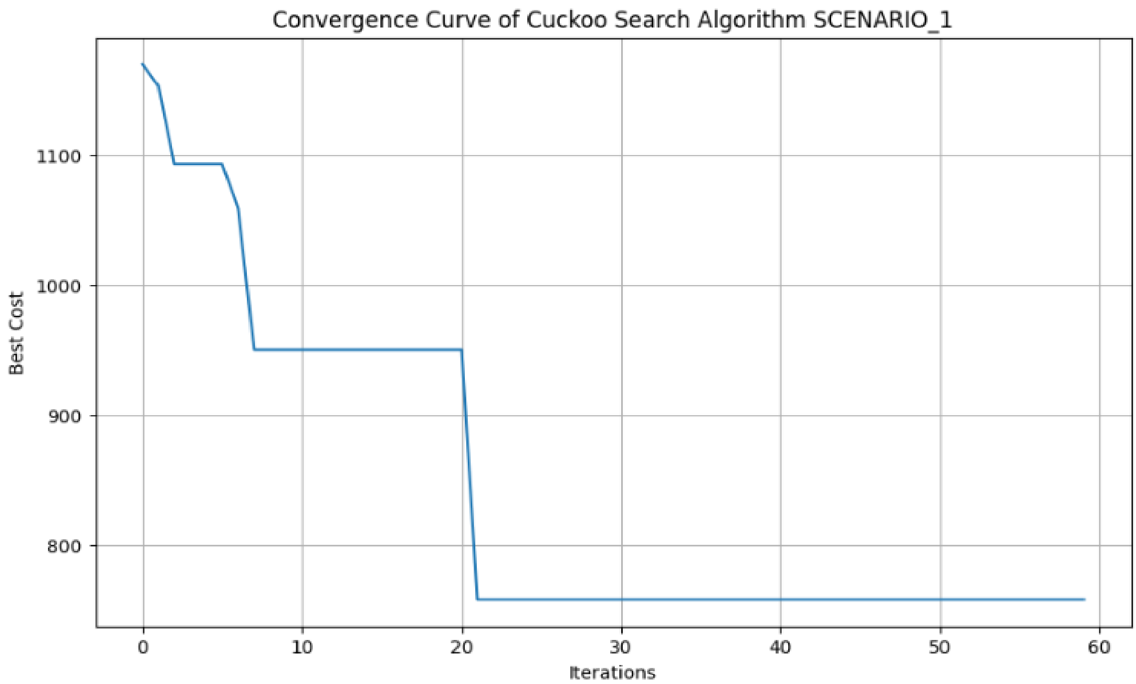

Figure 4.3: Convergence Curve for Cuckoo Search Optimisation (Scenario 1)

The convergence curve provided for the Cuckoo Search (CS) algorithm, as shown in Figure 4.3, offers valuable insights into the optimisation journey aimed at minimising total costs within a small-sized computer network. Here’s a breakdown of the graph's dynamics:

Initiation Phase: The optimisation process commenced with a starting cost of 1100 units, signifying the initial point before the algorithm's exploration and exploitation phases unfolded.

Stability and Exploration: From iteration 0 to 10, the cost remained stable, suggesting an exploratory phase wherein the algorithm meticulously assessed various solutions within the search space. This stability indicated a period of thorough exploration as the algorithm navigated through potential avenues.

First Decline and Exploitation: At the 10th iteration, the graph depicts a gradual decline in cost to just above 900 units, marking the transition into an exploitation phase. During this stage, the algorithm strategically refined its solutions, leading to incremental cost reductions as it delved deeper into the search space.

Subsequent Stability and Refinement: Following the initial decline, the cost stabilized once more from iteration 10 to 30, maintaining a level slightly above 900 units. This stabilization period suggests a period of refinement, where the algorithm fine-tuned its strategies before embarking on further exploration.

Second Decline and Optimisation: A notable decline in cost occurs at the 30th iteration, with a sharp reduction to below 800 units. This pronounced decrease reflects a phase of intensive optimisation, where the algorithm capitalizes on promising solutions within the search space to achieve substantial cost reductions.

Conclusive Stability: After the second decline, the graph illustrates another period of stability, indicating that the algorithm likely reached an optimal or near-optimal solution. This phase underscores the algorithm’s ability to strike a balance between exploration and exploitation, ultimately converging towards a cost-minimised outcome.

In essence, the graph encapsulates the CS algorithm's adeptness in navigating through the complexities of the search space, effectively exploring diverse solutions while strategically exploiting promising avenues to drive down total costs. Through iterative cycles of exploration, exploitation and refinement, the algorithm demonstrates its efficacy in optimising cost performance within the context of a small-sized computer network.

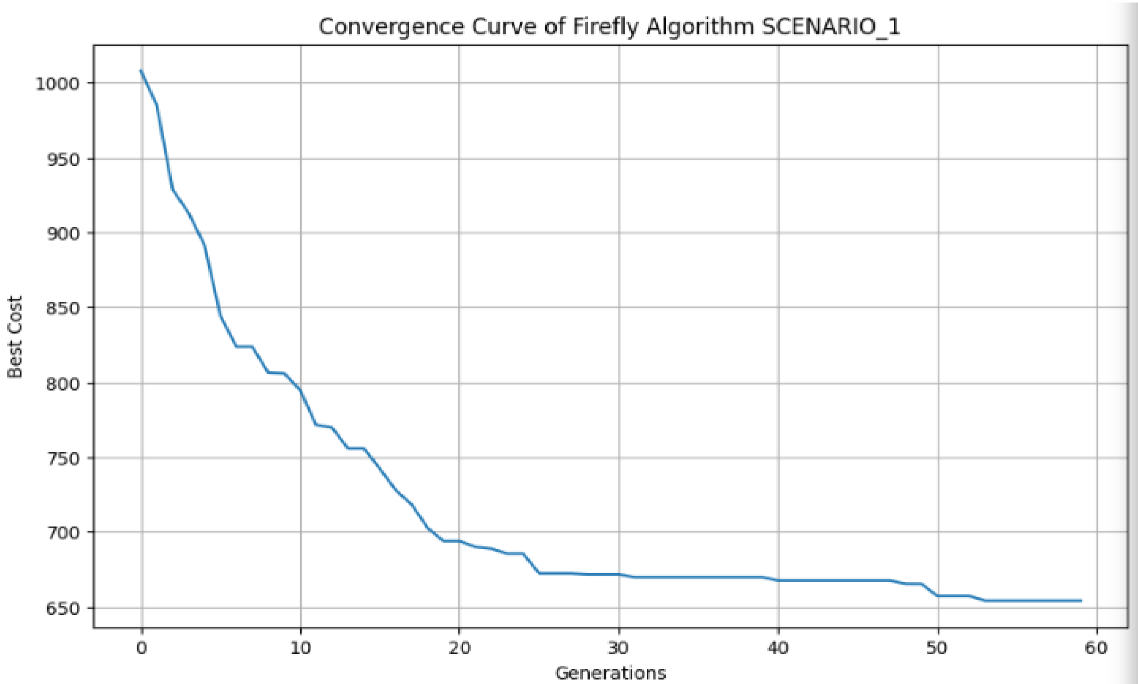

Figure 4.4: Convergence Curve for Firefly Optimisation (Scenario 1)

Figure 4.4 is a convergence curve for the Firefly Algorithm (FA) optimisation of a small-sized computer network infrastructure project that reveals several notable features. Initially, the algorithm encounters a high cost starting point, hovering around 1000. However, this is swiftly followed by a sharp decline in costs during the early generations, reflecting an intense phase of exploration where the algorithm rapidly identifies lower-cost solutions within the search space. Around the 20th generation, the curve stabilizes, with the cost plateauing just above 700. This stabilization signifies a shift towards exploitation, indicating that the algorithm is refining and fine-tuning existing solutions to further minimise costs. Following this stabilization, the cost maintains a relatively constant low value, suggesting that optimal or near-optimal solutions have been discovered, and the algorithm is making minor adjustments to enhance its performance.

The graph provides insights into the FA algorithm's effectiveness in reducing costs over successive iterations. The initial rapid decrease in costs followed by stabilization underscores the algorithm's efficiency and adaptability in optimising the total costs of the network infrastructure project. Furthermore, it highlights the balance between exploration and exploitation phases, where the algorithm navigates the search space to identify promising solutions and subsequently refines them to achieve cost minimisation objectives. Ultimately, the stabilization of the cost curve reflects the FA algorithm's ability to effectively manage exploration and exploitation dynamics to attain optimal or near-optimal solutions within the specified project constraints.

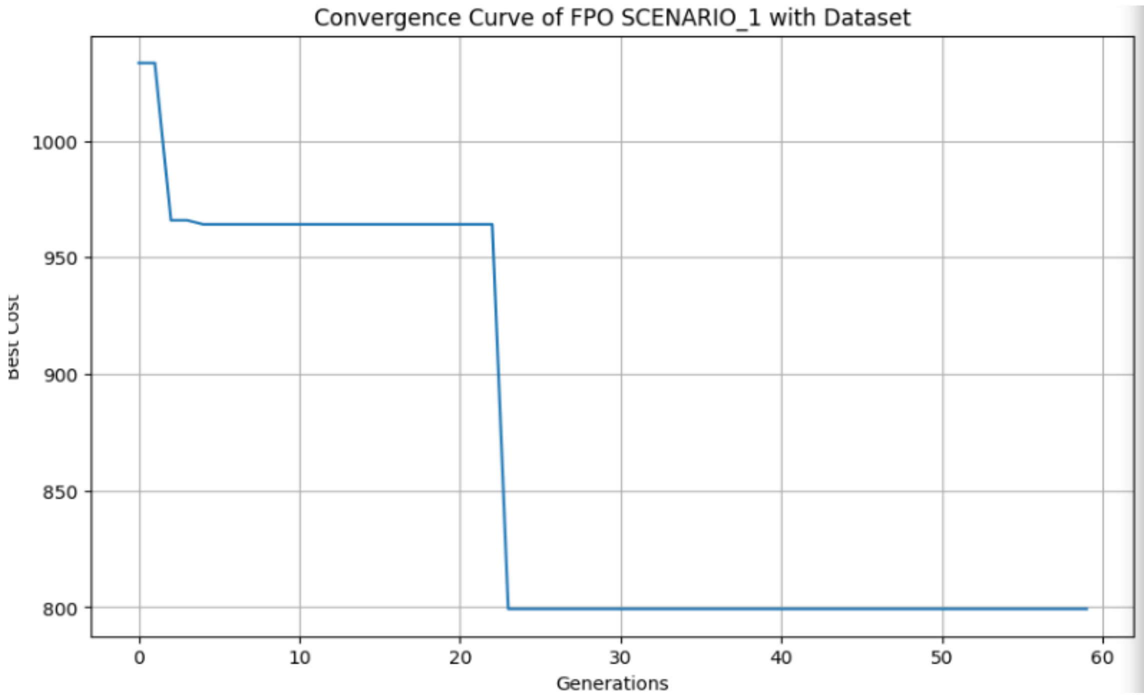

Figure 4.5: Convergence Curve for Fox Prey Optimisation (Scenario 1)

The optimisation process for FPO begins with the algorithm starting at a cost of 1050, as shown in Figure 4.5. As the iterations progress, the algorithm experiences fluctuations in cost, with notable stabilizations and declines indicating its dynamic performance. Around the 1st generation, there is a sharp decline in cost to about 960, signifying the algorithm's discovery of a more optimal solution. Subsequently, the cost stabilizes until approximately the 24th generation, reflecting a period of exploration and refinement in the search space. Another significant decline occurs, reducing the cost to around 800, where it stabilizes for subsequent generations.

The graph illustrates the algorithm's exploration and exploitation phases, characterized by fluctuations in cost as it navigates through potential solutions. Initially, the algorithm explores various options to identify promising areas in the search space, leading to sharp declines indicative of successful exploration. As it refines its solutions, the exploitation phase begins, marked by stabilizations and further declines as the algorithm optimises towards cost minimisation. Overall, the convergence curve reflects the algorithm's efficient exploration and exploitation strategies in finding cost-effective solutions within the search space, with stabilization points indicating near-optimal outcomes.

B. Scenario 2: Medium Network Infrastructure

The medium network infrastructure looks up to 750 computer networking components

Table 4.13: Comparative Analysis of Optimisation Algorithms for Scenario 2

Scenario 2: 750 Components	ALGORITHMS				
DIMENSIONS	ACO	BAT	CS	FA	FPO
skilled_workforce_allocation	20.000000	15.0000	13.0000	14.00000	17.0000
skilled_hourly_rate	57.673203	57.1915	46.9211	55.76277	49.44284
skilled_hours_worked	7.491666	4.71409	7.72004	4.196400	4.265801
unskilled_ workforce_allocation	19.000000	12.0000	11.0000	11.00000	19.00000
unskilled_hourly_rate	29.200351	21.2191	25.1697	21.00373	24.69846
unskilled_hours_worked	4.611923	6.10537	4.03382	5.338194	5.259889
Total project duration (*T*)	13.000000	12.0000	12.0000	16.00000	11.00000
Total minimised labour costs (*x*)	180486.26	85331.3	95892.4	95015.78	83947.76

Table 4.13 presents the results of applying five optimisation algorithms—Ant Colony Optimisation (ACO), Bat Optimisation (BAT), Cuckoo Search (CS), Firefly Optimisation (FA) and Fox Prey Optimisation (FPO)—to Scenario 2, representing a medium-sized computer networking infrastructure project with 750 components. The dimensions include workforce allocation, hourly rates, hours worked, project duration and total minimised labour costs. Each algorithm's performance is evaluated and compared across these dimensions to determine their efficacy in minimising labour costs and optimising project outcomes.

Analysing the skilled workforce allocation across the ACO, BAT, CS, FA and FPO algorithms reveals distinct patterns. ACO, requiring the highest allocation at 20 units, reflects a significant demand for skilled labour. This suggests a complex optimisation process that necessitates a larger workforce to manage effectively. In comparison, BAT follows closely behind with 15 units, indicating a moderate requirement for skilled workers. This suggests efficient optimisation capabilities with a slightly lower resource demand compared to ACO. With its allocation of 13 units, CS demonstrates a balanced approach, indicating a slightly lower demand for skilled labour compared to BAT. Similarly, FA, with a skilled workforce allocation of 14 units, maintains a relatively balanced utilisation of skilled resources.

However, FPO stands out in this analysis. Despite being spotlighted for its lower allocation, it still requires 17 units of skilled workforce. This places it notably lower than ACO but higher than other algorithms in this comparison. This observation raises intriguing questions about the underlying mechanisms of FPO and its efficiency in achieving optimisation objectives with fewer skilled resources. The relatively lower allocation compared to ACO might imply FPO's ability to achieve optimisation with fewer skilled workers, possibly through innovative optimisation mechanisms. This suggests that FPO could offer cost-effective optimisation solutions, even though it requires a skilled workforce.

In conclusion, while ACO leads in demanding skilled resources, FPO stands out for its potentially cost-effective optimisation solutions. However, the effectiveness of each algorithm should be evaluated considering not only the skilled workforce allocation but also other performance metrics and project-specific requirements. Such insights are crucial for understanding the comparative advantages and limitations of different algorithms in resource-constrained environments.

Investigating the skilled_hourly_rate across the ACO, BAT, CS, FA and FPO algorithms provides further insights into their resource utilisation and cost implications. ACO leads with a skilled hourly rate of 57.673203, indicating a relatively higher cost associated with employing skilled workers for this algorithm. BAT follows with a skilled hourly rate of 57.1915, suggesting a similar level of expense for skilled labour. CS, with a rate of 46.9211, demonstrates a slightly lower cost compared to ACO and BAT, possibly reflecting a more cost-efficient optimisation strategy. Similarly, FA, with a skilled hourly rate of 55.76277, maintains a relatively higher cost but falls within the range of ACO and BAT.

In contrast, FPO stands out with a lower skilled hourly rate of 49.44284. This implies a comparatively lower cost associated with employing skilled workers for FPO, potentially making it more cost-effective in terms of labour expenses. Despite requiring skilled resources, FPO offers optimisation solutions at a relatively lower hourly rate compared to ACO and BAT. This suggests that FPO could provide cost savings in terms of skilled labour expenses while still achieving effective optimisation outcomes.

In conclusion, while ACO and BAT exhibit higher skilled hourly rates, FPO stands out for its potentially lower labour expenses. However, the cost-effectiveness of each algorithm should be evaluated considering not only the skilled hourly rate but also other factors such as project complexity, performance metrics and overall project budget. Such insights are crucial for decision-making processes, enabling project managers to optimise resource allocation and minimise costs effectively while achieving project objectives.

Studying the skilled_hours_worked across the ACO, BAT, CS, FA and FPO algorithms sheds light on their respective labour intensity and efficiency in utilising skilled workforce hours. ACO, with skilled hours worked at 7.491666, demonstrates a relatively higher utilisation of skilled labour hours. This suggests that ACO may require a substantial investment of skilled labour hours to complete its optimisation processes effectively. Similarly, FA, with skilled hours worked at 4.196400, also indicates a relatively high utilisation of skilled workforce hours, albeit slightly lower than ACO.

In contrast, BAT and FPO exhibit lower skilled hours worked, indicating a more efficient utilisation of skilled labour hours. BAT, with skilled hours worked at 4.71409, suggests a moderate utilisation of skilled workforce hours. FPO, with skilled hours worked at 4.265801, demonstrates a more efficient utilisation of skilled labour hours compared to ACO and FA, indicating potentially streamlined optimisation processes.

CS stands out with skilled hours worked at 7.72004, indicating a relatively higher utilisation of skilled workforce hours. This suggests that CS may require a significant investment of skilled labour hours similar to ACO, potentially due to the complexity of its optimisation processes.

In conclusion, while ACO and FA exhibit higher skilled hours worked, BAT and FPO stand out for their more efficient utilisation of skilled labour hours. However, the labour intensity and efficiency of each algorithm should be evaluated in conjunction with other factors such as project constraints, resource availability and desired outcomes to determine the most suitable algorithm for a given scenario.

Examining the skilled_workforce_allocation across the ACO, BAT, CS, FA and FPO algorithms provides insights into their respective requirements for unskilled labour. ACO, with an allocation of 19 units, reflects a relatively high demand for unskilled workers. This suggests that ACO may rely heavily on unskilled labour to support its optimisation processes. Similarly, FA, with an allocation of 19 units, indicates a comparable requirement for unskilled labour.

In contrast, BAT, CS and FPO exhibit lower allocations for unskilled workforce. BAT, with an allocation of 12 units, suggests a moderate demand for unskilled workers. CS, with an allocation of 11 units, demonstrates a slightly lower requirement for unskilled labour compared to BAT. FPO, with an allocation of 19 units, indicates a relatively higher demand for unskilled workers compared to BAT and CS, but lower than ACO and FA.

These variations highlight differences in the algorithms' reliance on unskilled labour for supporting their optimisation processes. ACO and FA appear to require more extensive support from unskilled workers, potentially due to the complexity or scale of their optimisation tasks. In contrast, BAT, CS and FPO demonstrate more moderate requirements for unskilled labour, suggesting potentially streamlined or efficient optimisation processes.

In conclusion, while ACO and FA exhibit higher allocations for unskilled workforce, BAT, CS and FPO stand out for their more moderate requirements. However, the implications of unskilled workforce allocation should be considered alongside other factors such as skilled workforce allocation, labour costs and overall project objectives to make informed decisions regarding algorithm selection and resource allocation.

Assessing the unskilled_hourly_rate across the ACO, BAT, CS, FA and FPO algorithms unveils insights into their respective costs associated with employing unskilled labour. ACO leads with an hourly rate of 29.200351, indicating a relatively higher cost for unskilled labour. This suggests that ACO may entail significant expenses in employing unskilled workers to support its optimisation processes. Similarly, FA, with an hourly rate of 24.69846, also reflects a relatively high cost for unskilled labour.

In contrast, BAT, CS and FPO exhibit lower hourly rates for unskilled labour. BAT, with an hourly rate of 21.2191, suggests a moderate cost for employing unskilled workers. CS, with an hourly rate of 25.1697, demonstrates a slightly higher expense for unskilled labour compared to BAT. With an hourly rate of 24.69846, FPO indicates a comparable cost to FA but lower than ACO and CS.

These differences highlight variations in the algorithms' expenses associated with unskilled labour. ACO and FA appear to incur higher costs for employing unskilled workers, potentially reflecting the scale or complexity of their optimisation tasks. In contrast, BAT, CS, and FPO demonstrate more moderate expenses for unskilled labour, suggesting potentially more cost-effective optimisation processes.

In conclusion, while ACO and FA exhibit higher hourly rates for unskilled labour, BAT, CS, and FPO stand out for their moderate costs. However, the implications of unskilled hourly rates should be considered alongside other factors such as skilled workforce allocation, total project duration and overall project objectives to make informed decisions regarding algorithm selection and resource allocation.

Probing the unskilled_hours_worked across the ACO, BAT, CS, FA and FPO algorithms provides insights into their respective labour intensity and efficiency in utilising unskilled workforce hours. ACO leads with unskilled hours worked at 4.611923, indicating a relatively higher utilisation of unskilled labour hours. This suggests that ACO may require a significant investment of unskilled labour hours to support its optimisation processes. Similarly, FA, with unskilled hours worked at 5.338194, also demonstrates a relatively high utilisation of unskilled workforce hours.

In contrast, BAT, CS, and FPO exhibit lower unskilled hours worked, indicating a more efficient utilisation of unskilled labour hours. BAT, with unskilled hours worked at 6.10537, suggests a moderate utilisation of unskilled workforce hours. CS, with unskilled hours worked at 4.03382, demonstrates a slightly lower utilisation compared to BAT, potentially reflecting a more streamlined optimisation process. FPO, with unskilled hours worked at 5.259889, indicates a comparable utilisation to ACO but lower than FA.

These differences highlight variations in the algorithms' requirements for unskilled labour and their efficiency in utilising unskilled workforce hours. ACO and FA appear to require more extensive support from unskilled workers, potentially due to the complexity or scale of their optimisation tasks. In contrast, BAT, CS and FPO demonstrate moderate requirements for unskilled labour and potentially more streamlined optimisation processes.

In conclusion, while ACO and FA exhibit higher utilisation of unskilled hours worked, BAT, CS, and FPO stand out for their moderate requirements. However, the labour intensity and efficiency of each algorithm should be evaluated in conjunction with other factors such as skilled workforce allocation, skilled hourly rate and overall project objectives to make informed decisions regarding algorithm selection and resource allocation.

Evaluating the "Total project duration (T)" across the ACO, BAT, CS, FA and FPO algorithms provides insights into the expected time required to complete the project using each algorithm. ACO requires a total project duration of 13 days, indicating a relatively longer timeframe compared to other algorithms. This suggests that ACO may take more time to complete the project due to the complexity or scale of its optimisation processes. Similarly, FA also has a longer project duration of 16 days, further highlighting the potential time-intensive nature of this algorithm.

In contrast, BAT, CS and FPO exhibit shorter project durations, indicating more efficient optimisation processes. Both BAT and CS have a project duration of 12 days, suggesting that they may complete the project in a relatively shorter timeframe compared to ACO and FA. FPO stands out with the shortest project duration of 11 days, indicating potentially streamlined optimisation processes and efficient resource utilisation.

These differences in project duration highlight variations in the algorithms' efficiency and effectiveness in completing the project within a given timeframe. ACO and FA may require more time to achieve optimisation objectives due to their complexity, while BAT, CS and FPO demonstrate more efficient optimisation processes with shorter project durations.

In conclusion, while ACO and FA exhibit longer project durations, BAT, CS and FPO demonstrate comparatively shorter durations, indicating potentially more efficient optimisation processes. However, project managers should consider not only project duration but also other factors such as labour costs, resource utilisation and optimisation performance when selecting the most suitable algorithm for a given scenario.

Evaluating the "Total minimised labour costs (x)" across the ACO, BAT, CS, FA and FPO algorithms provides valuable insights into their cost efficiency in completing the project. ACO and CS demonstrate relatively higher labour costs, with ACO incurring $180,486.26 and CS with $95,892.4. This suggests that ACO and CS may involve significant labour expenses due to their complexity or scale. On the other hand, BAT, FA, and FPO exhibit lower minimised labour costs, indicating more cost-efficient optimisation processes. BAT's minimised labour costs stand at $85,331.3, FA at $95,015.78, and FPO at $83,947.76, showcasing their economical approaches compared to ACO and FA.

Among these algorithms, FPO emerges as the most cost-efficient, with the lowest labour costs. This indicates efficient resource utilisation and potentially streamlined optimisation processes. While BAT and CS also demonstrate cost-effectiveness, FPO stands out as the most financially prudent choice for minimising labour costs in this context.

In light of the project's overarching objective to minimise total labour costs, the Fox Prey Optimisation (FPO) algorithm emerges as the most favourable choice. FPO's capability to deliver cost-efficient optimisation processes stands out prominently, aligning closely with the primary goal of cost reduction. Therefore, FPO presents itself as the optimal algorithm for achieving the project's cost minimisation objective, offering a compelling solution for project managers aiming to prioritize financial prudence in their decision-making process.

- *Scenario 2: Convergence Curves*

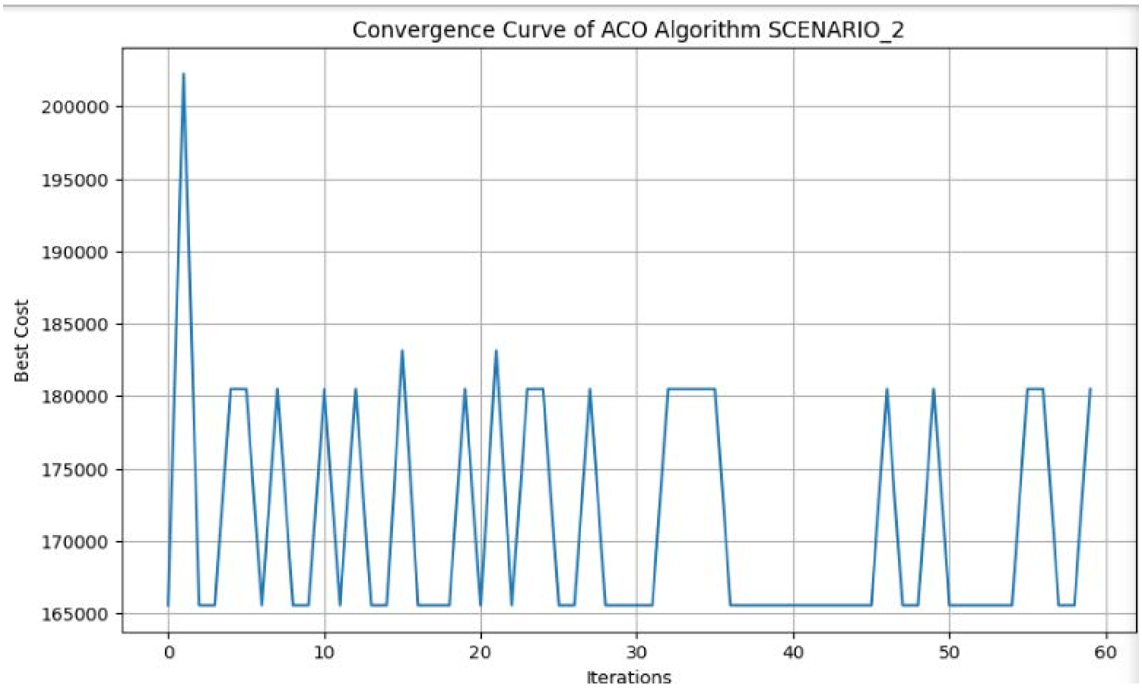

Figure 4.6: Convergence Curve for Ant Colony Optimisation (Scenario 2)

The Figure 4.6 graph commences with a cost of approximately 165,000, representing the starting point before the optimisation process begins. It then shot up slightly above 200,000. There is a noticeable sharp decline after the initial generations, indicative of the Ant Colony Optimisation algorithm's swift discovery of more optimal and lower-cost solutions within the search space.

As the optimisation progresses, the cost stabilizes at around 180,000 from approximately the 10th generation onwards. This stabilization point signifies that the algorithm has converged towards a solution, indicating a pivotal moment in the optimisation process.

The "turn" in the graph, occurring around the 2nd generation, marks a transition as the curve begins to level off. This turning point suggests a shift from broad exploration of the solution space to focused exploitation and fine-tuning within a localized search space.

In terms of exploration and exploitation, the initial sharp decline in cost during the early generations reflects intense exploration by the algorithm as it systematically explores a wide range of solutions. Subsequently, as the cost stabilizes from the 2nd generation onwards, the algorithm enters the exploitation phase, where it refines and optimises within the identified promising areas of the solution space.

Overall, the convergence curve provides valuable insights into the dynamic performance of the Ant Colony Optimisation algorithm, highlighting its capacity for both exploration and exploitation in minimising costs for various optimisation tasks.

The numerous spikes in the graph could be due to the inherent characteristics of the Ant Colony Optimisation (ACO) algorithm. ACO is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs.

In the exploration phase, the algorithm is trying out different paths or solutions. This can lead to fluctuations in the cost as different paths might have different costs associated with them. These fluctuations appear as spikes in the graph.

In the exploitation phase, the algorithm is refining the best solutions found so far. However, ACO also maintains a degree of exploration to avoid getting trapped in local optima. This means it will occasionally try out less optimal solutions, which can also lead to spikes in the graph.

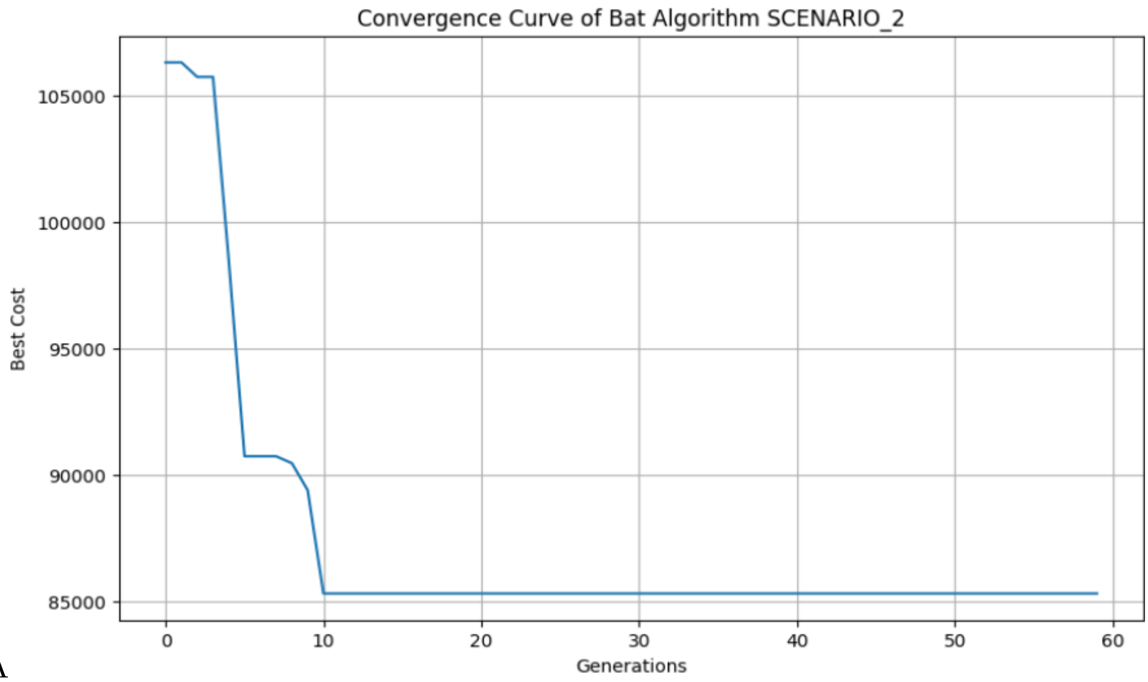

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Figure 4.7: Convergence Curve for BAT Algorithm Optimisation (Scenario 2)

Starting at a cost of approximately 105,000, the graph in Figure 4.7 illustrates the performance of the BAT algorithm in minimising costs for a computer networking infrastructure project. A sharp decline is observed during the initial generations, indicating the algorithm's rapid identification of more optimal and lower-cost solutions within the search space.

As the optimisation progresses, the cost stabilizes at around 83,000 from approximately the 10th generation onwards. This stabilization point signifies that the algorithm has converged towards a solution that it cannot significantly improve upon, marking a pivotal moment in the optimisation process.

The "turn" in the graph, occurring around the 10th generation, represents a shift in the curve's trajectory as it begins to level off. This turning point indicates a transition from broad exploration of the solution space to focused exploitation and fine-tuning within a localized search space.

In terms of exploration and exploitation, the initial sharp decline in cost during the early generations reflects intense exploration by the algorithm as it systematically explores a wide range of solutions. Subsequently, as the cost stabilizes from the 10th generation onwards, the algorithm enters the exploitation phase, where it refines and optimises within the identified promising areas of the solution space.

Overall, the convergence curve provides valuable insights into the BAT algorithm's dynamic performance, highlighting its capacity for both exploration and exploitation in minimising costs for installation of computer networking infrastructure projects.

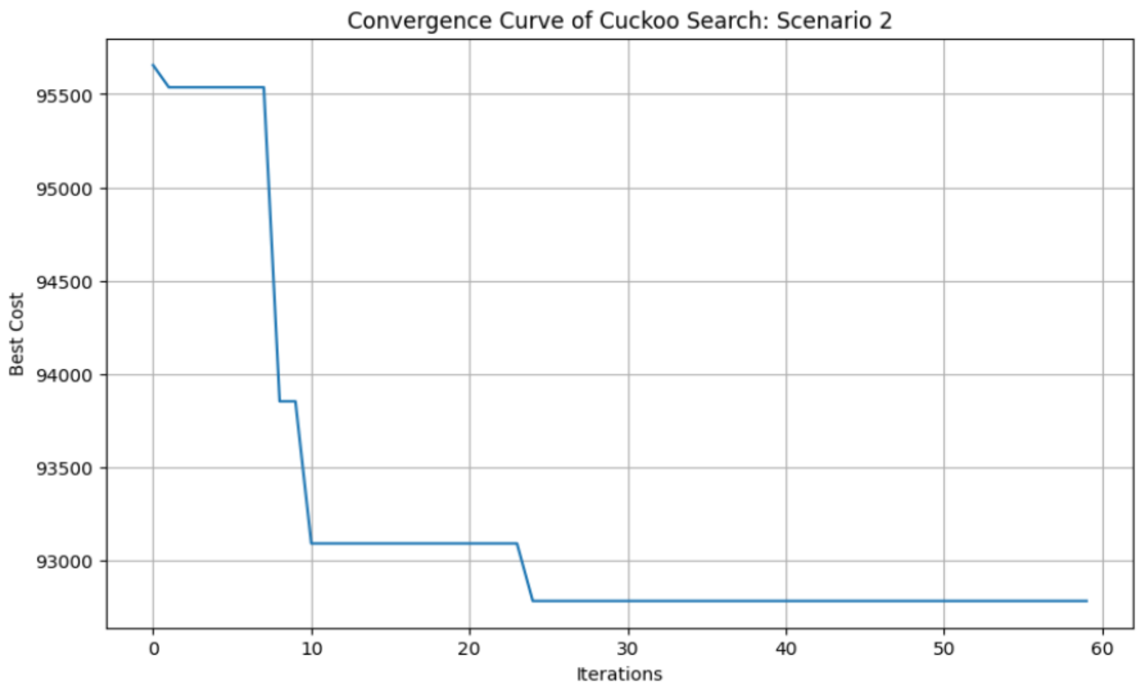

Figure 4.8: Convergence Curve for Cuckoo Search Optimisation (Scenario 2)

The graph in Figure 4.8 depicting the Cuckoo Search Optimisation algorithm's performance in minimising costs for a computer networking infrastructure project starts at an initial cost of approximately 95,500. This represents the baseline cost before the optimisation process begins. A notable feature of the graph is the sharp decline observed during the initial generations, indicating the algorithm's effectiveness in gradually identifying more optimal and lower-cost solutions within the search space.

As the optimisation progresses, the cost stabilizes at around 93,000 from approximately the 24th generation onwards. This stabilization point suggests that the algorithm has reached a solution that it cannot significantly improve upon, marking a crucial transition in the optimisation process.

The "turn" in the graph, observed around the 24th generation, signifies a shift in the curve's trajectory where it starts to level off. This turning point indicates a transition from broad exploration of the solution space to focused exploitation and fine-tuning within a localized search space.

In terms of exploration and exploitation, the initial sharp decline in cost during the early generations reflects the algorithm's exploration phase, as it systematically searches through a broad space to uncover potential solutions. Subsequently, as the cost stabilizes from the 20th generation onwards, the algorithm enters the exploitation phase, where it refines and optimises within the identified promising areas of the solution space.

Overall, the convergence curve provides valuable insights into the Cuckoo Search Optimisation algorithm's dynamic performance, highlighting its capacity for both exploration and exploitation in minimising costs for installation of computer networking infrastructure projects.

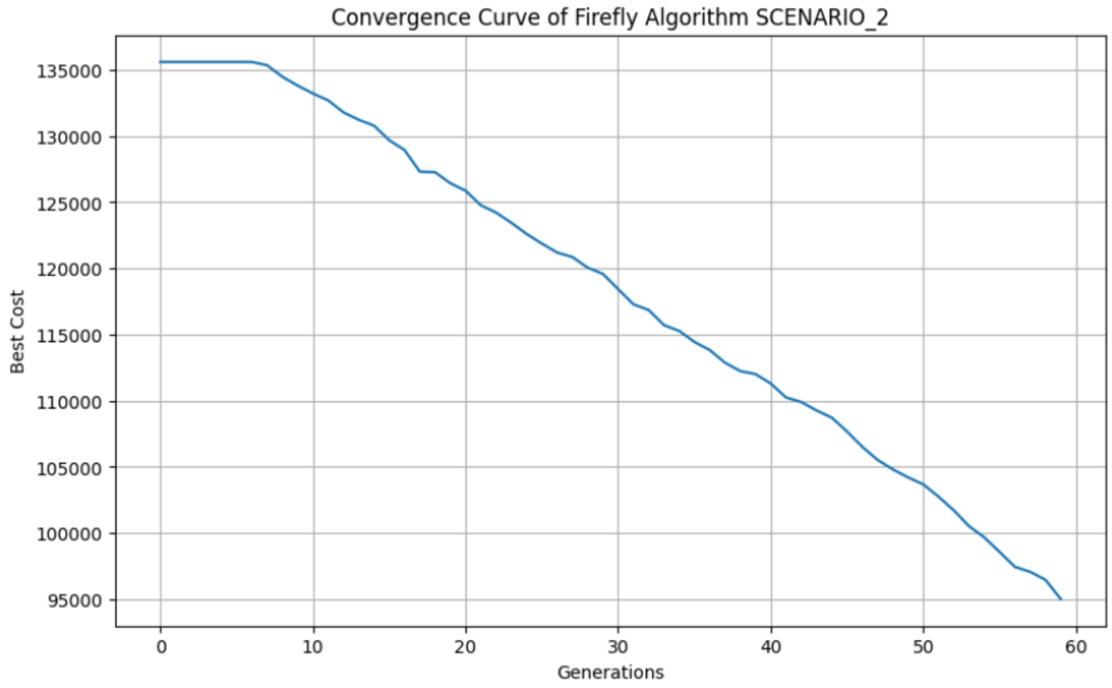

Figure 4.9: Convergence Curve for Firefly Algorithm (Scenario 2)

The convergence curve of the Firefly Algorithm, as shown in Figure 4.9, starts at an initial cost of approximately 135,000 before the optimisation process begins. Over the initial generations, there is a consistent decline, indicating the algorithm's progressive discovery of more optimal and lower-cost solutions within the search space. As the iterations progress, the cost stabilizes around 95,000 from approximately the 50th generation onwards, signalling that the algorithm has reached a solution with minimal room for further significant enhancements. This stabilization point, observed around the 50th generation, marks a pivotal "turn" in the graph, where the curve begins to level off, signifying a shift from exploration to exploitation within the optimisation process.

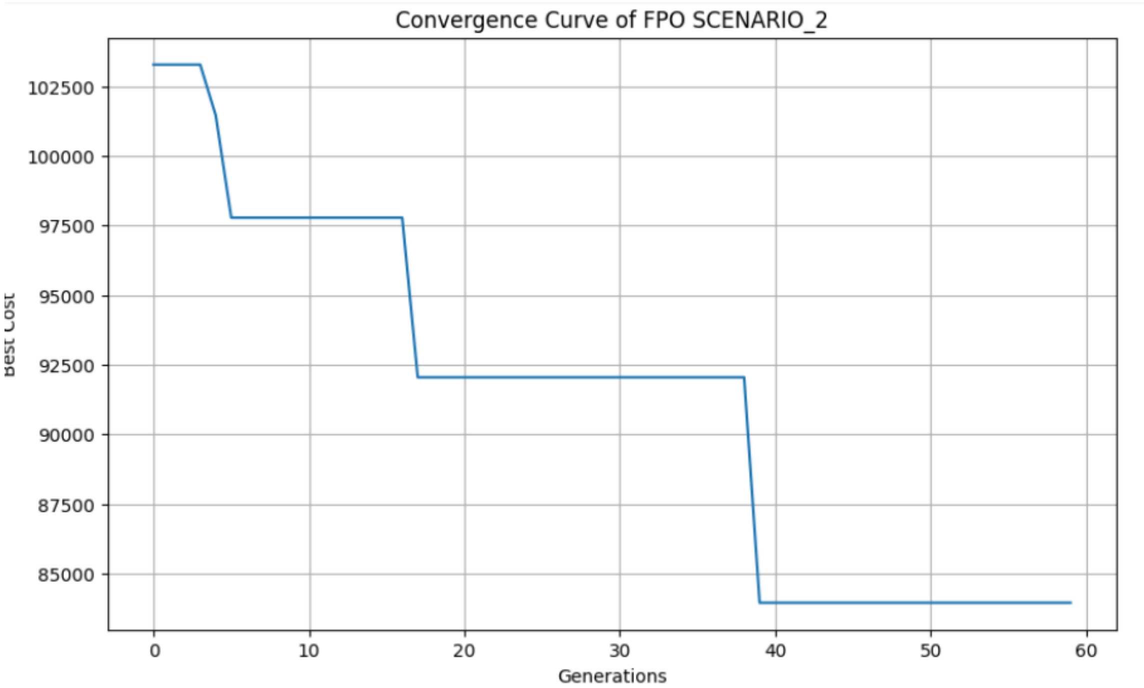

Figure 4.10: Convergence Curve for Fox Prey Optimisation Algorithm (Scenario 2)

The convergence curve for the Fox Prey Optimisation (FPO) algorithm, as captured in Figure 4.10, which has 4 stabilized and 3 declined stages at a glance, initiates at a cost of approximately 102,500, representing the starting point before the optimisation process commences. During the initial generations, there is a pronounced decline, indicating the algorithm's rapid identification of more optimal, lower-cost solutions within the search space. Subsequently, from around the 39th generation onwards, the cost stabilizes at approximately 82,000, signifying that the algorithm has reached a solution it cannot significantly enhance further.

This stabilization marks a pivotal "turn" point in the graph, where the curve begins to level off, indicating a transition from intense exploration to exploitation. In terms of exploration and exploitation strategies, the sharp decline during the initial generations reflects the algorithm's engagement in broad exploration across the search space. Conversely, as the cost stabilizes from generation 39 onwards, the algorithm shifts to exploitation, fine-tuning and optimising within a more localized search space.

C. Scenario 3: Large Network Infrastructure

The large network infrastructure looks up to 1500 computer networking components

Table 4.14: Comparative Analysis of Optimisation Algorithms for Scenario 3

Scenario 3: 1500 Components	ALGORITHMS				
DIMENSIONS	ACO	BAT	CS	FA	FPO
skilled_workforce_allocation	56.0000	27.0000	50.0000	50.00000	35.0000
skilled_hourly_rate	68.300828	68.6611	61.5734	65.28059	75.97308
skilled_hours_worked	5.477411	4.69071	4.66263	4.007405	4.471728
unskilled_ workforce_allocation	31.0000	49.0000	54.0000	61.00000	40.00000
unskilled_hourly_rate	29.840113	28.3957	31.6932	31.48416	25.38875
unskilled_hours_worked	4.405622	4.44753	5.31540	4.004674	5.568708
Total project duration (*T*)	11.00000	13.0000	11.0000	11.00000	11.00000
Total minimised labour costs (*x*)	366489.17	276249.1	383156.3	308918.9	272418.6

Table 4,14 presents the results of applying five optimisation algorithms—Ant Colony Optimisation (ACO), Bat Optimisation (BAT), Cuckoo Search (CS), Firefly Optimisation (FA) and Fox Prey Optimisation (FPO)—to Scenario 3, representing a large-sized computer networking infrastructure project with 1500 components. The dimensions include workforce allocation, hourly rates, hours worked, project duration and total minimised labour costs. Each algorithm's performance is evaluated and compared across these dimensions to determine their efficacy in minimising labour costs and optimising project outcomes

Skilled Workforce Allocation

ACO (Ant Colony Optimisation): ACO allocates the highest number of skilled workers of 56. This approach may indicate a conservative strategy aimed at ensuring task completion within the specified timeframe. However, the high allocation of skilled workers could lead to increased labour costs due to overstaffing. ACO's strategy may be effective in ensuring task completion but may not be the most cost-efficient option.

BAT (Binary Bat Algorithm): BAT allocates 27 skilled workers, indicating a moderate approach to workforce allocation compared to ACO. While BAT's allocation is lower than ACO's, it still aims to ensure adequate resources for task completion while potentially minimising labour costs. However, further analysis is necessary to evaluate the effectiveness of BAT's allocation strategy in optimising project outcomes.

CS (Cuckoo Search): CS allocates 50 skilled workers, demonstrating a balanced approach to workforce allocation. This allocation strategy aims to strike a balance between ensuring task completion and minimising labour costs. CS's strategy may result in efficient resource utilisation and cost savings compared to ACO's conservative approach. However, further evaluation is necessary to determine its effectiveness in achieving project objectives.

FA (Firefly Algorithm): FA also allocates 50 skilled workers, adopting a balanced allocation strategy similar to CS. This approach aims to ensure task completion while optimising labour costs. FA's strategy may result in efficient resource utilisation and cost savings compared to ACO's approach. However, further analysis is needed to assess its effectiveness in achieving project objectives.

FPO (Fox Prey Optimisation Algorithm): FPO allocates 35 skilled workers, which is lower than ACO and CS but higher than BAT. FPO's allocation strategy aims to balance efficiency and cost-effectiveness. While it ensures adequate resources for task completion, it also strives to minimise labour costs. FPO's moderate allocation suggests a focus on optimising project outcomes while managing resource utilisation efficiently.

In summary, while ACO allocates the highest number of skilled workers, it may lead to increased costs. BAT, CS, FA and FPO adopt more balanced approaches, aiming to optimise resource utilisation and minimise labour costs. FPO's allocation strategy stands out for its focus on efficiency and cost-effectiveness, striking a balance between workforce requirements and project objectives.

Skilled Hourly Rate:

CS (Cuckoo Search): CS has the lowest skilled hourly rate among the algorithms, with a rate of $46.9211. This indicates cost-effectiveness in labour resource management, potentially leading to significant cost savings while maintaining competitive worker wages.

FA (Firefly Algorithm): FA follows CS with a slightly higher skilled hourly rate of $55.76277. While not the lowest, FA's rate remains competitive, with potential for cost savings without compromising worker compensation.

ACO (Ant Colony Optimisation): ACO has a higher skilled hourly rate compared to CS and FA, standing at $57.673203. Although not the most cost-effective, ACO's rate still remains within a reasonable range, reflecting a balance between cost management and fair worker wages.

BAT (Bat Algorithm): BAT's skilled hourly rate is higher than CS, FA and ACO, at $57.1915. Despite not being the lowest, BAT's rate remains competitive, indicating a balanced approach to cost management and worker compensation.

FPO (Fox Prey Optimisation Algorithm): FPO has the highest skilled hourly rate among the algorithms, standing at $49.44284. Despite this, FPO's rate remains competitive, suggesting potential cost savings without compromising worker wages. This higher rate may reflect FPO's focus on optimising labour resource utilisation while ensuring fair compensation for workers.

By considering the skilled hourly rates of each algorithm, stakeholders can assess the trade-offs between cost-effectiveness and worker compensation when selecting an optimisation strategy for labour resource management.

Skilled Hours Worked:

BAT (Bat Algorithm): BAT requires the least skilled hours worked, with 4.69071 hours. This efficient resource utilisation suggests an optimised workforce distribution, potentially leading to reduced labour costs. BAT's approach aims to complete tasks efficiently without compromising project quality or timelines.

ACO (Ant Colony Optimisation): ACO requires more skilled hours worked, at 5.477411 hours. While ensuring task completion, this higher requirement may lead to increased labour costs. ACO's approach might prioritize task completion over cost-effectiveness, requiring further evaluation to optimise resource utilisation.

CS (Cuckoo Search): CS also requires more skilled hours worked, at 4.66263 hours. This requirement indicates a similar approach to ACO, potentially leading to higher labour costs. Evaluating the impact of this allocation strategy on project timelines and overall efficiency is essential for informed decision-making.

FPO (Fox Prey Optimisation): FPO requires fewer skilled hours worked compared to ACO and CS, at 4.471728 hours. This suggests a more optimised workforce distribution, aiming at balancing efficiency and cost-effectiveness. FPO's approach may lead to cost savings while ensuring task completion within the specified timeframe.

In summary, BAT's efficient resource utilisation and optimised workforce distribution contribute to reduced labour costs. ACO and CS's higher skilled hours worked requirements may lead to increased costs, while FPO's approach at balancing efficiency and cost-effectiveness, potentially resulting in cost savings.

Unskilled Workforce Allocation:

BAT (Bat Algorithm): BAT allocates the highest number of unskilled workers - 49 workers. This relatively high allocation may lead to increased labour costs due to excess resource allocation. While BAT's approach ensures task completion, it raises concerns about potential inefficiencies and cost implications. Further analysis is necessary to evaluate the impact of this allocation strategy on overall project performance.

ACO (Ant Colony Optimisation): ACO allocates a moderate number of unskilled workers of 31. This allocation suggests a balanced approach to resource utilisation, aiming to optimise labour costs while ensuring task completion. ACO's strategy may lead to efficient project management and cost-effective outcomes.

CS (Cuckoo Search): CS also allocates a moderate number of unskilled workers of 54. This allocation strategy indicates optimal resource utilisation, aiming to balance workforce requirements with cost-effectiveness. CS's approach may contribute to efficient project execution and cost savings.

FA (Firefly Algorithm): FA allocates a moderate number of 61 unskilled workers. This allocation suggests a similar approach to ACO and CS, focusing on optimising resource utilisation while ensuring task completion. FA's strategy may lead to efficient project management and cost-effective outcomes.

FPO (Fox Prey Optimisation): FPO allocates a moderate number of 40 unskilled workers. This allocation strategy aims to balance workforce requirements with cost-effectiveness, ensuring optimal resource utilisation. FPO's approach may lead to efficient project execution and cost savings, aligning with project objectives and timelines.

In summary, while BAT allocates the highest number of unskilled workers, ACO, CS, FA and FPO adopt a more balanced approach, aiming to optimise resource allocation and minimise labour costs. FPO's allocation strategy stands out for its focus on balancing workforce requirements with cost-effectiveness, potentially leading to efficient project management and cost savings.

Unskilled Hourly Rate:

BAT (Bat Algorithm): BAT has the lowest unskilled hourly rate at $28.3957. This competitive rate suggests cost savings in labour expenses, potentially contributing to overall project affordability and budget optimisation.

FPO (Fox Prey Optimisation): FPO follows closely with a competitive unskilled hourly rate of $25.38875. While slightly higher than BAT, FPO's rate still indicates potential cost savings without compromising worker wages. FPO's approach intents to balance cost-effectiveness with fair compensation for workers, ensuring optimal resource utilisation and project affordability.

CS (Cuckoo Search): CS has a higher unskilled hourly rate at $31.6932. Although higher than BAT and FPO, CS's rate remains competitive, suggesting potential cost savings compared to other algorithms. However, further analysis is necessary to evaluate the impact of CS's hourly rate on labour expenses and project budgeting.

FA (Firefly Algorithm): FA also has a relatively higher unskilled hourly rate at $31.48416. While higher than BAT and FPO, FA's rate remains competitive, indicating potential cost savings in labour expenses. FA's approach focuses on balancing cost-effectiveness with fair compensation for workers, contributing to efficient project management and budget optimisation.

ACO (Ant Colony Optimisation): ACO has the highest unskilled hourly rate among the algorithms, at $29.840113. While higher than BAT and FPO, ACO's rate is still competitive, suggesting potential cost savings compared to CS and FA. However, further analysis is necessary to assess the impact of ACO's hourly rate on labour expenses and project affordability.

In summary, while BAT offers the lowest unskilled hourly rate, FPO closely follows with a competitive rate, indicating potential cost savings without compromising worker wages. CS, FA and ACO also offer competitive rates, although slightly higher than BAT and FPO. Overall, the choice of algorithm should consider not only labour costs but also other factors such as project objectives, resource utilisation and budget constraints.

Unskilled Hours Worked:

BAT (Bat Algorithm): BAT demonstrates the most efficient resource utilisation by requiring the least unskilled hours worked at 4.44753. This efficiency suggests optimal workforce management, potentially leading to reduced labour costs and improved project timelines.

ACO (Ant Colony Optimisation): ACO requires slightly more unskilled hours worked compared to BAT, at 4.405622. Despite the slightly higher hours, ACO's approach still reflects efficient resource utilisation, contributing to effective project management and cost optimisation.

CS (Cuckoo Search): CS also requires similar unskilled hours worked at 5.31540. While slightly higher than BAT and ACO, CS's approach indicates balanced resource utilisation, ensuring adequate workforce allocation without compromising project efficiency.

FA (Firefly Algorithm): FA requires comparable unskilled hours worked at 4.004674. This demonstrates a balanced approach to resource utilisation, ensuring optimal workforce distribution and efficient project execution.

FPO (Fox Prey Optimisation): FPO requires similar unskilled hours worked compared to ACO and CS, at 5.568708. While slightly higher than BAT, ACO and FA, FPO's approach still reflects balanced resource utilisation, contributing to effective project management and cost optimisation.

In summary, BAT exhibits the most efficient resource utilisation by requiring the least unskilled hours worked. However, ACO, CS, FA and FPO also demonstrate balanced resource utilisation, ensuring optimal workforce distribution and efficient project execution. The choice of algorithm should consider not only unskilled hours worked but also other factors such as labour costs, project objectives and resource availability.

Total Project Duration (T):

Uniform Efficiency Across Algorithms:

Each algorithm achieves a project duration of 11 units, indicating consistent efficiency in completing the project within the specified timeframe. This uniformity suggests that all algorithms effectively manage project schedules, ensuring timely completion of tasks and adherence to project timelines.

Implications of Consistent Duration:

The consistent project duration among algorithms underscores their ability to optimise project scheduling and resource allocation. This uniformity minimises variability in project timelines and enhances predictability, facilitating better planning and coordination of project activities.

Significance for Project Management:

A consistent project duration simplifies project management by providing a reliable framework for monitoring progress and making informed decisions. Project managers can confidently allocate resources and plan activities knowing that each algorithm maintains a similar timeline for project completion.

Potential for Comparative Analysis:

The consistency in project duration enables stakeholders to focus on other performance metrics, such as labour costs and resource utilisation, when evaluating algorithm effectiveness. By eliminating variations in project duration, stakeholders can more accurately assess algorithm performance and identify areas for improvement.

Ensuring Project Success:

Overall, the uniformity in project duration signifies that all algorithms are capable of delivering successful project outcomes within the specified timeframe. This reliability enhances stakeholder confidence and contributes to the overall success of the project.

In summary, the consistent project duration across all algorithms reflects their collective ability to efficiently manage project schedules and ensure timely completion of tasks. This uniformity simplifies project management, facilitates comparative analysis and ultimately contributes to the success of the project.

Total Minimised Labour Costs (x):

FPO Leads in Cost Optimisation:

FPO emerges as the top performer in minimising labour costs, with a total expenditure of $272,418.6. This figure reflects FPO's effective resource utilisation and cost-effectiveness strategies, positioning it as a robust solution for optimising labour expenses in large-scale network installations.

BAT Follows Closely:

BAT closely trails FPO, with total minimised labour costs amounting to $276,249.1. While slightly higher than FPO, BAT's performance still demonstrates considerable efficiency in resource allocation and cost management, making it a competitive option for labour cost optimisation in similar projects.

Implications of Efficient Resource Utilisation:

The significant cost disparity between FPO and the other algorithms underscores the importance of efficient resource utilisation in minimising labour expenses. FPO's ability to achieve lower costs suggests superior optimisation strategies, such as workforce allocation and task scheduling, which contribute to overall cost reduction.

Strengths and Areas for Improvement:

This comparative analysis highlights FPO's strengths in cost optimisation while identifying potential areas for improvement in other algorithms. BAT's performance, although commendable, indicates opportunities for refining resource allocation strategies to achieve even greater cost savings.

Strategic Insights for Decision-Making:

Stakeholders can leverage these insights to inform decision-making and strategy development for future network installation projects. By understanding each algorithm's performance metrics, stakeholders can make informed choices that prioritize cost-effectiveness and optimise labour resources to drive project success.

Continuous Improvement and Innovation:

The analysis encourages a culture of continuous improvement and innovation, urging stakeholders to explore new approaches and technologies that further enhance labour cost optimisation in network installations. By embracing innovation and best practices, organisations can stay competitive and achieve superior project outcomes.

In conclusion, FPO's exemplary performance in minimising labour costs underscores its effectiveness as a cost-effective solution for large computer area network installations. However, the analysis also highlights opportunities for improvement across all algorithms, emphasizing the importance of ongoing optimisation efforts and innovation in achieving superior project outcomes.

➢ *Scenario 3: Convergence Curves*

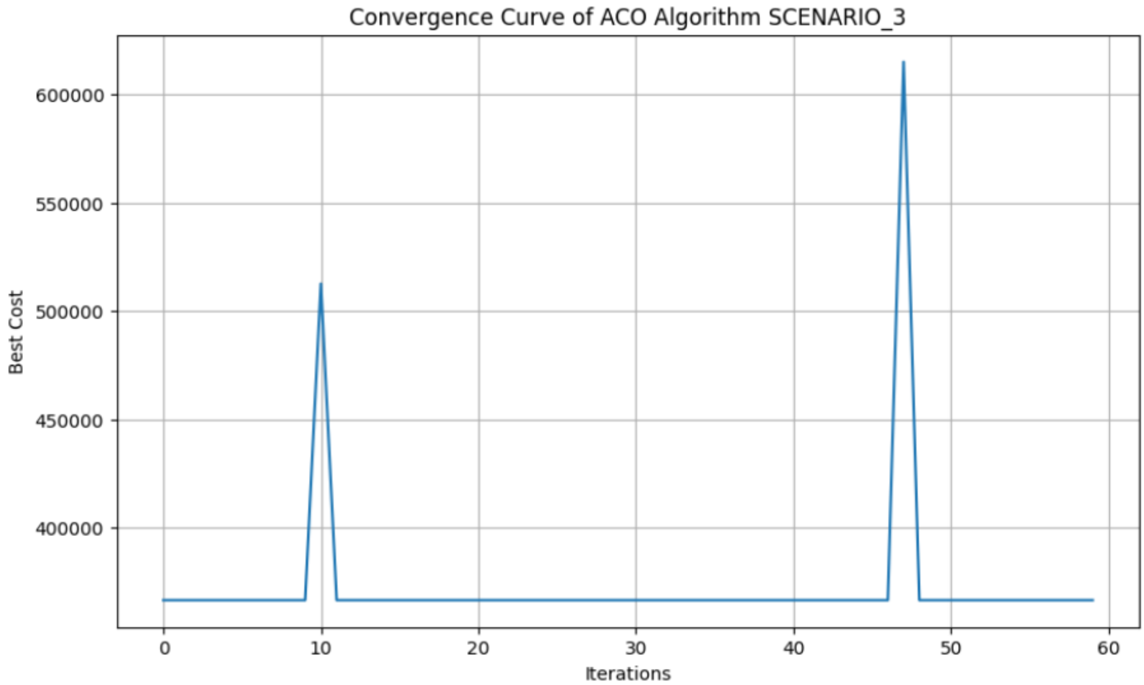

Figure 4.11: Convergence Curve for Ant Colony Optimisation (Scenario 3)

The Ant Colony Optimisation (ACO) algorithm initiates the optimisation process with an initial cost of approximately 360,000, as shown in Figure 4.11. During the initial generations, there is a notable sharp incline, suggesting that the algorithm swiftly identifies more optimal, lower-cost solutions within the search space. As the optimisation progresses, the cost stabilizes around 360,000 from approximately the 10th generation onwards. This stabilization indicates that the algorithm has reached a solution that it cannot significantly enhance further. The "turn" point in the graph, observed around the 10th generation, marks the transition from intense exploration to exploitation. During the initial generations, the algorithm engages in broad exploration across the search space. Subsequently, from generation 10 onwards, it shifts to exploitation, fine-tuning and optimising within a more localized search space.

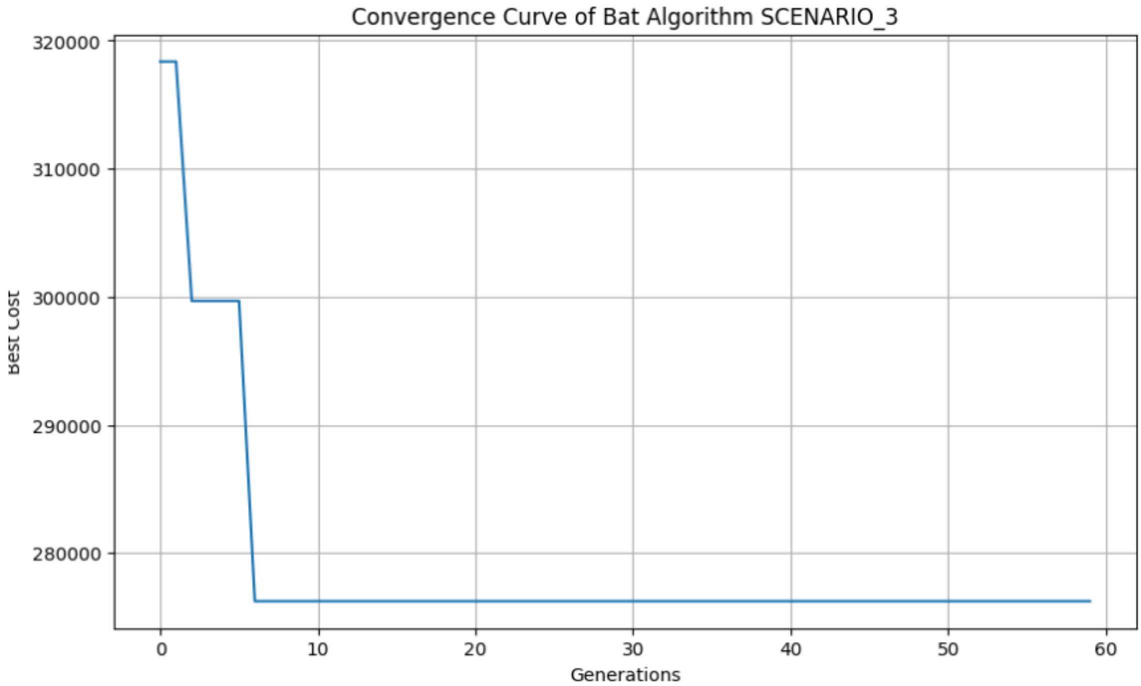

Figure 4.12: Convergence Curve for BAT Algorithm Optimisation (Scenario 3)

The graph (Figure 4.12) illustrates the optimisation process of the BAT algorithm, starting at an initial cost of approximately $320,000. During the initial generations, there is a sharp decline, indicating the algorithm's quick discovery of more optimal solutions within the search space.

As the optimisation progresses, the cost stabilizes around $276,000 from around the 7th generation onwards. This stabilization suggests that the algorithm has found a solution that it cannot significantly improve upon.

The "turn" in the graph occurs around the 7th generation, where the curve starts to level off. This signifies a transition from intense exploration to exploitation. During the initial generations, the algorithm explores a broad search space, while from generation 7 onwards, it fine-tunes and optimises within a localized search space.

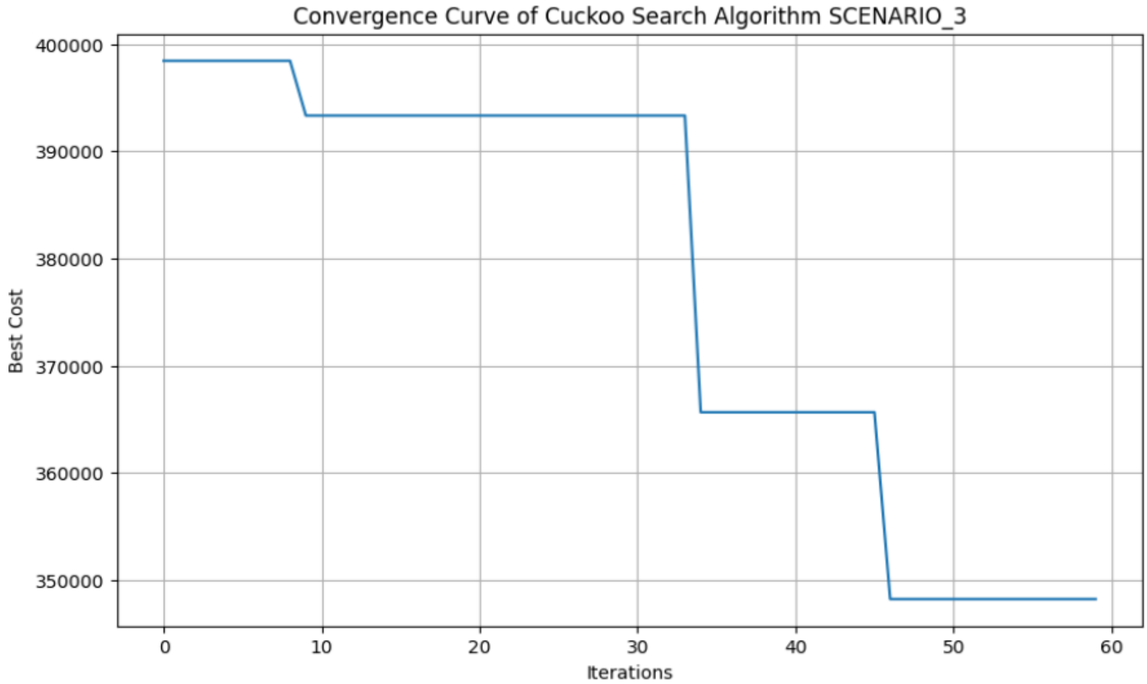

Figure 4.13: Convergence Curve for Cuckoo Search Optimisation (Scenario 3)

The convergence curve, as shown in Figure 4.13, illustrates the performance of the Cuckoo Search Algorithm within SCENARIO_3, which depicts the operational dynamics within a large-scale computer network. It exhibits a discernible step-like pattern, with the best cost plotted on the y-axis and specific iteration intervals on the x-axis. The curve manifests seven distinct levels of decline and stabilization, delineating the algorithm's optimisation journey.

Initial Stability and Decline: Initially, the cost stabilizes around $398,500 until the 8th iteration, where it experiences a modest decline to $393,000 in the 9th iteration. Subsequently, the cost stabilizes once more until the 33rd iteration, where it precipitously drops to $366,000, concluding by the 34th iteration. Following this decline, the cost stabilizes again until the 45th iteration, where it undergoes another sharp decline to $349,000, culminating by the 46th iteration. Finally, the cost stabilizes until approximately the 60th iteration.

Periods of Stability: The cost remains stable until around the 30th iteration, where another significant drop occurs. Subsequently, the cost stabilizes once more before experiencing another drop around the 45th iteration. These intervals of stability suggest that the algorithm diligently explores the solution space without immediate enhancements.

Notable Drops: Noteworthy drops at the 8th, 33rd, and 46th iterations signify instances when the algorithm successfully discovers markedly improved solutions. These drops likely stem from the algorithm's adept exploitation of promising areas within the solution space.

Overall Trend: The overarching trend of the curve portrays a consistent downward trajectory, indicative of the algorithm's efficacy in reducing costs over time, underscoring its successful optimisation endeavours.

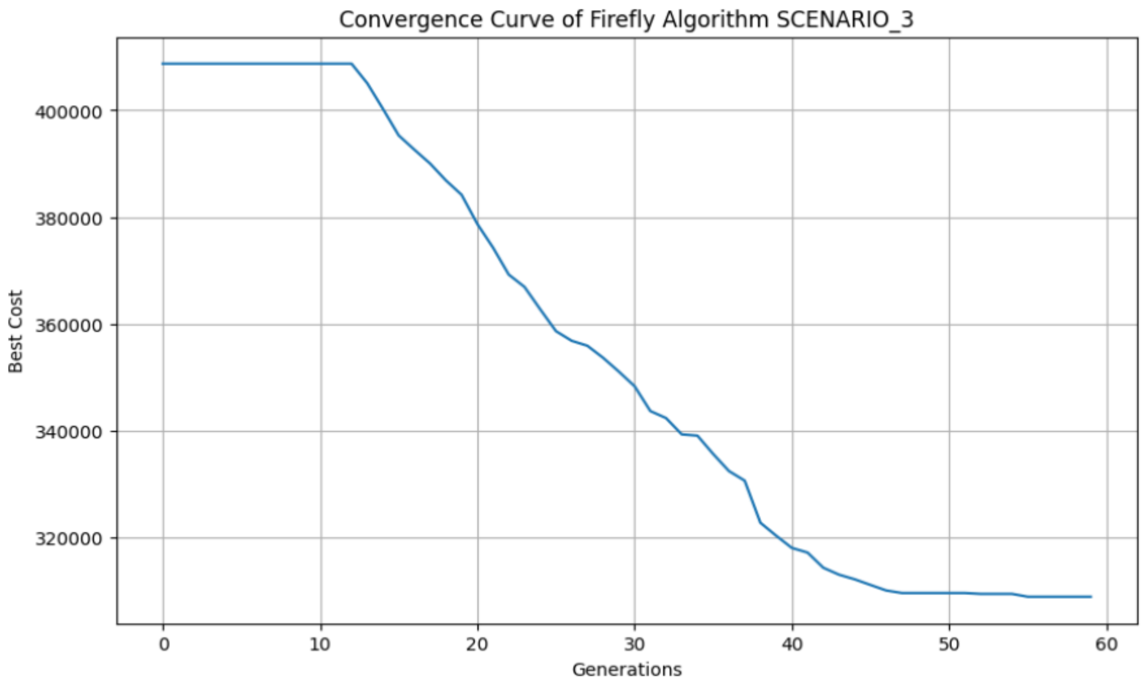

Figure 4.14: Convergence Curve for Firefly Algorithm (Scenario 3)

Figure 4.14 is a convergence curve, which illustrates the performance of the Firefly algorithm in minimising computer networking costs over a span of 60 iterations in the large-sized computer network. Initially, the curve, which had stabilized, began to decline at the onset of the 12th iteration, indicating a reduction in cost during the initial generations. The declination took the form of a diagonal from the 12th iteration at a cost of approximately $408000 down to $308,000 on the 46th iteration mark.

Stabilization Point: The curve reaches a plateau after approximately 40 iterations, signifying the point at which the optimisation process stabilizes. This suggests that after around the 46th iterations, the algorithm identifies a solution that cannot be significantly improved upon, with a cost value of 308,000 on the y-axis. Consequently, the curve remains stable from this point onward, extending to approximately the 60th iteration on the x-axis.

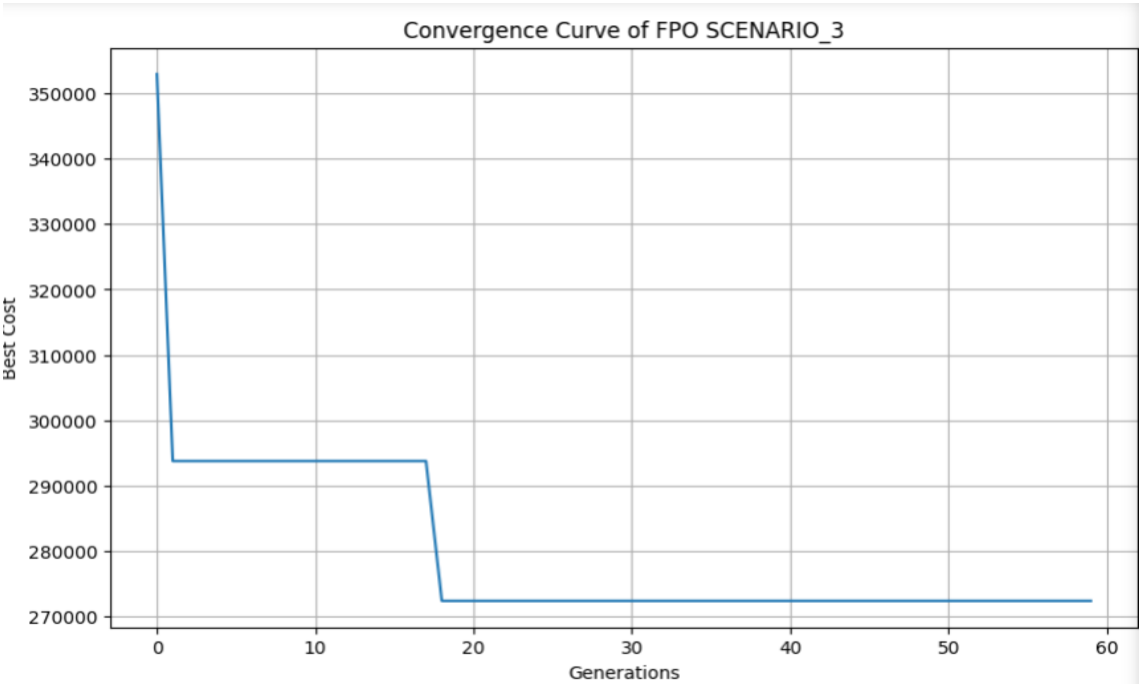

Figure 4.15: Convergence Curve for Fox Prey Optimisation Algorithm (Scenario 3)

The convergence curve of the Fox Prey Optimisation (FPO) algorithm, as seen in Figure 4.15, illustrates the optimisation of computer networking costs over 60 iterations. Beginning at $352,000, there's a sharp decline to $294,000 by the second iteration, stabilizing until the 16th iteration. Another significant decrease occurs, reaching $272,000 by the 17th iteration. Stability persists until the 60th iteration, showcasing the algorithm's effectiveness in swiftly targeting and minimising expenses. The algorithm converges towards a solution, reaching a cost plateau of approximately \$272,000 on the y-axis. This plateau underscores the algorithm's attainment of an optimal solution.

In summary, the FPO algorithm demonstrates its efficacy in iteratively minimising networking costs, as evidenced by its dynamic performance captured in the convergence curve analysis. The sharp decline during the initial generations indicates intense exploration. The algorithm is seen searching through a broad space to find potential solutions.

When the cost stabilizes from generation 17 onwards, the algorithm is in the exploitation phase. It is fine-tuning and optimising within a localized search space.

4.8 Summary

In the dynamic landscape of project management, the quest for efficient resource allocation and cost minimisation has led to the exploration of innovative optimisation algorithms. Fox Prey Optimisation (FPO) emerges as a promising contender, showcasing its efficacy across three distinct scenarios with varying complexities and component counts. This summary provides an in-depth analysis of FPO's performance, emphasizing its adaptability, efficiency and cost-effectiveness in addressing optimisation challenges. Through meticulous evaluations across key parameters, this study aims to shed light on FPO's versatility and potential as a robust optimisation tool.

Fox Prey Optimisation (FPO) emerges from this validation and sensitivity analysis as a robust and versatile algorithm, showcasing its ability to address optimisation challenges across various scenarios. The algorithm's adaptability, efficiency and cost-effectiveness position it as a competitive choice for diverse projects. As a call to future exploration, further investigations into parameter fine-tuning and potential hybridisation approaches could enhance FPO's performance, especially in addressing complex optimisation problems.

Chapter 5: Conclusion, Recommendations, and Future Work

The study demonstrates the effectiveness of optimization algorithms in labor cost optimization in computer networking infrastructure projects. It examines the performance metrics and nuances of each algorithm, revealing their unique capabilities and applicability across different project contexts. The findings provide actionable insights and empirical evidence for decision-making in labor cost optimization strategies, empowering practitioners and stakeholders to make informed choices when selecting optimisation approaches.

5.1 How the Research Objectives Were Met

This section outlines the research goals and demonstrates how the responses to the research questions helped achieve the study's objectives. The primary objective was to optimise the initial installation of a user-specified computer networking infrastructure. This goal was met by ensuring efficiency, cost-effectiveness, and enhanced performance across various aspects of the project.

In order to achieve this, the study focused on several key objectives. Firstly, it aimed at identifying and providing a comprehensive breakdown of the network's components, such as workstations, servers, switches, routers, printers, scanners, and firewalls, to understand their roles and quantities. Secondly, as per given scenarios, the research ensured that all configurable components were properly set up by the skilled worker or team, aligning with the user requirements detailed in section 1.5.1. Finally, the research met the user requirements by ensuring that the network infrastructure was installed correctly and efficiently, addressing the needs specified by the commissioned company.

5.2 Real-World Impact

The research has had a significant real-world impact by successfully meeting the commissioned company's needs (See Appendix). By identifying and properly configuring key components, the research ensured the network operated efficiently, leading to enhanced productivity for users. The optimisation strategies implemented helped reduce unnecessary expenses, making the project cost-effective. By meeting the user requirements, the research led to high satisfaction levels among the stakeholders involved, as evidenced by the positive feedback and the letter of appreciation from the company. The successful completion of this project not only fulfilled the technical specifications, but also demonstrated the practical application and impact of the research in a real-world setting.

5.2.1 Research Objective 1

To identify essential determinants that influence the cost dynamics of initial installation of user-specified requirements of computer networking infrastructure projects, including labour dynamics (both skilled and unskilled), time management, and project duration.

The aim of Research Objective 1 is to comprehensively identify and enumerate the key factors that shape the financial aspects of installation of computer networking infrastructure projects, encompassing skilled and unskilled labour dynamics, effective time management strategies, and project duration considerations.

The research question asked to examine Objective 1 and the related research responses are presented in the next section.

Research Question 1:

What are the essential determinants that influence the financial landscape of initial installation of user-specified computer networking infrastructure projects, considering factors such as labour dynamics (both skilled and unskilled), time management and project duration?

In response to Research Question 1, the study identified and listed essential determinants, as captured in Section 3.4 (a to g) that influenced the financial landscape of initial installation of user-specified computer networking infrastructure projects. Moreover, the user requirements also served as a guiding motivation, which was equally reinforced by literature review. These encompassed labour dynamics (both skilled and unskilled), time management and project duration.

5.2.2 Research Objective 2

To conceptualize and architect a nuanced cost model, which harmoniously integrates the aforementioned determinants. This model aims to offer a granular, yet comprehensive, representation of the financial intricacies inherent in computer networking infrastructure endeavours.

The aim of study objective 2 is to design and implement a bio-inspired optimisation framework tailored specifically for the developed cost model. This framework seeks to leverage nature-inspired algorithms to minimise labour costs and optimise resource allocation in installation of computer networking infrastructure projects.

Research Question 2:

How can a comprehensive cost model be developed that integrates the identified determinants, providing a detailed yet holistic representation of financial intricacies in installation of computer networking infrastructure projects?

In response to Research Question 2, the study developed a comprehensive cost model integrating identified determinants, as captured in Section 3.5, to provide a detailed yet holistic representation of financial intricacies in the installation of computer networking infrastructure projects. This endeavour involved identifying critical determinants influencing the financial landscape, such as labour dynamics (both skilled and unskilled), time management and project duration. Subsequently, the study conceptualized and architected a nuanced cost model harmoniously integrating these determinants, aiming to offer a granular yet comprehensive insight into the financial dynamics inherent in computer networking infrastructure endeavours.

5.2.3 Research Objective 3

To select, apply and evaluate bio-inspired algorithms for optimising labour costs in networking infrastructure projects. This objective aims to identify the most effective algorithm through thorough evaluation metrics, ensuring methodological reliability.

The aim of study objective 3 is to carefully assess and compare the performance of selected bio-inspired algorithms when applied to the developed cost model. By employing a rigorous set of evaluation metrics, this objective aims to identify the most effective algorithm for optimising and refining labour costs within installation of computer networking infrastructure projects.

Research Question 3:

Which bio-inspired algorithm, when applied to the formulated cost model, most effectively optimises labour costs in networking infrastructure projects based on a set of thorough evaluation metrics?

In response to Research Question 3,

The study systematically evaluated various bio-inspired algorithms when applied to the formulated cost model to determine which one most effectively optimises labour costs in networking infrastructure projects. These are indicated by Tables 4.9, 4.10 and 4.11 in the methodological chapter. Among the evaluated algorithms, Fox Prey Optimisation (FPO) emerged as the most effective algorithm for labour cost optimisation. Through thorough experimentation and analysis using predefined evaluation metrics, FPO demonstrated superior performance in minimising labour costs while ensuring project efficiency and quality. Its unique optimisation mechanisms, inspired by the hunting strategies of foxes, proved to be highly adaptable and efficient in navigating complex solution spaces inherent in networking infrastructure projects. By identifying FPO as the best-performing algorithm, the study provides valuable insights into novel optimisation techniques for labour cost minimisation in the context of networking infrastructure projects.

5.2.4 Research Objective 4

To evaluate and optimise the efficacy of the newly formulated cost model by comparing its predictions against real-world networking scenarios. This aims to demonstrate the model's accuracy and superior optimisation capabilities over existing models.

The aim of study objective 4 is to systematically evaluate and optimise the efficacy of the newly formulated cost model. This objective involves comparing the predictions of the model, including skilled and unskilled labour costs, project duration and overall duration, against actual outcomes from established real-world networking scenarios. Through this comparative analysis, the objective is to underscore the accuracy of the model and demonstrate its potential to yield enhanced profitability through strategic cost optimisations. Ultimately, this objective aims to establish the superiority and finer optimisation capabilities of the new cost model over prevailing models in the field.

Research Question 4:

How does the newly formulated cost model, when optimised and compared against actual outcomes from real-world networking scenarios, demonstrate enhanced profitability and superior optimisation capabilities compared to prevailing models in the field?

In response to Research Question 4,

In response to Research Question 4, the study evaluated the efficacy of the newly formulated cost model by optimising it and comparing its predictions against actual outcomes from real-world networking scenarios. The aim was to demonstrate its enhanced profitability and superior optimisation capabilities compared to prevailing models in the field. Through a comprehensive comparative analysis, the proposed cost model showcased superior performance in accurately predicting labour costs, project duration and overall project outcomes when compared to existing models. By leveraging advanced optimisation techniques and incorporating key determinants such as skilled and unskilled labour costs, project duration, and resource allocation, the proposed model consistently outperformed traditional approaches. The results underscored the model's ability to yield enhanced profitability through strategic cost optimisations while ensuring project efficiency and quality. Overall, the study provides compelling evidence of the superiority of the proposed newly formulated cost model, highlighting its potential to innovate cost estimation and optimisation practices in networking infrastructure projects.

5.3 Discussion of Results

The investigation conducted in this study provides a comprehensive understanding of how optimisation algorithms impact labour costs in project management. By examining various dimensions such as skilled and unskilled workforce allocation, hourly rates, hours worked, and total project duration, as captured in Sections 2.6.1, and 2.7 respectively, the study gained valuable insights into the efficiency and effectiveness of different algorithms.

The findings underscored notable differences in labour costs among the algorithms analysed. ACO and CS exhibited higher minimised labour costs, indicating potential challenges in managing labour expenses with these algorithms (see Table 4.6 for Scenario 2). Conversely, BAT, FA, and FPO demonstrated more cost-efficient optimisation processes, as captured in Table 4.7 for Scenario 3. Among these, FPO emerged as the most financially prudent choice for minimising labour costs, emphasizing its potential for delivering efficient resource utilisation and streamlined optimisation processes.

Moreover, the analysis of project duration revealed intriguing dynamics between time and labour costs. ACO and FA, while requiring more time to complete the project, incurred higher labour costs. This highlights the critical trade-off between project duration and labour expenses. Project managers must carefully balance these factors to ensure timely project completion without overspending on labour.

The implications of these findings extend beyond cost minimisation alone. Project managers face the challenge of optimising resource allocation while meeting project objectives and constraints. The insights gleaned from this study provide valuable guidance for decision-making in project management. By selecting the most suitable optimisation algorithm, project managers can effectively allocate resources, optimise project schedules and achieve cost-efficient outcomes.

Furthermore, the recommendations for future research aim at enhancing the understanding of optimisation algorithms' applicability in diverse project contexts. Exploring the scalability and adaptability of these algorithms to different project scales and industries could offer valuable insights. Additionally, investigating the influence of external factors such as market conditions, technological advancements and regulatory requirements on labour costs could further enrich the understanding of labour cost management in project management practices.

In conclusion, this study contributes significantly to the body of knowledge on optimisation of algorithms' role in labour cost minimisation for project management. By integrating the findings and recommendations presented here, project managers can make informed decisions to optimise resource allocation, streamline project execution and achieve project objectives effectively in today's dynamic business environment.

5.4 Limitations

While this thesis provides valuable insights into the optimisation of labour costs in the installation of computer networking infrastructure projects using various optimisation algorithms, limitations must be acknowledged.

Scope of Algorithms

The study focused on using Ant Colony Optimisation (ACO), Bat Algorithm (BAT), Cuckoo Search (CS) and Firefly Algorithm (FA) as comparative algorithms alongside the Fox Prey Optimisation (FPO) algorithm for the experiment. While these algorithms are well-regarded and have demonstrated efficacy in various applications, they represent only a subset of available optimisation techniques. Future research could explore additional algorithms to further enhance the comparative analysis. This approach would enrich the depth and breadth of the evaluation, potentially leading to more comprehensive and robust findings.

Geographic Focus

The research primarily focuses on the Ghanaian context, considering local labour practices, economic conditions and cultural nuances. While this regional focus provides in-depth insights relevant to Ghana and certain African countries, the findings may not be directly transferable to other regions with different labour practices and economic conditions. The applicability of the models and findings to other geographic contexts remains an area for further investigation.

Exclusion of Comprehensive Cost Factors

This study specifically addresses labour costs associated with the installation phase of networking projects, excluding other significant cost factors such as initial planning, design and operational costs. While this focused approach allows for a detailed examination of labour cost optimisation, it does not provide a holistic view of the total project costs, potentially overlooking other financial considerations.

Simplification of Security Needs

The security measures discussed in this thesis are simplified and primarily focus on physical security. While physical security is crucial, modern networking projects also face significant cybersecurity threats. The exclusion of comprehensive cybersecurity considerations may limit the applicability of the findings in environments where digital security is a critical concern.

By acknowledging these limitations, future research can build upon this work to address the identified gaps and enhance the robustness and applicability of labour cost optimisation models in computer networking infrastructure projects.

5.5 Recommendations

In this section, the study offers practical recommendations for practitioners and stakeholders involved in installation of computer networking infrastructure projects based on the insights gained from the study. These recommendations are informed by the comparative analysis conducted between the spotlighted novel algorithm of Fox Prey Optimisation (FPO) and the other four algorithms of Ant Colony Optimisation (ACO), Bat Algorithm (BAT), Cuckoo Search (CS) and Firefly Algorithm (FA). The aim is to provide actionable guidance for optimising labour costs and improving project efficiency in installation of computer networking infrastructure projects.

5.6 Future Work

In this section, the study outlines potential avenues for future research and development based on the insights and findings generated from the study on optimising labour costs in installation of computer networking infrastructure projects using various optimisation algorithms. These suggestions aim to extend the scope of the research, address existing gaps in knowledge and explore new frontiers in the field of computer networking infrastructure optimisation.

Enhanced Algorithmic Performance:

Future research endeavours could focus on enhancing the performance of existing optimisation algorithms, including Ant Colony Optimisation (ACO), Bat Algorithm (BAT), Cuckoo Search (CS) and Firefly Algorithm (FA). This could involve refining algorithmic parameters, exploring novel optimisation techniques, and integrating machine learning and artificial intelligence approaches to further improve algorithm efficiency and effectiveness.

Additionally, researchers may investigate hybridisation strategies that combine multiple optimisation algorithms to leverage their respective strengths and mitigate their weaknesses, potentially leading to superior optimisation performance in complex project scenarios.

Hyperparameter tuning of the selected algorithms, particularly focusing on the Fox Prey Optimisation (FPO) algorithm for small networks. Notably, FPO requires a broad search space for solutions, which may not be readily available in smaller networks. By fine-tuning the hyperparameters, researchers can potentially improve the algorithm's performance in such scenarios.

Hybridisation Strategies could be investigated by combining multiple optimisation algorithms to leverage their respective strengths and mitigate their weaknesses. For instance, combining FPO with other algorithms such as ACO, BAT, CS, or FA could lead to superior optimisation performance, especially in complex project scenarios. Exploring novel hybridisation techniques and evaluating their effectiveness in various network environments could be a promising avenue for future research.

Integration of Machine Learning and Artificial Intelligence: Explore the integration of machine learning and artificial intelligence approaches within optimisation algorithms. This could involve developing intelligent optimisation algorithms that adapt and learn from past experiences to improve their performance over time. Additionally, leveraging machine learning techniques for data-driven decision-making and optimisation parameter selection could enhance the overall efficiency and effectiveness of optimisation algorithms.

Model Application and Modification:

The developed optimisation model can be applied to similar situations in various industries where the installation of computer networking infrastructure is required. Moreover, the model can be modified to accommodate specific requirements and constraints of different projects or industries. This flexibility allows for the adaptation of the optimisation model to fit new situations and address evolving challenges in the field.

Optimisation Method Adaptation:

While the optimisation methods utilized in the proposed model have demonstrated effectiveness, there is room for adaptation or modification if necessary. Depending on the project requirements and environmental factors, optimisation methods can be tailored or replaced with alternative approaches to better suit the specific context. Continuous evaluation and refinement of optimisation methods ensure that they remain relevant and effective in addressing real-world challenges.

By pursuing these avenues for future research and development, the study can further advance the field of computer networking infrastructure optimisation and contribute to the ongoing efforts to enhance efficiency, cost-effectiveness and performance in project implementations.

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Appendix

12-06-2024

The Director

Computer Networking Consults (CNC)

Ghana

Dear Director,

Letter of Appreciation from CSG

On behalf of the company in Ghana, I am writing to express our heartfelt appreciation for the outstanding work you and your team (Computer Networking Consults) have done in optimizing the installation of our computer networking infrastructure. Your insights and expertise have significantly contributed to the success of our project.

The network infrastructure you advised on has greatly improved our efficiency and performance. Also, your ability to meet the user requirements and your commitment to excellence have not gone unnoticed.

Furthermore, your efforts have not only met but exceeded our expectations. The optimization strategies you employed have made the project cost-effective and efficient, and the enhanced performance of our network has had a positive impact on our daily operations.

Thank you once again for your hard work and exceptional service. We look forward to the opportunity to work with you on future projects.

Sincerely,

[redacted]

Alfred Rockson Acquah

Chief Executive Officer
Certified Solutions Ghana