

Integrated Cost-Availability Based Maintenance Management Models for Data Centers

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A Thesis

In the Department

Of

Building, Civil and Environmental Engineering (BCEE)

Presented in Partial Fulfillment of the Requirements

For the Degree of

Doctor of Philosophy (Building Engineering)

at Concordia University

Montréal, Québec, Canada

July 2025

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**CONCORDIA UNIVERSITY
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Abstract

Integrated Cost-Availability Based Maintenance Management Models for Data Centers

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Data centers (DCs) are the backbone of modern digital infrastructure, but their complexity, energy intensity, and need for continuous uptime pose major maintenance challenges. This dissertation reviews current Operations and Maintenance (O&M) practices and develops three novel optimization models specifically tailored to DCs.

The literature review highlights research gaps: existing O&M models rarely address DC-specific issues such as balancing cost and high availability. It underscores the importance of integrating reliability and availability analyses into predictive maintenance, energy efficiency, and system optimization.

Building on these findings, three optimization models are introduced. The first applies Dynamic Programming (DP) and the multiple knapsack problem to prioritize maintenance of UPS units under budget constraints, achieving a 61% improvement in availability with optimized resource allocation. The second model develops an availability-based cost optimization framework for UPS units in k-out-of-n configurations. Case studies show optimal selection ($k = 5$ of 10), delivering 99.991% availability above Tier I standards while minimizing costs. Sensitivity analysis confirmed that availability is more affected by repair times than failure rates, and the validation under varying conditions confirmed the robustness of the results. The third model, formulated as a Mixed-Integer Nonlinear Program (MINLP), optimizes maintenance in Series-Parallel systems. Results

demonstrate 99.974% availability (above Tier I targets) while maintaining costs within budget.

Together, these models advance DC maintenance by integrating cost, reliability, and availability into scalable decision-making frameworks. The contributions provide operators with practical tools to reduce costs, improve reliability, and ensure compliance with strict uptime standards.

Dedication

This thesis is dedicated to my parents, my wife (Zahra), and my daughter (Helen),

whose endless love, support, patience and encouragement made the completion of this work possible.

Acknowledgments

My deepest gratitude goes to all those who supported, understood, and stood by me throughout my PhD journey at Concordia University. Words cannot fully capture how much their presence meant during one of the most challenging and transformative periods of my life. I thank God for granting me the strength to persevere and for surrounding me with compassionate and supportive individuals. Without this, completing my doctoral studies would not have been possible. I carry this blessing forward with the hope of passing it on to others in both my professional and personal life.

I am profoundly grateful to my supervisors, Professor Fariborz Haghighat and Professor Fuzhan Nasiri, for their invaluable guidance, unwavering support, and insightful feedback throughout the planning and execution of this research. Their generosity with their time and knowledge has been deeply appreciated and instrumental to my academic development.

I would also like to extend my sincere thanks to the members of my examination committee—Dr. Radu Zmeureanu, Dr. Yong Zeng, and Dr. Bruno Lee—for their constructive comments and helpful suggestions, which enriched the quality of this dissertation. I am also especially thankful to Dr. Champika Liyanage from the University of Central Lancashire for kindly accepting to serve as the External Examiner on my examination committee.

Special thanks to my past and present colleagues at the Sustainable Energy and Infrastructure Systems Engineering (SEISE) Lab, whose contributions—both direct and indirect—played a meaningful role in the completion of this work. I would also like to acknowledge the technical staff, program advisors, and faculty members of the Department of Building, Civil, and

Environmental Engineering at Concordia University for their support and assistance throughout my academic journey.

This dissertation is lovingly dedicated to my wonderful wife, Zahra, and my dear daughter, Helen, whose enduring love, patience, and care have inspired me throughout this journey. I am also deeply thankful to my parents, whose endless love, support, and prayers have uplifted me every step of the way.

Finally, I would like to acknowledge the partial financial support provided by Concordia University through the Faculty Research Support (FRS) program. I am sincerely grateful for this assistance. Additionally, I gratefully acknowledge the funding received from the NSERC Engage Partnership Project awarded by the Natural Sciences and Engineering Research Council of Canada (NSERC). This project provided important support during the early stages of my research.

List of Publications

1. Journal publications:

- Fadaeefath Abadi, M., Bordbari, M. J., Haghighat, F., & Nasiri, F. (2025). Dynamic Maintenance Cost Optimization in Data Centers: An Availability-Based Approach for K-out-of-N Systems. *Buildings*, 15(7), 1057. <https://doi.org/10.3390/buildings15071057>
- Fadaeefath Abadi, M., Haghighat, F., & Nasiri, F. (2025). Availability-based maintenance prioritization for data centres: a dynamic programming approach. *Safety and Reliability* (pp. 1-36). Taylor & Francis. <https://doi.org/10.1080/09617353.2024.2441545>
- Mostafa Fadaeefath Abadi, Mohammad Hosseini Rahdar, Fuzhan Nasiri and Fariborz Haghighat (2022). Fault Identification and Fault Impact Analysis of the Vapor Compression Refrigeration Systems in Buildings: A System Reliability Approach, *Energies*, 15(16), 5774. <https://doi.org/10.3390/en15165774>
- Fadaeefath Abadi, M., Haghighat, F., and Nasiri, F. (2020). Data Center Maintenance: Applications and Future Research Directions, *Facilities*, Vol. 38 No. 9/10, pp. 691-714. <https://doi.org/10.1108/F-09-2019-0104>

2. Conference proceedings and presentations:

- Fadaeefath Abadi, Mostafa; Haghighat, Fariborz and Nasiri, Fuzhan (2022). "Application of Dynamic Programming in Developing an Availability Based Maintenance Prioritization Model for Data Centers". *INFORMS Conference on Service Science (ICSS)*, Tsinghua University, Shenzhen, China. July 2 - 4.

- Fadaeefath Abadi, Mostafa; Haghighat, Fariborz and Nasiri, Fuzhan (2022). "An Integrated Cost and Availability Based Maintenance Scheduling Model for Data Centers Using Dynamic Programming Approach". *Optimization Days annual conference*, HEC Montréal, QC, Canada. May 16 -18.
- Esmaeili, F.; Fadaeefath Abadi, Mostafa and Nasiri, Fuzhan (2021). "Deterioration Prediction Model Development and Analysis for Alberta's Provincial Highway Road Network's Pavement Condition". *Canadian Society for Civil Engineering (CSCE 2021) Virtual Annual Conference*. May 26-29.
- Hosseini Rahdar, Mohammad; Rezaei, Masoud; Fadaeefath Abadi, Mostafa and Nasiri, Fuzhan (2021). "Reliability analysis of the vapor compression refrigeration system for office building applications". *Canadian Operational Research Society (CORS 2021) Annual Conference*. June 7-10.
- Fadaeefath Abadi, M. and Esmaeili, F. (2021). "Development of Pavement Deterioration Prediction Models for Montreal's Road Network". *Canadian Network of Asset Managers Student Research Symposium (CNAM 2021) Virtual Conference*. May 10-13.

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List of Symbols and Abbreviations

<i>DC</i>	Data Center
<i>O&M</i>	Operation(s) and Maintenance
<i>DP</i>	Dynamic Programming
<i>UPS</i>	Uninterruptible Power Supply
MINLP	Mixed-Integer Nonlinear Programming
<i>FMECA</i>	Failure Mode, Effects, and Criticality Analysis
<i>FCI</i>	Facility Condition Index
<i>FCA</i>	Facilities Condition Analysis
<i>HVAC</i>	Heating, Ventilation, and Air Conditioning
<i>CAGR</i>	Compound Annual Growth Rate
<i>KPIs</i>	Key Performance Indicators
<i>RBD</i>	Reliability Block Diagrams
<i>MTTF</i>	Mean Time To Failure
<i>MTBF</i>	Mean Time Between Failure
<i>MTTR</i>	Mean Time to Repair (Restore or Recover)

$C_{F(i,t)}$	Costs of Services for each incident/failure
$C_{PM(i,t)}$	Preventive Maintenance Costs
$C_{CM(i,t)}$	Corrective maintenance Costs
$C_{PC(i,t)}$	Costs of Power and Cooling services
$C_{CR(i,t)}$	Component Renewal Costs
$C_{B(i,t)}$	Costs of Battery replacement service
$C_{I(i,t)}$	Investment Costs
$w_i(t)$	Weight of each item (component) in each timeframe (t)
C_k	Maximum weight capacity of each knapsack (k)
W_t	Maximum weight capacity of the knapsack in each timeframe (t)
Z	Total value of items (components) included in the knapsack
λ	Failure (Hazard) rate showing the number of failures for each year
A_t	Component's availability in timeframe (t)
λ	Failure (Hazard) rate showing the number of failures for each year
$\lambda(t)$	Failure (Hazard) rate function, which represents the probability of failures per unit of time (t)
A_t	Component's availability in timeframe (t)

Chapter 1: Introduction

1.1. Introduction to Data Centers and Their Features

A Data Center (DC) is a major infrastructure and facility which contains a high quantity of servers and computers to provide internet services for many companies in the world (such as Google, Amazon, etc.). The term “Data Center” may have different meanings from various points of view and there are also some other similar names such as data hall, data farm, data warehouse, computer room, server room, etc. which have been used by researchers and scholars. Over the past two decades, DCs have evolved from being relatively unknown to becoming indispensable for companies across different sectors to meet digital demands and provide online services (Fadaeefath Abadi et al., 2020). According to the U.S. Environment Protection Agency (EPA), DC is a type of principal electronic equipment that is used for processing data (server devices), storing the data (storage equipment) and communications including networking tools and devices. DC requires special power conversion and backup equipment to preserve high quality and reliable power system. The system maintains important environmental factors such as proper temperature and humidity for the Information and Communication Technology (ICT) equipment (Geng, 2015a). The principal components and equipment located in DCs are computers, servers, cooling systems, storage devices, and supply devices. Three main subsystems located in a general (traditional) DC are continuous power supply, air conditioning and network connectivity (Saha et al., 2016a).

DCs have become indispensable pillars of contemporary society, serving as the backbone for critical infrastructure and operations. Their intricate systems and components demand meticulous

attention, particularly in the realm of Operations and Maintenance (O&M). As technology advances, the DC industry undergoes rapid evolution, with transformative changes reshaping its landscape. Based on recent reports (Informa PLC - AFCOM, 2024), this sector is witnessing exceptional expansion, emerging customer demands, and shifts in the approach to deploying physical infrastructure.

Corresponding to different references, there have been various changes in the technology of DCs such as other technologies in the world. As there were computer rooms in the middle of the 20th century, DC began to operate in those computer rooms as a shelter or house. Later, these computer housings became large and complex infrastructures. The ARC net is recognized as the first DC, placed in a special area. About 10,000 ARC net DCs were used globally by 1980. From the beginning of the 1990 decade, as the usage of personal computers was increasing in the world, users had access to a network. Therefore, the real difference appeared and the mainframe which existed before, was converted into places hosting many servers. These places were later named “Data Centers” (Carey et al., 2017).

DCs are industrialized centers located worldwide and the number of them is growing due to high demand for several services. As specified by references and reports, the total number of DCs worldwide in 2017 was about 8.4 million. Based on the literature, there are about 8.6 million enterprise DCs operating globally. Also, the number of Cloud DCs has been increased recently. Colocation DCs accommodate a diverse range of retail and wholesale clients. Retail colocation services, encompassing power and cooling, are provided through monthly service agreements, similar to cloud computing offerings. While the typical contract durations for cloud computing DCs are 12, 24, or 36 months, the wholesale colocation entails longer-term leases, generally spanning 5 to 20 years (Equinix Editor, 2024). DC facilities have been combined and became

hyperscale DCs. A hyperscale DC represents a specialized form of wholesale colocation facility designed to meet the stringent technical, operational, and economic requirements of large-scale enterprises, including Amazon, Alibaba, Meta, Google, IBM, and Microsoft. These entities, commonly termed “hyperscalers,” necessitate substantial spatial and power resources to support the deployment and scaling of thousands of servers for cloud computing, big data analytics, and high-volume storage operations (Equinix Editor, 2024).

Therefore, because of hyperscale DCs, the total quantity of DCs has decreased from 8.55 million in 2015 to about 8.4 million in 2017, but the demand for data storage and processing is still rising (Statista, 2017; Williams, 2018). According to statistics, the amount of DC storage consumed by big data worldwide required about 124 exabytes of DC storage space globally until the end of 2018 and was estimated to grow up to 403 exabytes by 2021 (Cisco Systems, 2018a). In addition, in 2018, the storage capacity of DCs reached 1450 exabytes in the world with 250 exabytes being consumed by collaboration activities and data (Cisco Systems, 2018b). Based on statistics and predictions, the global amount of data will reach 200 zettabytes by 2025 (Edge Delta, 2024).

Figure 1 presents the countries' ranks by the number of DCs as of March 2024, showing the United States with the highest count at 5,381, followed by Germany, the United Kingdom, China, and Canada (Cloudscene, 2025). According to Figure 2, the Global DC colocation Market was valued at USD 65.04 billion in 2023 and increased to USD 72.98 billion in 2024. This market is projected to reach approximately USD 205.65 billion by 2033, growing at a Compound Annual Growth Rate (CAGR) of 12.2% from 2024 to 2033 (Precedence Research, 2024). Also, Figure 3 highlights the expected growth in the Global DC construction market from 2023 to 2033, broken

down by DC tier types, with total market size rising from \$237.1 billion in 2023 to \$453.5 billion in 2033 (Tajammul Pangarkar, 2024).

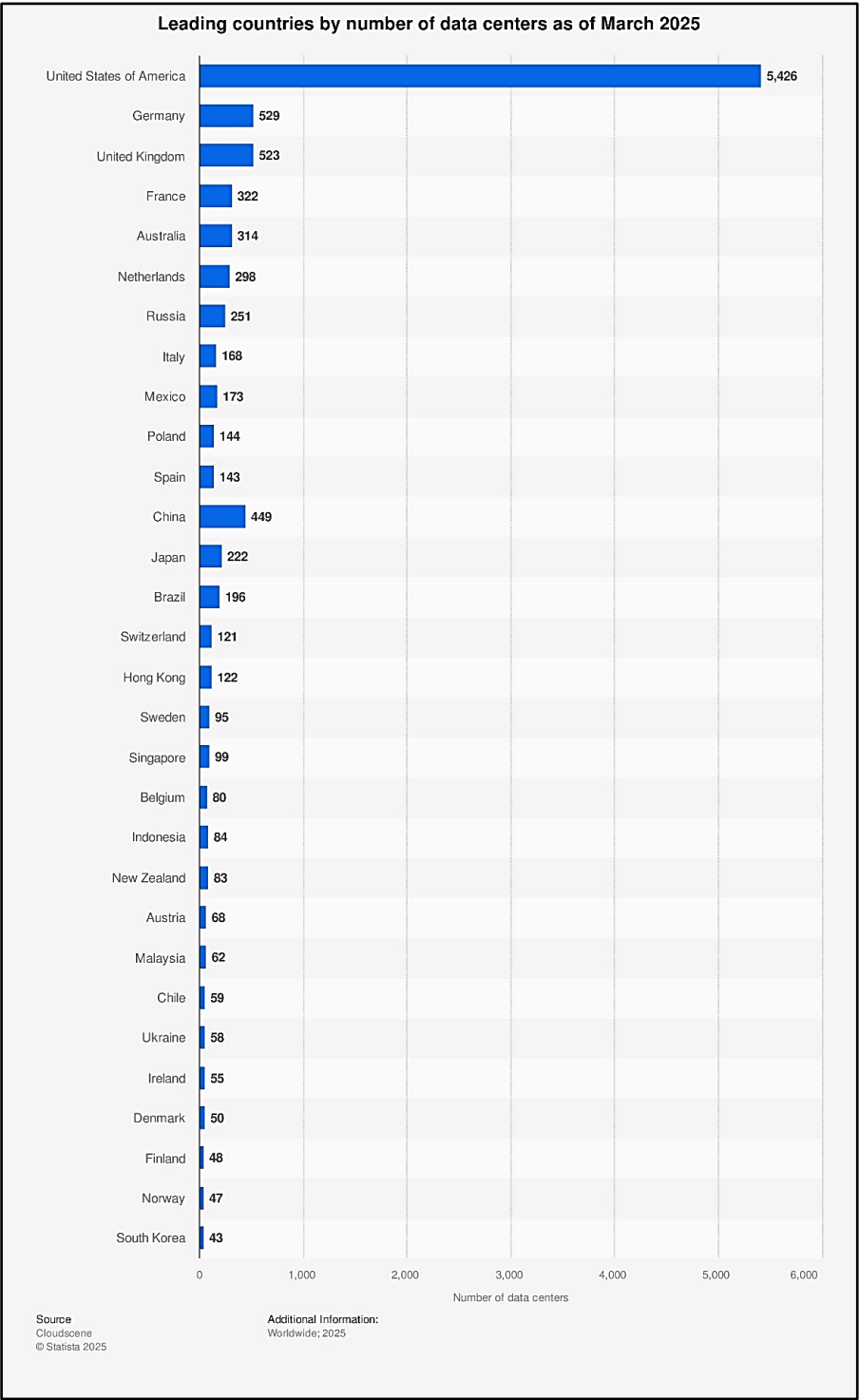


Figure 1. Leading countries by number of DCs in 2025 (Cloudscene, 2025)

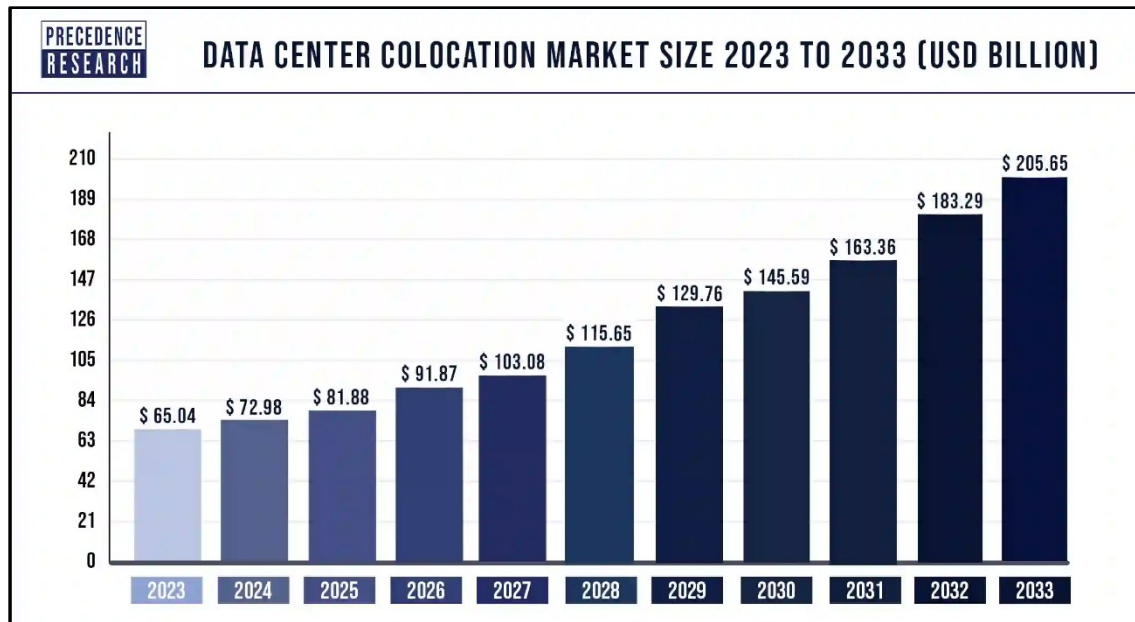


Figure 2. DC colocation market size (Precedence Research, 2024)

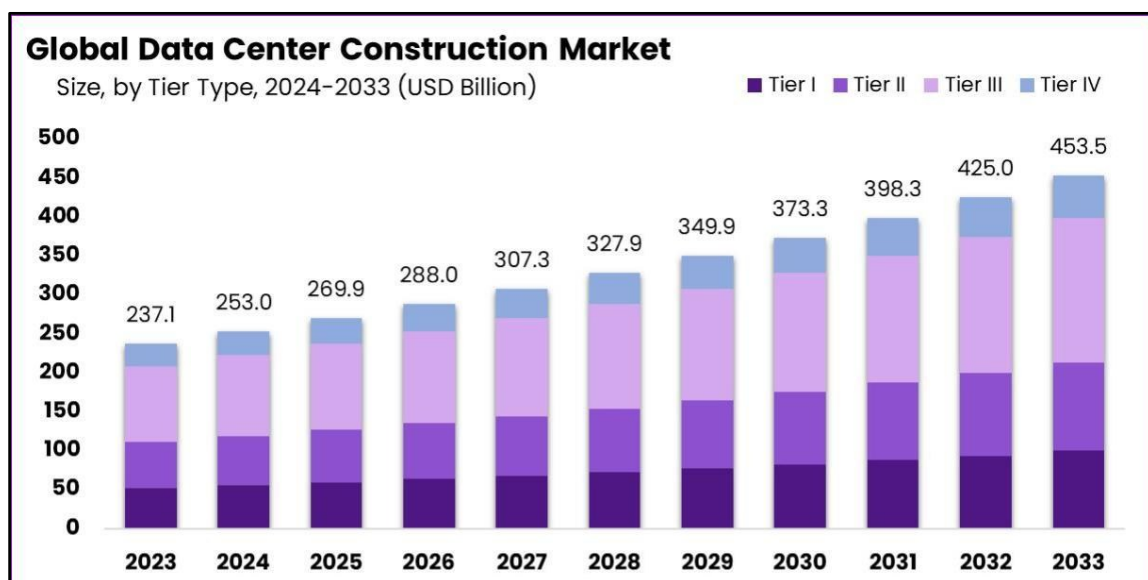


Figure 3. Global DC construction market from 2023 to 2033 (Tajammul Pangarkar, 2024)

Regarding the provided statistics related to DCs, there are several challenges and issues in managing DC facilities and their components. Especially, the amount of power being consumed by servers is noticeable. Concerning energy consumption, it should be noted that DCs utilize about 40 times energy than other standard buildings such as offices. Thus, energy management tools that

have been used for regular office buildings could not be easily applied to DCs since the energy simulation of DCs is complicated. There are considerable differences in terms of energy loads and the structure of buildings between DCs and commercial buildings (Cho et al., 2015). Research and studies have been performed on DC operations by scientists to effectively apply the DC operations management framework for reducing the staff workload. In addition, the other goal is to increase the work efficiency to bring maximum overall effectiveness for the DC operations management system (Bai & Geng, 2015). In terms of DC power and energy usage, the indicated numbers express high and increasing energy demands. The servers and DCs have used 61 billion kWh, costing \$4.5 billion in the year 2006 and it was expected to be doubled by the year 2011. Based on recent studies, one server with 300W power has about \$330 energy cost in a year (Saha et al., 2016a; Shehabi et al., 2016). In addition, the total electricity consumption of DCs in the United States has reached 60 billion kWh per year in 2014 and was estimated to rise to 70 billion kWh per year by 2020. Fortunately, based on the presented numbers, responsiveness about infrastructure operations in DC has increased and thus the efficiency has been improved, specifically in cloud DCs. Moreover, recently, the cloud DCs have been designed to maximize the efficiency of the DC infrastructure. Generally, Cloud DCs host around 10,000 servers for offering various services to be used by the applications (Saha et al., 2016a; Shehabi et al., 2016).

DCs play an essential role in our fast-developing society as the main Information Technology (IT) infrastructures. Due to the complexity of IT equipment placed in DCs, the reliability, availability, and maintenance of its components require more attention. Based on recent studies, DCs should adjust themselves to the fast-developing industry. In addition, the O&M System should be carefully considered and formed based on the required standards to obtain a standard management system to meet DC's acceptable performance (Zhan & Zhang, 2014).

A DC may exist independently within its own facility or be housed within a facility that accommodates various functions or organizations (F. Alshakhshir & Howell, 2021). DCs are known as critical infrastructures which have various subsystems and components such as heating, ventilation, and air conditioning systems, chillers, cooling towers, computer room air conditioning units, backup power sources, boilers, generators, lighting systems, servers, and other relevant components.

There are numerous difficulties and concerns in overseeing DC facilities and their elements. Notably, the substantial power consumption by servers stands out. According to recent research findings (F. Alshakhshir & Howell, 2021) (Fadaeefath Abadi et al., 2020), approximately 2% of the annual energy consumption in the United States is allocated to DCs. Furthermore, another objective is to enhance work efficiency, ultimately achieving maximum overall effectiveness for the DC operations management system.

DCs are being built across the globe to cater to various needs, reflecting a growing demand for their services. Various companies in the world have these major infrastructures and facilities for providing different online and cloud services. These essential facilities have undergone significant transformations over time, transitioning from small computer rooms to today's hyperscale and cloud-based DCs. Moreover, researchers (Fadaeefath Abadi et al., 2020) state that the technology advancements have led to increased complexity in DC operations in recent years.

As financial strain and economic unpredictability continue to rise, IT departments are increasingly compelled to adopt cost-saving measures. One common strategy is extending the lifespan of existing hardware and postponing major capital expenditures, a practice now seen across businesses of all sizes, including large corporations such as Amazon Web Services (AWS) (Kirkwood, 2023).

Canada's DC market, valued at \$4.05 billion in 2022, is projected to reach \$6.5 billion by 2028, with an annual growth rate of 8.21%. Across 21 cities, Canada hosts 336 DCs. Toronto leads as the largest market, with a DC capacity of 267 MW, while Montreal follows as the second largest with 126 MW in current capacity and an additional 51 MW under development. Notably, Montreal boasts the most affordable power among major global markets, at a rate of \$0.0533 per kilowatt-hour (John Minnix, 2024).

1.2. The COVID-19 Pandemic and the Role of Data Centers

The COVID-19 pandemic has significantly altered global business operations, making DCs more crucial than ever. As companies have adapted to remote work and new digital infrastructures, the demand for DC services has surged (Babar, 2020; Hevey, 2020).

According to recent reports (Technavio Research, 2020), this pandemic has had a significant impact on the hyperscale DC market, with a predicted CAGR of 21% from 2020 to 2024. The global expansion of DCs is expected to have varying effects on the IT Industry due to this rapid growth.

Maintaining DC resiliency and business continuity has become more urgent, with a focus on minimizing downtime and enhancing infrastructure reliability. Despite the expectation for 100% uptime, one-third of DCs experienced service outages in the past year, highlighting the need for improved maintenance strategies. The pandemic has also made day-to-day monitoring and maintenance more challenging due to the remote work transition, increasing the pressure on IT infrastructure and support solutions. Consequently, risk mitigation and maintenance prioritization tools have become essential for managing these critical infrastructures (Hevey, 2020; Roxtec Inc, 2020; Rubenoff, 2020).

Therefore, the COVID-19 pandemic has amplified the critical role of DCs in supporting global business continuity, particularly as remote work and digital infrastructures have expanded. The increased demand for DC services, coupled with rising service outages, highlights the urgent need for enhanced maintenance strategies and risk mitigation tools to ensure DC resiliency and minimize downtime in this rapidly growing industry.

1.3. Maintenance Scheduling and Management for Data Centers

Given the critical role of DCs in today's fast-evolving world, effective maintenance management and scheduling are essential to ensure the reliability and availability of Information Technology (IT) components. As 24/7 mission-critical facilities, DCs require continuous attention and optimized maintenance scheduling to minimize downtime (Fadaeefath Abadi et al., 2020; Hevey, 2020). Optimizing maintenance for each component or subsystem, such as hard drives, fans, and chips, is vital to maintaining efficient overall system performance, despite these components being vulnerable to failure (CommScope, 2020; Roxtec Inc, 2020).

DC companies have introduced best practices to enhance operations and prevent maintenance issues, such as implementing metrics-based predictive maintenance strategies to reduce reactive corrective practices. While some DCs use multiple vendors for O&M, a more efficient approach involves self-performing maintenance by Subject Matter Experts (SMEs), which can optimize the efficiency of mission-critical facilities (Hevey, 2020).

Traditional maintenance strategies, based on historical data and asset lifespans, are still common, but the high cost of DC downtime necessitates exploring alternative maintenance approaches (Lachance, 2016). Effective DC Maintenance Management, as part of Facilities Management, focuses on secure and efficient operations, emphasizing technical documentation,

operational processes, and the human factor. In a field study by Jürgen Bieser, it was found that approximately 70% of DC costs are driven by energy consumption, 20% by construction, and 10% by technical facilities management and maintenance, highlighting the financial impact of maintenance in DCs (Statista, 2017; Williams, 2018).

The 2024 Data Center & Infrastructure Report (Service Express, 2023) shows that for IT professionals, cost, quality of service, and resolution speed are the primary considerations in DC maintenance decisions. Equipment failures and downtime heavily affect business operations and productivity. To control costs while improving support and customer experience, organizations are turning more frequently to automated solutions for infrastructure management and support. Additionally, ongoing supply chain disruptions have reinforced equipment lifespan extension as a key approach for cost savings and sustainability.

1.4. Data Centers Reliability and Availability

The intersection of communication networks and the rising demand for substantial storage and processing capabilities, especially in recent years, has spurred a heightened request for everything-as-a-service, resulting in the proliferation of new DC constructions (Camboim et al., 2020). Nonetheless, guaranteeing the dependability of these infrastructures, with a predominant emphasis on achieving system availability, remains paramount

In assessing the system's reliability, the configuration of the components plays a crucial role. One strategy involves organizing components in parallel, where the functioning of one or more elements is necessary for the system's operation. If there are n elements arranged in parallel, the system may necessitate a minimum of k elements to function properly, where k must be less than or equal to n . When k equals n , the configuration represents a series system, as all elements must

be operational. Conversely, when $k = 1$ and n is greater than 1, it signifies a straightforward parallel system. For instance, in a scenario where $k = 2$ and $n = 4$, the system remains operational as long as any two of the four elements are functioning. Consequently, this configuration offers some advantages of parallelism while being more cost-effective and less reliable compared to a simple redundancy system (Schenkelberg, 2020). A schematic diagram of the k -out-of- n configuration is shown in Figure 4. This figure presents the Reliability Block Diagram (RBD) assuming that the system has ideal failure detection and switching (Birolini, 2017).

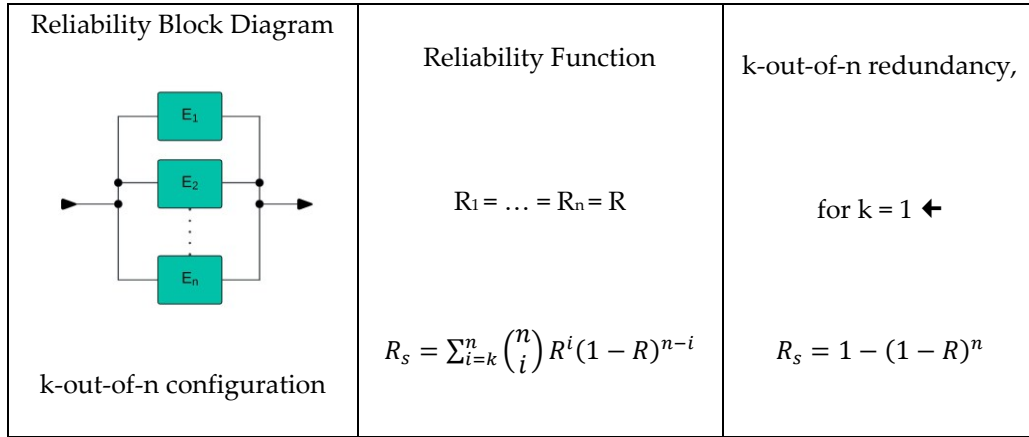


Figure 4. Reliability Block Diagram of the k -out-of- n configuration (Birolini, 2017; Fadaeefath Abadi, Bordbari, et al., 2025)

1.5. Research Gaps

The existing body of research on maintenance management has explored various industrial systems, such as power plants, Heating, Ventilation, and Air conditioning (HVAC) systems, and power distribution networks, employing advanced techniques like Artificial Intelligence (AI), Machine Learning (ML), and Dynamic Programming (DP) to optimize decision-making, reliability, and cost-efficiency. Despite this progress, there are notable gaps in the application of these methodologies within DC environments, which present unique operational challenges and

requirements. A review of the literature, which will be presented in the next chapter, reveals several specific gaps in DC maintenance strategies that this research aims to address.

- Limited Focus on DC-Specific Maintenance Models: Most maintenance models in the literature are designed for broader industrial applications, including energy generation and distribution, but few are specifically tailored to the needs of DCs. These models often fail to account for the distinct requirements of DCs, which demand high levels of availability, reliability, and operational efficiency. This gap underscores the need for research dedicated to developing comprehensive and efficient maintenance strategies that meet the evolving demands of DC infrastructures.
- Integration of Reliability and Availability Analysis: Although reliability and availability are critical components of any maintenance strategy, the literature lacks detailed methodologies that incorporate these analyses into maintenance scheduling specifically for DCs. The few existing studies that do address DC maintenance often overlook the integration of failure rates and system availability in a cohesive manner. Developing robust models that align maintenance scheduling with reliability and availability analysis is vital for ensuring uninterrupted operations and minimizing downtime in DCs.
- Optimization of Maintenance Scheduling in DCs: Optimization techniques, particularly DP, have been successfully applied to maintenance scheduling in various industries, but their use in DC maintenance remains underexplored. Given the complex and recursive nature of maintenance tasks in DCs—such as ensuring continuous power, cooling, and network availability—there is a pressing need for optimization models that account for the unique operational constraints of DC environments. This research addresses this gap by exploring

multi-stage optimization models that leverage DP to enhance maintenance decision-making in DCs.

- *Innovative Approaches to Maintenance Management*: Emerging technologies like AI, ML, and data analytics offer predictive maintenance and improved resource allocation but have not been fully integrated into DC maintenance frameworks. Exploring these tools can enhance operational efficiency and decision-making.
- *Development of Comprehensive Frameworks for DC Maintenance*: Finally, the reviewed literature reveals a lack of comprehensive, coherent frameworks specifically designed for DC maintenance. Most existing models focus on isolated aspects of maintenance, such as energy efficiency or component reliability, without offering a holistic approach that addresses strategic, operational, and technical challenges in DCs. The development of an integrated framework that considers all facets of DC maintenance, including system availability, reliability, and cost constraints, will be crucial for the future of maintenance management in this critical sector.

By addressing these research gaps, this study makes a significant contribution to the advancement of maintenance strategies in DCs. Specifically, it introduces three novel optimization models designed to improve maintenance decision-making. The first two models apply DP techniques to prioritize maintenance actions and optimize cost in k-out-of-n system configurations, integrating system availability constraints, reliability metrics, and budget considerations. The third model extends the framework to more complex series-parallel system architectures to minimize maintenance costs while satisfying the DC availability requirements. Collectively, these models offer tailored solutions to the unique operational and structural challenges of DC maintenance management. Hence, this research aims to develop and validate novel dynamic optimization

models for DC maintenance that minimize costs while ensuring compliance with availability standards defined by the Uptime Institute. This aim directly guides the dissertation by linking the identified research problem with the proposed methodological contributions and sets the foundation for the objectives and models presented in the subsequent chapters.

1.6. Motivation and Significance

The continuous operation of DCs is vital to supporting global digital infrastructure. Any service disruption due to equipment failure or suboptimal maintenance planning can lead to significant financial and operational losses. This research is motivated by the need to develop decision-support tools that allow DC operators to maintain high system availability and reliability while minimizing maintenance costs. By focusing on availability-aware, data-driven optimization strategies, this work provides a much-needed contribution to both academic literature and real-world applications in DC asset management.

The significance of this research lies in its comprehensive approach to addressing the critical gaps identified in the literature and contributes to the body of knowledge in the following key areas:

- *Tailored Maintenance Management for DCs*: By integrating practical maintenance management models specifically designed for DC components, this research addresses the unique challenges of DC infrastructures, such as maintaining continuous power supply.
- *Optimization of Maintenance Costs*: Through the development of mathematical optimization models, this research provides optimal solutions to minimize the maintenance costs associated with DC components. The model considers factors such as system configurations and system availability thresholds, resulting in potential cost savings and improved efficiency.

- Optimal Component Selection for k -out-of- n Systems: The proposed availability-based maintenance cost optimization model determines the k optimal components in DCs within a parallel k -out-of- n configuration. This model minimizes maintenance costs while ensuring the system meets the required total system availability threshold, potentially reducing operational expenses and enhancing efficiency.
- Prioritized Maintenance and Budget Allocation: This research presents a novel maintenance prioritization plan that ensures maintenance activities are prioritized based on their impact on total system availability and budgetary constraints. By maximizing component availability, this model facilitates informed decisions regarding maintenance resource allocation, thereby maximizing the overall availability of the DC infrastructure.
- Dynamic Programming Approach: The proposed DP approach captures the recursive and agile nature of maintenance scheduling in DCs, allowing for more precise decision-making and improved resource and budget allocation.
- Reliability and Availability Analysis: This research conducts detailed reliability and availability analysis for DC components, forming the foundation for the optimization models and ensuring that the proposed strategies meet the high availability standards.
- Optimizing DC Maintenance with International Availability Standards: Integration of system availability constraints derived from international DC standards into the proposed optimization models ensures that maintenance strategies not only satisfy mandatory industry requirements but also do so in a cost-efficient and dynamic manner. The contribution lies in embedding these non-negotiable compliance thresholds within advanced optimization frameworks, thereby supporting uninterrupted DC operations while enhancing decision-making efficiency.

In summary, this research advances the field of DC maintenance management by addressing critical gaps in the literature and offering innovative, optimized solutions that meet the growing demands of the DC industry.

1.7. Problem Statement

DCs are highly complex environments where asset failures can occur unpredictably, ranging from minor faults to critical disruptions. Traditional maintenance scheduling methods, which rely on long-term planning, are insufficient due to the high operational demands and dynamic nature of DC assets.

In response to these challenges, there is a critical need for a robust, integrated maintenance management model that incorporates both cost and availability considerations while accommodating flexible, short-term planning horizons. DP offers a promising approach, as it enables adaptive, “plan-as-you-go” maintenance scheduling. By analyzing historical data, DP can optimize real-time decision-making for maintenance prioritization, thereby enhancing asset availability and reducing operational disruptions. This thesis addresses the identified research gaps by proposing integrated cost and availability-based maintenance management models tailored for the unique demands of DCs, aiming to optimize maintenance schedules on monthly, daily, or even hourly intervals. Through the proposed models in this thesis, the research seeks to formulate solution approaches that uphold high availability standards and minimize maintenance costs, even amidst the complex and critical operational environment of DCs.

1.8. Research Objectives

The overarching objective of this research is to develop a comprehensive framework for availability-aware maintenance optimization in DCs. This objective is achieved through the following sequential research steps:

- Literature Review: A systematic review of current DC O&M practices and availability-based maintenance models was conducted to identify research gaps and establish a foundation for model development.
- Development of Three Maintenance Management Models:

➤ **Model 1: Dynamic Availability-Based Maintenance Prioritization Model**

This model aims to prioritize maintenance actions across assets based on their condition and impact on system availability to maximize the asset's availability improvement while respecting budgetary and operational constraints.

➤ **Model 2: Dynamic Availability-Based Maintenance Cost Optimization Model for K-out-of-N Systems**

Building on the first model, this approach aims to minimize the total maintenance costs in k-out-of-n DC systems to ensure required availability with minimal expenditures.

➤ **Model 3: Availability-Constrained Maintenance Cost Optimization Model for Series-Parallel Systems**

Extending the scope to more complex DC configurations, this optimization model minimizes maintenance costs while meeting availability thresholds.

These models are interconnected and progressive, each addressing increasingly complex system configurations and constraints:

- The first model provides a foundational decision-support tool for maintenance prioritization based on asset condition and availability gains.
- The second model builds on this by optimizing cost and redundancy in k-out-of-n systems with dynamic failure rates and costs.
- The third model extends the optimization framework to hybrid DC architectures, integrating both series and parallel configurations.

1.9. Thesis Organization

According to the 2023 Student's Guide to Thesis Preparation, Examination Procedures and Regulations provided by the School of Graduate Studies of Concordia University, this thesis has been organized based on a collection of three manuscripts which are either published or submitted for publication in high quality and prestigious scientific journals in the fields of Facilities, Maintenance, Reliability and Buildings. Additional information and updates are also included in the chapters of this thesis for enrichment.

In the first Chapter, a general introduction on Data Centers is provided, which clearly states the rationale, objectives and motivations of the research. The thesis structure and sections are also explained in this chapter.

In Chapter 2, a comprehensive review of the literature in the fields of DCs and O&M management is presented that frames the thesis research area and includes information derived from the published article below:

- Fadaeefath Abadi, M., Haghighat, F., & Nasiri, F. (2020). Data center maintenance: applications and future research directions. *Facilities*, 38(9/10), 691-714.

The methodologies and case studies have been presented and discussed in Chapters 3 and 4, respectively, which are derived from the two following articles:

- Fadaeefath Abadi, M., Bordbari, M. J., Haghghat, F., & Nasiri, F. (2025). Dynamic Maintenance Cost Optimization in Data Centers: An Availability-Based Approach for K-out-of-N Systems. *Buildings*, 15(7), 1057.
- Fadaeefath Abadi, M., Haghghat, F., & Nasiri, F. (2025, January). Availability-based maintenance prioritization for data centres: a dynamic programming approach. In *Safety and Reliability* (pp. 1-36). Taylor & Francis.

Finally, the research conclusions, contributions and future research directions have been discussed in Chapter 5 which also addresses the entire contents of the thesis.

Chapter 2: Literature Review

This chapter presents a critical and systematic review of the relevant literature, evaluating strengths, limitations, and gaps in previous studies to establish the foundation for this thesis. It explores the current state of knowledge across several key areas, including maintenance management in industrial systems, O&M management in DCs, DC Infrastructure Management (DCIM), maintenance scheduling optimization, and the applications of DP in maintenance management. By critically examining these fields, the chapter identifies the primary research gaps and limitations within the DC domain, highlighting areas that warrant further research and investigation.

2.1. Maintenance Management in Industrial Systems and Applications

While maintenance models in diverse industrial systems continue to evolve with emerging technologies, many studies focus on energy and HVAC systems rather than DC-specific requirements, limiting direct applicability to DC operations. The integration of Artificial Intelligence (AI) and Machine Learning (ML) has enabled data-driven decision-making in building maintenance (F. S. Alshakhshir & Howell, 2021; Fadaeefath Abadi et al., 2020), promoting energy efficiency and offering early detection of equipment issues. For instance, recent studies on Heating, Ventilation, and Air Conditioning (HVAC) systems (Fadaeefath Abadi et al., 2022), particularly the Vapour Compression Refrigeration System (VCRS), highlight how optimizing partial load usage across components can boost system reliability. This shift toward using high-quality, load-sharing components has demonstrated a near 10% improvement in system reliability over extended operation periods. Furthermore, availability-centred maintenance models, such as

those applied to Domestic Hot Water (DHW) systems (Pourhosseini & Nasiri, 2018a), reveal that prioritizing maintenance activities based on their impact on overall system availability reduces unnecessary interventions, enhancing uptime and cost-effectiveness. The Keeping System Availability (KSA) method, originally designed for power plants, has been adopted by researchers to incorporate the impact of maintenance activities. A recent focus on power distribution systems highlights the critical role of asset management and strategic maintenance planning in preventing costly failures and improving overall performance. Comprehensive reviews (Mirhosseini & Keynia, 2021) emphasize that well-planned maintenance reduces operational costs and prevents shutdowns while also addressing economic, social, and environmental impacts, including those arising from deregulated power markets. A comparative analysis indicates that while research on industrial systems provides useful insights on reliability and predictive maintenance, they lack DC-specific considerations, including continuous operation, strict uptime requirements, and complex system interdependencies.

2.2. Data Center Operations and Maintenance Management

Operations are defined as tasks recurrently executed during an application's lifecycle to ensure continuous service availability (Diouri et al., 2015). Given the critical requirement for uninterrupted services, any operational disruptions in DCs can result in significant systemic challenges. Rapid restoration of services is thus paramount to maintain DC functionality. The rise of cloud services has amplified the role of DCs in delivering information to a global audience using diverse smart devices and portable technologies (Janacek & Nebel, 2017). This section reviews contemporary research on DC operations and maintenance management strategies.

Effective cooling systems are essential in optimizing DC performance and reducing operational and maintenance costs. Emerging technologies, such as free-air and liquid cooling, are under

investigation as potential alternatives to traditional air cooling (Li et al., 2016). Researchers are studying economically viable cooling solutions to optimize energy use within DCs. Using simulation and numerical analyses, these studies explore design-specific cooling systems under various conditions to identify the most efficient option (Cho et al., 2015). As cooling systems are a primary energy consumer in DCs, energy-saving methods are evaluated through case studies, demonstrating the potential for considerable energy conservation (Hassan et al., 2015).

To enhance operational resilience, predict behaviours, and improve DC responsiveness, researchers have developed low-cost, low-power wireless sensor networks. These sensors monitor critical parameters such as temperature, humidity, airflow, pressure, water presence, closures, motion, and vibration within the facility (Levy & Hallstrom, 2017). Their study aims to provide users with actionable data to reduce downtime and operational costs, improve energy audits and space planning, and support predictive modelling for DC operations.

Regarding maintenance management, extensive studies have explored various models and methodologies to improve DC infrastructure reliability. This section synthesizes current research on maintenance management issues in DCs and IT infrastructure, reviewing practices across sectors to identify optimal maintenance frameworks. Such an approach is essential for developing effective maintenance schedules and frameworks tailored for DC environments.

Maintenance is a critical stage within DC systems, given the numerous essential components operating continuously. An effective maintenance management system is essential for monitoring operations, identifying failures, and implementing repair strategies (Xia et al., 2017). Scholars emphasize the importance of DC maintenance, proposing solutions that address energy consumption, reliability, and the performance of vital DC systems. Techniques that integrate improved cooling technology and server management strategies are vital for minimizing

operational costs. According to some surveys and studies, maintenance expenses account for approximately 80% of total DC costs (Saha et al., 2016). Other reports (Howell, 2024) indicate that, in a large DC, the costs of procuring and maintaining hardware, software, networking infrastructure, and other essential equipment can account for approximately 50% of annual operating expenses.

Additionally, recent studies consider the economic advantages of implementing Computer-Aided Facility Management (CAFM) software, with an example from a manufacturing company in the Czech Republic focusing on machinery maintenance as a core component of the facility management industry (Poór et al., 2014). The influence of human performance during maintenance operations has also been investigated, with researchers analyzing data from structured questionnaires in marine systems, though findings are limited to marine applications without specific maintenance schedules or frameworks (Islam et al., 2018).

Since much of the reviewed research originates from industrial and power systems rather than DCs, applying these insights to DCs necessitates consideration of continuous power supply, cooling interdependencies, and IT workload criticality.

2.3. Data Center Infrastructure Management (DCIM)

The cost of DC infrastructure represents nearly one-third of the total IT budget, a significant investment that also covers DC operations. However, organizations have not yet fully adopted innovative strategies, models, or technologies to optimize capital expenditures related to DC infrastructure management. This section examines the concept of Data Center Infrastructure Management (DCIM), recently introduced to facilitate comprehensive monitoring and management of various systems within a DC (Geng, 2015b). Some studies define DCIM as an

integration of IT systems management and facility management (FM) systems (Hubbell et al., 2015).

Previously, IT professionals focused exclusively on IT hardware (such as servers, storage, and networks), while facility managers were responsible for the physical DC environment. However, with rising investments in high-performance computing (HPC) and cloud infrastructure, considering the DC and its IT equipment as a unified system is now seen as advantageous. Advanced tools and methods, such as the Big Data model, 3D gaming technology, and 3D monitoring and management (MM3D), developed by MIT Lincoln Laboratory, support in-depth trend analysis and operational optimization, enhancing both efficiency and reliability. These approaches aim to manage computing resources, troubleshoot issues, and provide real-time insights into critical facilities, including IT infrastructure, lifecycle management, and cost optimization. Additionally, the U.S. government and major technology companies (e.g., Google, Microsoft, and Facebook) are investigating DCIM implementation costs. Based on current findings, future initiatives may focus on developing intelligent tools for energy-efficient DCs, such as scheduling tasks during off-peak hours to take advantage of lower electricity rates (Hubbell et al., 2015).

DCIM enables the monitoring, assessment, control, and management of IT energy consumption within DCs. Its key components include input, process, and output. Sensors, as input devices, collect data which is processed for analysis and presented as output to users. The insights provided by DCIM are valuable for DC asset management, enabling accurate predictions of critical parameters such as space, power, and cooling capacity. Furthermore, DC availability can be enhanced by tracking real-time power levels and cooling capacity, while operational costs are reduced through improved overall efficiency (Abbas et al., 2015).

Recent advancements in DCIM have positioned it as an essential tool for optimizing DC efficiency and sustainability while addressing the growing complexity of digital and hybrid IT environments. Contemporary DCIM platforms, such as Schneider Electric's EcoStruxure IT, are adopting AI-powered automation and predictive analytics to address the increasing scale and distribution of DCs. These systems now provide real-time insights, enabling proactive management of energy usage, asset tracking, and environmental monitoring, which helps DCs achieve compliance with strict environmental regulations and sustainability standards (Bjarke Fenger, 2024; Ella Hutchinson, 2023).

Moreover, the rise of "DCIM 3.0" reflects a significant evolution in infrastructure management. Unlike earlier versions, DCIM 3.0 solutions integrate seamlessly with cloud-based and edge environments, supporting universal interoperability with Building Management Systems (BMS) and IT Service Management (ITSM) tools. This integration enables operators to achieve centralized visibility across multiple sites, enhancing capacity planning and resource allocation, particularly in colocation facilities where tenant-driven demand for transparency and sustainability reporting is high. By tracking metrics such as Power Usage Effectiveness (PUE) and Carbon Usage Effectiveness (CUE), these modern DCIM tools also facilitate compliance with global and regional sustainability mandates, making them crucial for DCs committed to green practices and operational efficiency (Data Centre Dynamics, 2024; Datacenter Dynamics, 2023).

These enhancements in DCIM not only streamline management processes but also support DCs in adapting to emerging needs driven by AI and other high-power technologies. AI integration allows for dynamic workload management, predictive maintenance, and automated response to system anomalies, thereby minimizing downtime and optimizing performance in an increasingly data-intensive landscape. As DCIM continues to evolve, it is expected to play a transformative

role in supporting the digital infrastructure's future through sustainable and adaptive management practices (Bjarke Fenger, 2024; Jeff Safovich, 2024).

2.4. Maintenance Scheduling Optimization

Recent literature emphasizes the growing sophistication of maintenance scheduling optimization, particularly through the integration of predictive maintenance technologies. Leveraging Artificial Intelligence (AI) and the Internet of Things (IoT), modern predictive maintenance frameworks enable accurate failure forecasting, thereby reducing downtime and improving cost-efficiency across various sectors. For instance, AI-driven solutions in Electric Vehicle (EV) systems and urban infrastructure, including City Information Modelling and sewer network analysis, have enabled proactive maintenance and enhanced system reliability (Cavus et al., 2025). Concurrently, optimization efforts in k-out-of-n systems have explored maintenance strategies that address load-sharing constraints and common-cause failures (Wu et al., 2023). Approaches such as two-threshold group maintenance and opportunistic scheduling have demonstrated significant potential in minimizing operational costs while ensuring uninterrupted performance. In parallel, DCs represent another domain where maintenance optimization is critical yet underexplored. Studies highlight the strategic shift in DC maintenance—from a technical necessity to a core management function—and recommend incorporating advanced models like Monte Carlo simulations, stochastic reliability analysis, and ITIL-based frameworks. Collectively, these advancements underscore a cross-sectoral movement toward intelligent, cost-effective, and resilient maintenance strategies (Fadaeefath Abadi, Bordbari, et al., 2025). According to the reviewed studies on maintenance scheduling optimization, comparative analysis reveals few models explicitly evaluated for DC cost, availability, and operational constraints. Table 1 summarizes the strengths and limitations of the major applied methods.

Table 1: Comparative analysis of maintenance scheduling approaches

Method	Key Features	Strengths	Limitations	Applicability to DCs
Time-Based Maintenance (TBM)	Fixed intervals	Simple, easy to implement	Ignores real-time conditions; may over-maintain	Limited; not optimal for high-availability DCs
Condition-Based Maintenance (CBM)	Sensors monitor real-time component health	Reduces unnecessary interventions; predictive	Requires sensor deployment; data may be noisy	Moderate; depends on DC sensor coverage
Predictive Maintenance (AI/ML)	Uses historical and sensor data for failure prediction	Reduces downtime; proactive	Needs sufficient historical data; model complexity	High potential; promising for DCs with monitoring systems
Opportunistic & Group Maintenance	Combines maintenance across assets	Minimizes disruption; cost-efficient	Complex scheduling may conflict with availability	Moderate; must integrate with DC priority systems
Monte Carlo & Stochastic Reliability	Probabilistic failure modelling	Captures uncertainties	Computationally intensive	Limited without simplification in large DCs

2.5. K-out-of-N Configurations and Fault-Tolerant Frameworks

In complex engineering applications, fault-tolerant system design is critical for ensuring reliability. These k-out-of-n systems have been widely studied and compared with other fault-tolerant strategies such as $N + 1$ redundancy, active/standby redundancy, and system-level redundancy.

Component-level versus system-level redundancy for k-out-of-n configurations has been analyzed by researchers (Kuiti et al., 2017), demonstrating that component-level redundancy often enhances fault tolerance more efficiently than system-wide redundancy. Similarly, the reliability of k-out-of-n data storage systems has been investigated with deterministic repair times under serial and parallel repair models (Aggarwal, 2016). The study found that parallel repair strategies enhance system reliability by minimizing downtime compared to sequential repairs. Also, the redundancy allocation in k-out-of-n systems was explored by evaluating active versus standby redundancy, concluding that selecting an optimal redundancy strategy improves both reliability and cost efficiency (Aghaei et al., 2017). The researchers demonstrated how the k-out-of-n configuration is a viable alternative to traditional $N + 1$ redundancy models.

Further research on comparing k-out-of-n systems with other fault-tolerant methods has been seen in recent studies. The Matrix-cased System Reliability Method (MSRM) and the Reliability Growth Models (RGMs) have been applied to k-out-of-n systems for reliability growth analysis evaluation (Byun et al., 2017). The results of the numerical examples in the study demonstrated the efficiency and applicability of the proposed method, concluding that the k-out-of-n configurations can offer superior fault tolerance compared to traditional redundancy schemes, particularly in large-scale and complex systems.

Furthermore, an optimal condition-based maintenance policy for k-out-of-n systems has been developed, considering the interdependencies between internal deterioration and external shocks using a Markov decision process framework (Kasuya & Jin, 2025). By modelling stochastic dependencies, this approach improves maintenance decision-making, achieving up to 9.9% cost savings in a case study on offshore wind turbines. The findings highlight the importance of integrating degradation interactions into maintenance strategies, making the approach valuable for reliability-critical industries (Fadaeefath Abadi, Bordbari, et al., 2025) .

2.6. Utilization of Dynamic Programming in Maintenance Management

Because of the nature of maintenance activities that should be considered in a DC system, implementing a multi-stage model could have several advantages in allocating maintenance actions and costs for a component or system. Thus, the DP method and algorithm is a promising and valuable multi-stage approach that can lead to an optimal maintenance scheduling and management solution for various multi-state deteriorating components and systems placed in a DC system and infrastructure. As a quantitative analysis technique, in various large and complex problems that have sequences in their decision-making process, DP can solve these problems by dividing them into many decision stages. In the DP problem-solving process, the output of a decision at one stage will be impacted by the decision(s) made at the beginning of the next stage (Render et al., 2012). This section highlights relevant publications and research on applying DP in several industrial systems, applications or infrastructures.

Although the concept of DP was introduced decades before (Bellman, 1957; Bradley et al., 1977), many publications have recently become available considering the application of DP in maintenance management and scheduling. In vessel engines (Kian et al., 2019), a mathematical programming model is used as well as the shortest path DP formulation for a single part and

multiple parts of the vessel. This model is applied to solve a spare part ordering problem arising within a logistics system and obtain optimal solutions. The researchers have also used Condition-Based Monitoring (CBM) as part of predictive maintenance to collect real-time information about the health condition of the vessel parts (Kian et al., 2019). Another study (Kim et al., 2016) has worked on comparing Time-Based Maintenance (TBM) and Condition-Based Maintenance (CBM) policies considering various cost environments for a highway pavement section, which is part of a stochastically deteriorating infrastructure system. Researchers have selected the DP algorithm and applied it to obtain the optimal maintenance activity for each year in the CBM strategy based on the inspection results. According to the literature, DP is one of the most widely used models to solve maintenance optimization problems for stochastically deteriorating infrastructures (Kim et al., 2016). Also, in the case of substation equipment (Kuang et al., 2016), the DP algorithm is proposed to solve the optimal maintenance planning problem considering Life Cycle Cost (LCC) and reliability. They used DP to minimize the LCC while satisfying the substation equipment's reliability requirements and final condition state. The results of their model are compared with the genetic algorithm results, and eventually, the effectiveness of the DP model in providing less LCC for maintenance planning is proved. In addition, researchers implemented the DP method for the maintenance of electric power systems and manufacturing systems to obtain the optimal maintenance strategy and minimize the maintenance costs for a component (Korpijärvi & Kortelainen, 2009; Liu et al., 2019).

The knapsack problem combined with DP has been studied and conducted in several recent research works. Using DP, a knapsack problem approach was developed in power distribution networks to find the optimal preventive maintenance budget for one and two years of the planning horizon. The research objective was to obtain the best relationship between system reliability and

maintenance resource allocation (Bacalhau et al., 2013). The DP approach and knapsack model are capable of solving various problems such as allocation, payload, capital budgeting inventory control, and other problems in the industry (Fawzy et al., 2017)

In another research, to determine the most cost-effective maintenance and rehabilitation (M&R) activities, an optimization model was developed. The selected case study was the highway pavement network within an extended planning horizon (Yoo & Garcia-Diaz, 2008). In their research work, a multi-dimensional 0–1 knapsack problem with M&R strategy selection considering priority and feasibility constraints was applied. The formulation has been conducted based on total benefits dollar value maximization regarding the chosen pavement improvement activities. Furthermore, the integer 1/0 knapsack Problem has been applied as a DP optimization method to determine the maintenance activities schedule for maintaining buildings in Indonesia (Fawzy et al., 2017). In the study conducted by Viska Dewi Fawzy et al., building damage, occupant participation rate, and maintenance costs are considered criteria based on limited funding and budget to obtain the optimum solution.

Hence, according to the literature concerning the importance of resource allocation and budget constraints in different industries and facilities, the knapsack problem is a helpful tool and model since it deals with maximum capacity as the primary constraint. In various research works, optimization problems have focused on budget allocation for prioritizing elements and parameters for maintenance and rehabilitation actions in buildings and facilities (Shehab et al., 2021).

Recently, studies have been conducted on improving the planning and organization of rail grinding operations which are used in the rail grinding trains (Ilinykh & Bondarev, 2022a) (Ilinykh & Bondarev, 2022b). The researchers have identified the drawbacks in current approaches through organizational and technological analysis and proposed a novel approach for planning

technological interventions concerning the classification of rail defects by importance which serves as the basis for targeting rail grinding activities, determined through a stochastic decision-making process utilizing DP methods. An optimal strategy based on DP has been formed for maximizing income and minimizing expenses by representing the process structure as a matrix, with elements representing income values resulting from transitions between defect importance groups due to grinding. Transition probabilities and income values are dependent on available solution alternatives. The proposed methodology aims to expedite the removal of defects prone to catastrophic development, thereby enhancing safety, while also addressing less critical defects economically without compromising safety.

DP has also been used in studies for the Network-Level Pavement Asset Management System addressing the challenge of selecting Maintenance and Rehabilitation (M&R) activities for Low Volume Roads (LVRs). Scholars (Albatayneh et al., 2021) have developed an optimization algorithm using DP and Ant Colony Optimization (ACO) to maximize pavement performance within budget constraints. Their DP model efficiently explores various treatment combinations, considering factors such as road condition, available budget, and desired performance outcomes. By leveraging DP techniques, the study provides practical solutions for road agencies to enhance network-level pavement management.

Researchers (Mirhosseini & Keynia, 2021) have examined an optimal strategy for a multiyear maintenance schedule using a risk-based approach and a decoupled failure risk factor model in distribution networks. Introducing a novel state transition model has resulted in the formulation of new variables, which are tackled using DP techniques.

Based on the reviewed research works, while DP has demonstrated effectiveness in solving maintenance optimization problems, it is not without limitations. The most critical drawback is the

curse of dimensionality, where the state and action spaces grow exponentially with system size, rendering exact solutions computationally intractable for large-scale applications such as DCs (Bertsekas, 2012; Puterman, 2014). Furthermore, DP models often rely on simplified Markovian assumptions that may not fully capture the complex interdependencies of DC infrastructures. These scalability and modelling challenges restrict the applicability of DP in real-time DC maintenance planning. To overcome such drawbacks, researchers increasingly turn to Approximate Dynamic Programming (ADP) and hybrid optimization methods as more practical alternatives (Powell, 2007).

In summary, this literature review critically evaluated advancements and challenges across industrial and DC maintenance studies, highlighting gaps in availability-centred, cost-aware, and predictive maintenance for DCs. These insights form the basis for the research design and methodological approach presented in the following chapter. Chapter 3 details the proposed methodology for addressing these identified gaps, with a focus on developing a dynamic, availability-centred maintenance prioritization framework for DC infrastructure. Specifically, three models are introduced to support decision-making in maintenance planning, addressing prioritization, cost optimization for K-out-of-N systems, and cost minimization under availability constraints for series-parallel system architectures.

Chapter 3: Methodology

This chapter outlines the research methodology and addresses the overarching problem and sub-problems related to DC maintenance management. The proposed methodological approach involves the development and application of optimization models designed to improve the cost-effectiveness, availability, and reliability of critical infrastructure components.

This chapter presents the following three models developed to support decision-making in maintenance planning for DCs:

➤ ***Dynamic Availability-Based Maintenance Prioritization Model***

This model employs a 0/1 multiple knapsack formulation to prioritize maintenance actions under availability and budget constraints. The knapsack problem was chosen because it allows explicit quantitative trade-offs between maintenance costs and availability improvements, providing a rigorous decision-making framework under resource constraints.

➤ ***Dynamic Availability-Based Maintenance Cost Optimization Model for K-out-of-N Systems***

integrates dynamic failure rates and variable maintenance costs to determine the optimal number of operational components (k) required to satisfy system availability targets while minimizing total costs. This model allows explicit incorporation of dynamic, time-dependent failure probabilities and cost variations, enabling decision-makers to optimize maintenance schedules over multiple periods. Moreover, it provides a flexible framework for balancing cost-efficiency and reliability, supporting strategic trade-offs between

preventive maintenance investments and system availability—critical in DCs where both operational continuity and budget constraints are key considerations.

➤ ***Availability-Constrained Maintenance Cost Optimization Model for Series-Parallel Systems***

This model is formulated as a Mixed-Integer Nonlinear Programming (MINLP) problem to minimize maintenance costs in series-parallel DC configurations while ensuring compliance with required availability thresholds. MINLP was selected because series-parallel systems introduce nonlinear availability expressions that cannot be adequately captured with linear formulations. The approach accommodates discrete decision variables, nonlinear availability functions, and multiple interdependent constraints, making it well-suited for optimizing cost while maintaining system reliability in complex DC architectures.

These models collectively provide a robust framework for strategic maintenance scheduling, enabling DCs to maintain high reliability and availability standards within constrained budgets and varying infrastructure configurations.

3.1. Dynamic Availability-Based Maintenance Prioritization Model for Data Centers

This section presents the proposed maintenance scheduling and prioritization model for DCs based on DP optimization. The structure, elements, and parameters of the model are defined and thoroughly described. Aligned with the research objectives outlined in Chapter 1, the model is designed to optimize the scheduling, prioritization, and maintenance of components (devices) within DCs. The goal is to determine the optimal number of components requiring maintenance while ensuring compliance with the availability requirements of DC systems, which are derived from global DC standards. Specifically, the model incorporates the four primary levels of DC

availability, known as DC Tiers (Gabriel, 2014; Institute, 2014). Table 2 outlines the corresponding availability requirements according to the Uptime Institute standards.

Table 2: DC availability requirements based on Uptime Institute tiers (Gabriel, 2014)

DC Tier	System's Description	DC Availability Percentage
1	Single non-redundant distribution path serving the IT equipment. Non-redundant capacity components.	99.671%
2	Meets or exceeds all Tier 1 requirements. Redundant site infrastructure capacity components	99.741%
3	Meets or exceeds all Tier 1 and Tier 2 requirements, Multiple independent distribution paths serving the IT Equipment. All IT equipment must be dual-powered and fully compatible with the topology of a site's architecture. Concurrently maintainable site infrastructure.	99.982%
4	Meets or exceeds all Tier 1, Tier 2, and Tier 3 requirements. All cooling pieces of equipment are individually dual powered, including chillers and heating, ventilating, and air-conditioning (HVAC) systems. Fault-tolerant site infrastructure with electrical power, storage and distribution facilities.	99.995%

According to Table 2, the system or component's availability (A_t) parameters, which are further explained in the "Problem Formulation" section, are integrated into our methodology and considered the primary thresholds.

Therefore, depending on the desired availability level for the Data Center are:

- $A_t \geq 99.671\%$, (Tier 1 Data Center) (1)

- $A_t \geq 99.741\%$, (Tier 2 Data Center) (2)

- $A_t \geq 99.982\%$, (Tier 3 Data Center) (3)

- $A_t \geq 99.995\%$, (Tier 4 Data Center) (4)

Hence, in order to meet the availability constraints, the following equation should be valid:

$$A_t \geq A_{t \text{ (Required)}} \quad (5)$$

To reach the model's objective, among several models of DP, the "Knapsack problem" has been selected as a non-network problem that could involve maximizing or minimizing a specific parameter such as costs or profits. In the general knapsack problem, some restrictions such as certain weights or volumes may be considered. The main goal of this type of problem is to put different items in the knapsack to maximize the total value considering the knapsack's total capacity, which could be weight or another similar constraint (Render et al., 2012).

Therefore, the knapsack problem can be considered a combinatorial optimization problem with a set of items such as loads, volumes, or other parameters. The summation of these items should be less than or equal to the total capacity of this knapsack (Fawzy et al., 2017).

Some important terms and concepts are inherent in a DP problem of any size, type, and complexity. These parameters are described briefly below based on the DP knapsack problem.

- Problem's Stage: This is a period or a logical subproblem within the whole problem.
- Problem's State variables: The stage's conditions which are the input variables.
- Problem's Decision variables: At each stage, there are alternatives or possible decisions.

- Problem's Decision criterion: The statement related to the problem's objective.
- Optimal policy: These are the rules for each decision and are developed based on the decision criteria. This policy provides the optimal decisions for any entering condition at any stage.
- Transformation: The relationship which is established between the problem's stages
(Render et al., 2012)

Therefore, in each DP problem, in the first step, the original problem is divided into several sub-problems defined as the problem's stages. The second part includes solving the problem's final stage considering all possible conditions or states. In step 3, the recursive process is conducted to work on the problem from the last stage to solve each intermediate stage by defining optimal policies from that stage to the problem's final stage. Finally, the optimal solution is achieved in step 4 for the original problem when all stages are solved logically (Render et al., 2012).

According to resources, there are different types of knapsack problems such as the 0/1 knapsack, the Bounded knapsack, the Unbounded knapsack, the Subset-Sum, Integer knapsack, Fractional knapsack, Multiple knapsacks and the Bin-Packing Problem which can be applied in different cases (Codesdope, n.d.; Motion and Shape Computing Group, n.d.). Some of these types have been selected and modelled in this research.

3.1.1. Model's Formulation

In this research, the 0-1 (or 0/1) knapsack problem, combined with the multiple knapsack problem has been selected to formulate the proposed maintenance management and prioritization problem. This version of the knapsack problem is applied when indivisible and discrete items or parameters are considered (Shehab et al., 2021).

Based on the general definition, there are different kinds of items (i), and each item has a weight (w) and a corresponding value (v). The number of i types of items selected to be placed in the multiple knapsacks are notated with x_i , and the full knapsack's capacity is W (maximum weight) (Codesdope, 2023).

According to this version's requirements, at the selected timeframe (week or month), an item can be either included in the knapsack or excluded. So, including a fraction of the item or more than one item of each type is not allowed in this version of the knapsack problem (Terh, 2019).

Therefore, regarding the information mentioned above, the primary and general formulation (Equations 1 and 2) derived from various resources (Jensen & Bard, 2003; Optimization Expert, n.d.) of the knapsack problem is structured as follows:

$$\text{Maximize } Z = \sum_{i=1}^n x_{i(t)} V_{i(t)} \quad (6)$$

Subject to:

$$\sum_{i=1}^n x_{i(t)} w_{i(t)} \leq W_t \quad (7)$$

The parameters are defined as follows:

Z = Number of maintained components within a fixed budget in a specific timeframe,

$x_{i(t)}$ = Quantity of each item included in the knapsack (which could be binary or non-binary depending on the problem's type in each timeframe (t),

$V_{i(t)}$ = The value of each item included in the knapsack in each timeframe (t),

$w_{i(t)}$ = The item's weight in each timeframe (t),

And W_t = Maximum weight capacity of the knapsack in a specific timeframe.

In the DP approach for solving the knapsack problem, each item is represented as the problem's stage, which has a corresponding decision of either including the item in the knapsack or not.

Equation (6) represents the objective function, which aims to minimize the total maintenance costs over a specified planning horizon. The costs considered include six types of maintenance costs such as preventive, corrective and other associated maintenance costs which have been demonstrated further in this section. Thus, the objective function integrates multiple cost components to provide a comprehensive cost minimization strategy.

Also, Equation (7) demonstrates the constraints associated with the maintenance scheduling problem. It ensures that the maintenance activities are scheduled within the allowable time windows and resource limitations. The constraints take into account the availability and reliability requirements of the DC components, which are critical for maintaining optimal operational performance.

3.1.2. Application of Dynamic Programming

As mentioned previously, the DP approach has been selected and applied to solve a Multiple and 0-1 knapsack problem. Based on studies, this powerful algorithmic technique has the capability of solving complex problems and breaking them down into simpler overlapping subproblems. The DP model stores the solutions of the subproblems in a table to avoid redundant computations.

The model used in this research includes the main and important features of DP which as described below.

- Overlapping Subproblems

Since the core feature of DP is identifying and solving the overlapping subproblems, the multiple knapsack Problem finds the optimal value for different capacities of each knapsack and considers different subsets of items. A 3D table[k][i][j] has been created and used in this formulation to store the optimal values for the subproblems. The k parameter represents the knapsack index, i is defined as the item index, and j is the remaining capacity.

- Optimal Substructure

The optimal substructure property is another important feature of DP which defines the optimal solution to a larger problem, and it is constructed using optimal solutions to the smaller subproblems. In our problem, the optimal value for a specific knapsack and its capacity is built upon the optimal values for smaller capacities and subsets of items, which leads to a bottom-up calculation and model.

- Memorization

The 3D table[k][i][j] stores the intermediate results to avoid repetitive calculations which improves the algorithm's efficiency by omitting the extra computations for the same subproblems.

- State Transition

In the DP approach, we have the recurrence relation which is determined by the transition between the subproblems considering the items and capacity of the knapsack. This transition mechanism is useful to dominate the items and to obtain the optimal value at each subproblem.

Therefore, according to the above-mentioned features and the systematic approach, the code used in this research implements a specific Multiple and 0-1 Knapsack Problem, which has a

maximum constraint value for each knapsack (the fixed monthly budget). This algorithm breaks down the whole problem into subproblems, stores the solutions, and calculates the optimal distribution of items among all knapsacks (12 knapsacks representing 12 months in our specific model) as well as checking the capacity limitation of each knapsack and ensures that each of the 12 knapsacks has the maximum value (availability improvement factor in our research model) and the maximum permitted item (the components) (Bellman, 1957; Cormen et al., 2022; Dasgupta & Papadimitriou, 2006; Kleinberg & Tardos, 2006).

3.1.3. Application of the Knapsack Problem in DC's Maintenance Management

In this research and according to our specific application, the parameters of the knapsack problem are defined as follows:

- The items packed in the knapsack are the devices (components) classified based on their condition state according to their Facility Condition Index (FCI).
- The value of each device (component) in the DC is considered based on a novel scoring system calculated according to its availability improvement after maintenance action.
- The weight of each item is the total maintenance costs each year for each device (component) to improve their availability percentage.
- Maximum weight is defined as the total allocated maintenance budget (financial resources) for the DC to conduct the maintenance action for the components (devices) each year.

3.1.3.1. Multiple and 0-1 Knapsack Problem

In this scenario, components with different condition states in a DC have a low availability percentage (lower than 99.982% for tier 3 DC) and need maintenance improvement to maintain their operations. Thus, this model aims to obtain the maximum number of these components which can reach the minimum availability threshold within a fixed budget each month by conducting proper maintenance actions. In this scenario, a component can be selected only once for the maintenance action(s).

3.1.4. Mathematical Formulation

In this model, there are a set of n items, each having a weight (w_i) and a value (v_i) with the capacity of (C_k) to have the maximum items with maximum values distributed monthly within a one-year time horizon while respecting the capacity constraint of each knapsack (budget limitation).

Hence, the inputs of this model are:

- Set of items: $I = \{1, 2, \dots, n\}$
- Set of knapsacks: $K = \{1, 2, \dots, m\}$
- Item weights: w_i , for i in I
- Item values: v_i , for i in I
- Knapsack capacities: C_k , for k in K
- Maximum allowed items per knapsack: M

The decision variable is $x_{ik} = 1$ if item i is selected for knapsack k (or t), 0 otherwise

Thus, this parameter is a binary variable (0 or 1), indicating whether item i is selected for knapsack k .

The objective function is to maximize the total value of each knapsack as follows:

$$Maximize = \sum_{i=1}^n x_{i(k)} V_i \quad (8)$$

The model's constraints are:

Each item (component) can be selected at most once:

$$\sum_{i=1}^n x_{i(k)} \leq 1, \text{ for all } i \text{ in } I \quad (9)$$

There is a capacity constraint (fixed monthly budget) for each knapsack:

$$\sum_{i=1}^n w_i * x_{i(k)} \leq C_k, \text{ for all } k \text{ in } K \quad (10)$$

There is also a maximum allowed items (components) per knapsack constraint:

$$\sum_{i=1}^n x_{i(k)} \leq M, \text{ for all } k \text{ in } K \quad (11)$$

3.1.5. Model's Parameters

There are several parameters and criteria which are considered and included in the proposed maintenance management model. In this section, before presenting the case study implementation and the problem's solution and results, these parameters are elaborated and explained.

3.1.5.1. System's Reliability and Availability

These terms are crucial criteria for any system, subsystem or component in a complex infrastructure such as a DC. Reliability is defined as the ability of a component, subsystem or

system to have operational performance considering specific conditions and periods. Also, this term is applied as a performance-based metric presenting the component's success ratio or success probability during its operation (Heising, 2007a). Moreover, the failure rate is another critical parameter for performing a system's reliability analysis which is defined as the mean number of system failures within a timeframe (Rahmat et al., 2013a).

System availability is generally calculated based on the two (or three) following metrics. The first one is the Mean Time Between Failure (MTBF), which is the computed average time between failure occurrences (Heising, 2007a) or the Mean Time to Failure (MTTF). MTTF is used for replaceable or non-repairable components or devices in a system for component failure rate prediction. Otherwise, MTBF will be considered (Kidd, 2019).

In addition, the Mean Time to Repair (MTTR) is the second parameter used to calculate the system's availability. It represents the average time consumed to repair a component and restore it to full operating functionality after a failure. MTTR is also known as Mean Time to Restore or Mean Time to Recover. This factor could be obtained by dividing the total maintenance time by the total number of maintenance actions within a time horizon (Riello Elettronica Group, 2021).

The system's Availability is expressed as several "nines," which represent the percentage of operational time within a year for a component or system. The system availability formulas are shown below (Loeffler & Spears, 2014; Pourhosseini & Nasiri, 2018b).

$$\text{Availability of system/component} = \frac{\text{MTBF (or MTTF)}}{\text{MTBF (or MTTF)} + \text{MTTR}} \quad (12)$$

This formulation is also defined as “Inherent Availability” by some references such as RAC Toolkit, MIL-STD 338, and IEEE Dictionary (Heising, 2007a), which only includes the time for repairing failures and the logistics time is not included.

According to relevant resources, the term “Availability” specifically for IT infrastructure is defined as follows: “The degree of readiness expected of information systems and IT resources to deliver an appropriate and timely level of service, regardless of circumstances.” (Treasury Board Secretariat, 2021).

Hence, to conduct the reliability and availability analysis, the main parameters: failure rate, MTBF (MTTF) and MTTR, are obtained and presented in the following sections.

3.1.5.2. Condition State Index

There are several guidelines, approaches, methods, and standards for asset condition assessment (Federal Transit Administration, 2018; The Regional Municipality of Durham, 2019)

According to various condition assessment reports and relevant research works, different measuring systems, criteria, ratings, and rankings have been used to assess and measure an asset’s health condition in a facility or infrastructure (Ahmed et al., 2020; Town of Ajax, 2017).

In some Facilities Condition Analysis (FCA) references, the Facility Condition Needs Index (FCNI) metric has been calculated for DCs and other facilities to conduct the condition analysis (DTZ, 2013). This parameter is obtained by dividing the recommended upgrade costs divided to the facility replacement costs.

In this research, by conducting a general search on some of these resources, a condition assessment and analysis ranking based on the information provided by the Institute of Public

Works Engineering Australasia (IPWEA) and the National Asset Management System (NAMS) Group (New Zealand) is assumed and implemented.

The following asset condition grading system shown in Table 3, is the Simple Approach presented by the International Infrastructure Management Manual (IIMM) (IPWEA and NAMS, 2012). This approach is adopted and applied in this research to assign a condition state ranking to DC's assets and components for the maintenance management model.

Table 3: Asset condition grading system (IPWEA and NAMS, 2012)

Rank (Rating)	Asset Condition	Description of Condition
1	Excellent or Very Good	A brand-new device or near new condition - Only routine maintenance required
2	Good - Minor Defects Only	Minor maintenance required (5%)
3	Adequate - Maintenance Required to Return to Accepted Level of Service	Significant maintenance required (10-20%)
4	Marginal - Requires Renewal	Significant renewal/upgrade required (20-40%)
5	Poor - Asset Unserviceable	Over 50% of asset require replacement

3.1.5.3. Maintenance Costs

Since the goal of this model is to minimize total maintenance costs, data on the maintenance costs of each component over a specific time horizon in the DC were collected from reliable sources, including manufacturer data, industry reports, and field observations. These costs serve

as critical inputs into the proposed optimization model, capturing the economic implications of maintenance strategies across varying operational scenarios.

As briefly mentioned in Subsection 3.1.1 (Problem Formulation), the model considers multiple types of maintenance costs. These costs encompass both preventive maintenance (aimed at minimizing failure risks) and corrective maintenance (which addresses unexpected repairs). Additionally, they incorporate real-world variations in repair complexity, system requirements, and component-specific needs. To comprehensively represent these aspects, the following six distinct maintenance cost categories are specified:

$C_{F(i,t)}$: Costs of services for each incident/failure

$C_{PM(i,t)}$: Preventive maintenance costs

$C_{CM(i,t)}$: Corrective maintenance costs

$C_{PC(i,t)}$: Costs of power and cooling services

$C_{CR(i,t)}$: Component renewal costs

$C_{I(i,t)}$: Investment costs

Hence, to calculate the total maintenance costs of each ‘i’ component at time ‘t’ which is defined as $w_i(t)$, the following formula is used.

$$w_i(t) = C_{F(i,t)} + C_{PM(i,t)} + C_{CM(i,t)} + C_{PC(i,t)} + C_{CR(i,t)} + C_{I(i,t)} \quad (13)$$

This formula reflects the cumulative nature of maintenance expenses, ensuring that all cost dimensions are accounted for in the optimization process.

To provide further clarity, additional details regarding the calculation and application of these costs, as well as their integration into the optimization framework, are elaborated in Chapter 4 (Case studies and Results).

3.1.5.4. Algorithmic Framework and Case Study Context

In addition, a flowchart illustrating the Dynamic Availability-Based Maintenance Prioritization Model's algorithm is presented in Figure 5, providing a clear and concise step-by-step visual representation of the process. It outlines the key stages, including input identification and validation, DP table initialization, iterative evaluation of components against budget constraints, and optimal solution computation, culminating in the generation of a prioritized maintenance plan.

The Uninterruptible Power Supply (UPS) system (APC Symmetra PX 500 kW with Right-Mounted Maintenance Bypass and Distribution) has been selected as the component for the case study in this model, as well as in the two other maintenance optimization models. These models will be further elaborated and discussed in Chapter 4 under Section 4.1, Case Study Implementation.

Furthermore, the analytical procedures and findings of the Dynamic Availability-Based Maintenance Prioritization Model for DCs are comprehensively presented in Chapter 4. In particular, this includes the detailed reliability and availability analysis of the case study, together with the outcomes of the knapsack problem formulated for maintenance management and scheduling.

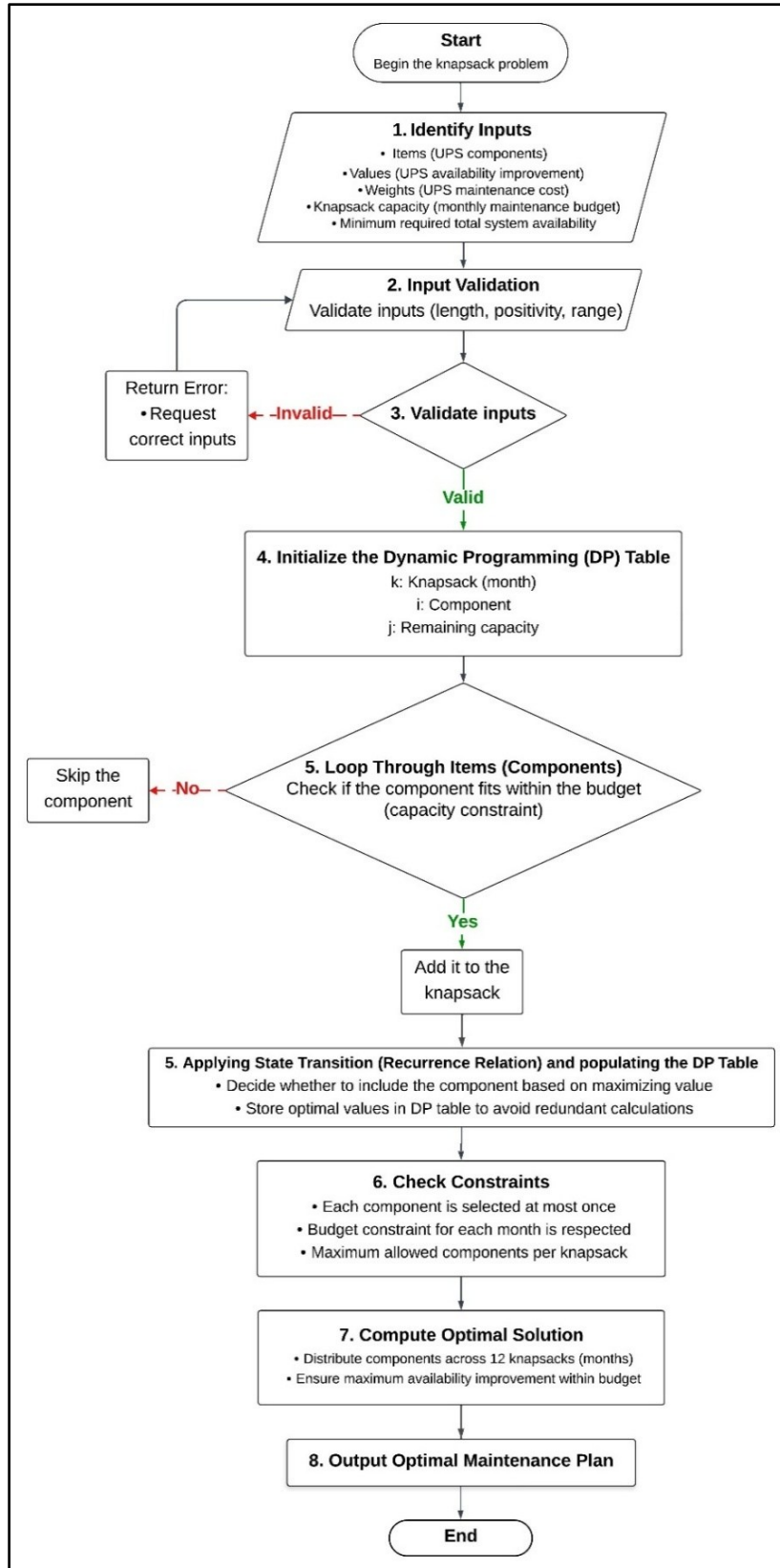


Figure 5. Flowchart of the dynamic availability-based maintenance prioritization model algorithm

3.2. Dynamic Availability-Based Maintenance Cost Optimization Model for K-out-of-N Systems in Data Centers

This section presents and discusses the proposed availability-based maintenance cost optimization model for a k-out-of-n parallel system in DCs by implementing the DP method. Before presenting quantitative analysis, the structure of the model and its elements and parameters as well as the assumptions, are defined and described.

This model formulates a dynamic maintenance cost optimization model specifically designed for parallel k-out-of-n-configured components in DCs. It optimizes the selection of k components to minimize maintenance costs, while ensuring the system meets the required total availability threshold. This k-out-of-n configuration is particularly relevant in DC environments where uninterrupted operations are critical, and maintenance budgets are constrained. It is imperative to acknowledge that within the proposed model, the optimal (minimum) count of k components in the k-out-of-n configuration is attained precisely when the prescribed minimum total system availability percentage is fulfilled. This constraint has been discussed earlier in this thesis since it has also been considered to formulate the first model (Dynamic Availability-Based Maintenance Prioritization).

3.2.1. Model's Formulation and Algorithm

According to the information mentioned above, the primary optimization formulation is structured as follows:

Minimize Z = Total maintenance costs of assets (components) in the DC =

$$\sum_{i=1}^n C_{i,t} \times X_{i,t} \quad (14)$$

Where:

$C_{i,t}$ represents the maintenance cost of each component at time t .

$X_{i,t}$ represents the binary variables for each component, where i ranges from 1 to n and indicates whether a specific component is chosen (1) or not chosen (0) at time t .

The above optimization formula is subject to the total system's availability constraint (discussed earlier) as follows:

$$1 - \prod_{i=1}^n [(1 - A_{i,t})] \geq A_{t, \text{Required}} \quad (15)$$

Where:

$A_{i,t}$: availability of the i th component at time t , which is the probability that the component is operational at time t .

$A_{t, \text{Required}}$: the required system availability threshold at the time, which represents the minimum acceptable level of system availability required for the system to meet its operational objectives.

This constraint represents the system's availability condition in a parallel k -out-of- n system.

Thus, the above information demonstrates the objective of minimizing the total maintenance costs by selecting the optimal combination of components, subject to constraints ensuring that the selected components achieve the required system availability.

The DP algorithm used and applied in this research efficiently determines the optimal number of components to minimize the total maintenance costs while ensuring that the total system availability meets the specified minimum availability requirement (based on DC standards). By utilizing DP, the algorithm calculates the minimum maintenance cost for each possible combination of components. It considers both cases: choosing or not choosing the current component. Then, the system availability is computed, and the optimal number of components (k), the corresponding minimum maintenance cost, and the final system availability are given as the algorithm's outputs.

3.2.2. Model's Parameters

Before detailing the case study implementation and addressing the problem's solution, this section explains the main parameters and criteria used in this maintenance cost optimization model as follows:

n: total number of components

MTBF [MTBF1, MTBF2, ..., MTBFn]: the list of Mean Time Between Failures (MTBF) for each component.

MTTR [MTTR1, MTTR2, ..., MTTRn]: the list of mean time to repairs (MTTR) for each component.

Maintenance costs [cost1, cost2, ..., costn]: list of maintenance costs for each component.

K (integer variable) represents the number of components to choose (from a total of n components).

Min_availability: the minimum required system availability.

The concepts of system reliability, failure rate, and system/component availability - along with the associated metrics such as Mean Time Between Failures (MTBF), Mean Time To Failure (MTTF), and Mean Time To Repair (MTTR) - have been previously introduced in Section 3.1.

Additionally, the interpretation of system availability expressed through "nines," the standard availability formula, and the DC availability thresholds based on the Uptime Institute's Tier classification have been comprehensively discussed in Section 3.1. As such, these fundamental principles are regarded as already established within the framework of the proposed methodology and will not be reiterated in subsequent sections unless further specification or refinement is required for the model's development.

Consistent with the formulation of the first model (Dynamic Availability-Based Maintenance Prioritization) outlined earlier, the Asset Condition State Index - previously detailed through the discussion of condition assessment methodologies, grading systems, and corresponding maintenance strategies - has likewise been considered and incorporated into the development of the proposed optimization model. As the same condition state indexing system has already been established and applied to categorize maintenance costs and guide the optimization process, further elaboration in this section is deemed unnecessary.

In this model, the same six maintenance cost categories used in the previous model ($C_{F(i,t)}$, $C_{PM(i,t)}$, $C_{CM(i,t)}$, $C_{PC(i,t)}$, $C_{CR(i,t)}$, and $C_{I(i,t)}$) are considered to ensure consistency and comparability in cost estimation. In addition, an extra cost component, $C_{B(i,t)}$ (costs of battery replacement service), is incorporated to address the specific maintenance needs of K-out-of-N system configurations where battery reliability is critical. Accordingly, the total maintenance cost of component i at time t is calculated using the following formula:

$$C_{i,t} = C_{F(i,t)} + C_{PM(i,t)} + C_{CM(i,t)} + C_{PC(i,t)} + C_{B(i,t)} + C_{CR(i,t)} + C_{I(i,t)} \quad (16)$$

This formulation ensures comprehensive coverage of all relevant cost dimensions within the optimization process.

Additional details regarding the calculation and application of these costs are presented in Chapter 4 (Case studies and Results).

3.2.3. Dynamic Programming Approach

In this section, the Dynamic Programming (DP) approach is described. The DP model optimizes maintenance costs for k-out-of-n configurations while ensuring system availability thresholds are met.

The DP algorithm identifies the optimal combination of k components from n available units by solving recursive subproblems. Each decision state represents a set of operational components, with transitions reflecting maintenance actions and costs. This algorithm evaluates the following:

System Availability: ensures the selected configuration meets or exceeds the availability threshold, depending on the selected tier.

Cost Minimization: selects the configuration with the lowest total maintenance cost while meeting the minimum availability requirement.

The following steps show how DP is applied in the algorithm to solve the problem.

- DP Table Initialization

First, the algorithm creates a 2D table, which is initialized with dimensions $(n + 1) \times (n + 1)$, where n is the total number of components.

Each cell $dp[i][j]$ in the DP table represents the minimum maintenance cost to achieve system availability with i components, where j out of the total i components are selected.

- Base Cases

The base cases handle the scenarios with 0 or 1 components:

The $dp[i][0]$ is set to 0, which indicates no cost for 0 availability (no component is selected), and when it is set to infinity, it means that there is an infinite cost for non-zero availability with no components available.

- Filling the DP Table

The DP bottom-up approach has been utilized to iteratively complete the DP table, and the nested loops iterate through all possible numbers of components (i) and all possible component selections (j).

Two cases are considered for each cell $dp[i][j]$:

In Case 1, the current component is not chosen and $dp[i][j]$ is updated with the minimum cost from the previous row, indicating not choosing the current component.

In Case 2, the current component is selected and if the current component is chosen ($j \leq i$), the system availability is calculated.

Then, if the calculated system availability meets the minimum requirement, the minimum maintenance cost is updated based on the previous row and the maintenance cost of the current component.

It should be noted that each state in the DP algorithm represents the operational status and maintenance cost of specific components, with decisions based on recursive evaluations of the subproblems.

- Obtaining the Optimal k and the Minimum Maintenance Costs

After the DP table completion, a loop iterates over possible numbers of components (k) to find the optimal solution, which is the one achieving the minimum maintenance costs while meeting the availability requirement.

- Final Output

The minimum cost and corresponding optimal number of components are determined, and the final system availability and other relevant information, such as the optimal number of components and minimum maintenance costs, are provided as the algorithm outputs.

Therefore, the proposed DP application efficiently solves the optimization problem by breaking it down into smaller subproblems and reusing solutions to those subproblems, resulting in an optimal solution with improved time complexity compared to brute force or other recursive approaches. A summary of the proposed algorithm is provided below.

This algorithm takes as inputs the total number of components (n), their Mean Time Between Failures (MTBF), Mean Time To Repairs (MTTR), maintenance costs, and the minimum acceptable system availability. The outputs include the optimal number of components (k) to achieve the required availability, the minimum associated cost, the final system availability, and the specific combination of selected components.

The process begins with input validation to ensure all lists are consistent, the MTBF and MTTR values are positive, and the minimum availability is within the valid range (0–1) depending on the

DC's tier. Next, the availability of each component is calculated using Formula (3) ($\text{Availability} = \text{MTBF}/(\text{MTBF} + \text{MTTR})$), which was presented earlier. A DP table is then initialized to systematically store the best combinations of components for varying selections, tracking both availability and cost. The table is populated by evaluating all possible combinations of components to identify those that meet or exceed the minimum availability requirement at the lowest cost.

The algorithm subsequently determines the optimal number of components (k) by selecting the configuration that satisfies the availability constraint while minimizing costs, ensuring that at least five components are included. Finally, the results—optimal k , minimum cost, final system availability, and the chosen combination of components—are extracted from the DP table and returned as the solution.

The following pseudocode presented in Algorithm 1, provides a high-level overview of the model to assist readers unfamiliar with the DP algorithm. It outlines the key steps, from input validation to determining the optimal component selection while minimizing the total maintenance costs and meeting the total required system availability.

Pseudocode for the optimal UPS component selection algorithm:

Algorithm 1. Optimal UPS Component Selection.

```

1: FUNCTION FindOptimumUPSCombination(components, requiredAvailability):
2:   // Validate Inputs
3:   FOR each component IN components:
4:     IF component.MTBF  $\leq$  0 OR component.MTTR < 0 OR component.MaintenanceCost <
0:
5:     RETURN "Error: Invalid input values."

```

```
6:  // Compute Availability for Each Component
7:  FOR each component IN components:
8:      component.Availability = component.MTBF/(component.MTBF + component.MTTR)

9:  // Initialize DP Table
10:  DPTable = Array[NumComponents][requiredAvailability + 1] filled with Infinity

11:  // Check Feasibility
12:  IF no valid configuration exists:
13:      RETURN "Error: No valid component configuration found."

14:  // Populate DP Table
15:  FOR k FROM 1 TO NumComponents:
16:      FOR each combination OF components:
17:          totalAvailability = ComputeTotalAvailability(combination)
18:          totalCost = ComputeTotalCost(combination)
19:          IF totalAvailability  $\geq$  requiredAvailability:
20:              DPTable[k][totalAvailability] = MIN(DPTable[k][totalAvailability], totalCost)

21:  // Determine Optimal k
22:  OptimalK = -1, MinCost = Infinity
23:  FOR k FROM 5 TO NumComponents:
```

```

24:   FOR j FROM requiredAvailability TO 0:
25:       IF DPTable[k][j] < MinCost:
26:           MinCost = DPTable[k][j]
27:           OptimalK = k

28: // Output Results
29: IF OptimalK = -1:
30:     RETURN "Error: Required availability cannot be met."

31: SelectedComponents = RetrieveSelectedComponents(DPTable, OptimalK, MinCost)
32: RETURN OptimalK, MinCost, ComputeTotalAvailability(SelectedComponents),
SelectedComponents

33: FUNCTION ComputeTotalAvailability(components):
34:     RETURN PRODUCT(component.Availability FOR component IN components)

35: FUNCTION ComputeTotalCost(components):
36:     RETURN SUM(component.MaintenanceCost FOR component IN components)

37: FUNCTION RetrieveSelectedComponents(DPTable, OptimalK, MinCost):
38:     //Backtrack to retrieve selected components
39:     RETURN SelectedComponents

```

In addition, a flowchart illustrating this algorithm is presented in Figure 6, providing a clear and concise step-by-step visual representation of the steps, decision points, and iterative loops.

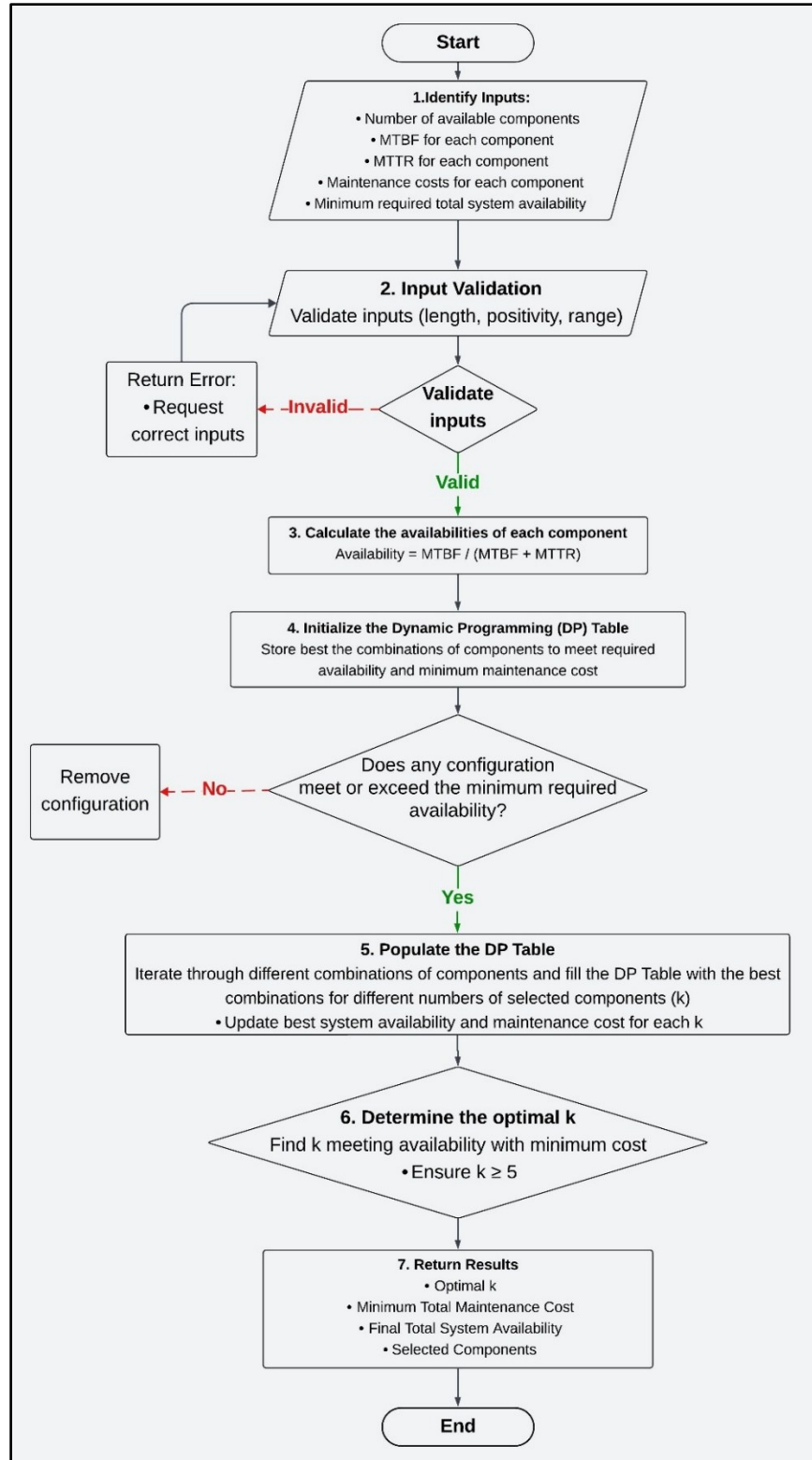


Figure 6. Flowchart of the dynamic cost and availability-based optimization algorithm for DC components in a

k-out-of-n parallel configuration

3.2.3.1. *Dynamic Maintenance Costs*

It should also be noted that in the implemented algorithm, the concept of variable failure rates is employed to derive dynamic maintenance costs based on the condition of each asset. By applying this approach, different failure rate functions are considered, which reflect the varying reliability and performance characteristics of individual assets within a system, and a more dynamic model is proposed and implemented.

In the following parts of this subsection, it will be expressed how variable failure rates are integrated into the code to achieve dynamic maintenance costs:

- Individual asset characteristics: Each asset in the system is characterized by its own Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR). These parameters define the asset's failure rate and repair rate, respectively, and serve as a basis for calculating its availability and determining the impact of its failure on the overall system performance.
- Dynamic availability calculation: The availability of each asset is dynamically calculated based on its MTBF and MTTR. Availability represents the probability that the asset will be operational at any given time, considering its historical failure and repair patterns.
- Dynamic maintenance costs: maintenance costs are tied to the condition and reliability of each asset. As the availability of an asset changes dynamically over time, so does the associated maintenance cost. Lower availability, resulting from higher failure rates or longer repair times, leads to increased maintenance costs to restore the asset to operational status.

- DP optimization: The DP approach is used to optimize maintenance costs while ensuring system availability meets specified requirements. By considering different combinations of assets and their associated maintenance costs, the DP algorithm identifies the most cost-effective configuration of assets that satisfies the availability target.
- Cost-effectiveness analysis: the use of variable failure rates and dynamic maintenance costs allows for a more accurate cost-effectiveness analysis of maintenance strategies.

Based on the above-mentioned information, failure rates (λ), Mean Time To Repair (MTTR), and Mean Time Between Failures (MTBF) are central to this optimization model and are integrated into the cost and reliability calculations. The method ensures scalability and adaptability, providing solutions for various subsystems and operational scales.

To ensure real-world applicability, the model accounts for:

- Variable component aging and failure trends.
- Budget constraints and cost variations for different maintenance actions.

3.3. Availability-Constrained Maintenance Cost Optimization Model for Series-Parallel Systems

This section presents an optimization model tailored for Series-Parallel systems to support maintenance decision-making in DCs. The model aims to minimize the total maintenance costs while ensuring that system availability requirements, aligned with Uptime Institute Tier standards (presented in Table 2 under section 3.1), are met or exceeded within a fixed monthly budget.

3.3.1. Model's Formulation

The model is formulated as a Mixed-Integer Nonlinear Programming (MINLP) problem, where the decision variable is the number of components—grouped by condition states—selected for maintenance. The objective function is defined as:

Minimize $Z = \text{Total maintenance costs of assets (components) in the DC} =$

$$\min \sum_{i=1}^n C_i * x_i \quad (17)$$

Where:

- C_i : Maintenance cost per unit for component in condition state i
- x_i : Number of selected components for maintenance in condition state i ($x_i \in \mathbb{Z}$)
- i : Condition state index from 1 to 10
- n : number of series subsystems (asset condition states)

As with the two previously presented models, this formulation incorporates availability constraints defined by the Uptime Institute Tier standards (outlined in Table 2 of Section 3.1). These constraints ensure that the selected maintenance strategy maintains the required service-level expectations for DC operations.

3.3.1.1. Model's Configuration and Constraints

The system under consideration consists of multiple parallel subsystems, each containing several assets connected in series, as illustrated in Figure 7. This hybrid structure reflects a realistic DC architecture where redundancy and fault tolerance are achieved through parallelism, while critical dependencies are modelled through series connections. The model assumes that each

component's availability and condition state are known and that maintenance decisions are made periodically based on these inputs.

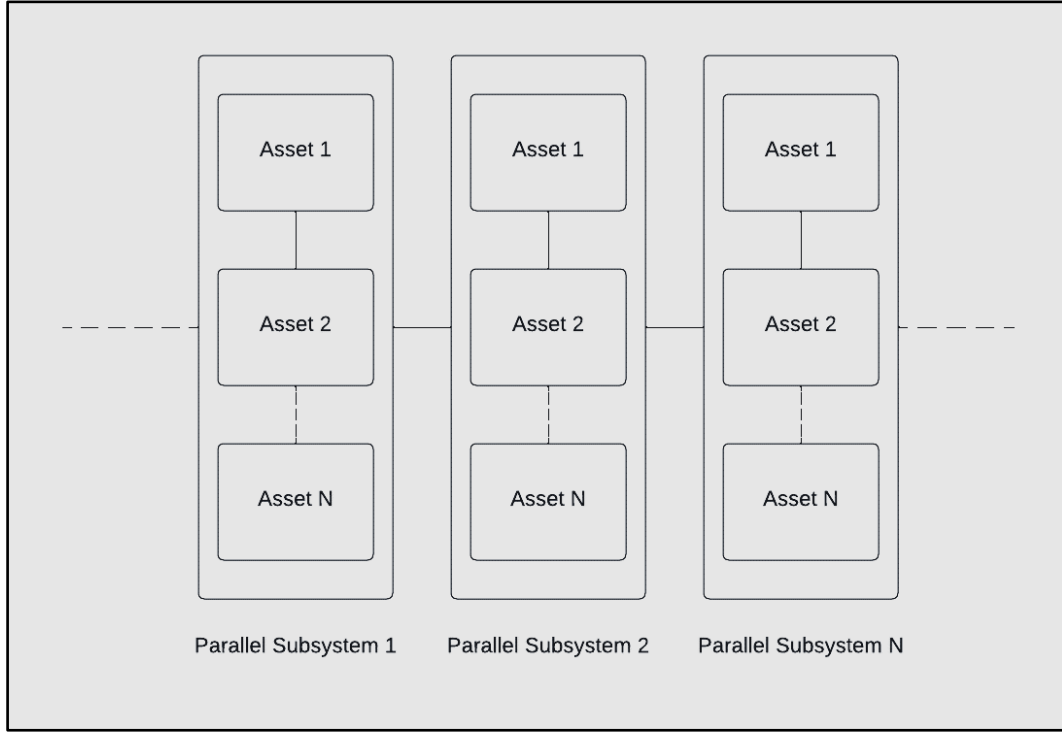


Figure 7. Series-Parallel configuration of DC assets

- Key constraints:

First, for each parallel configuration, the probability of at least one component functioning (i.e., system availability) must also satisfy or surpass the target availability level:

$$A_{Subsystem,i} = 1 - \prod_{i=1}^m (1 - A_i) \geq A_{Required} \quad (18)$$

Where:

m: number of units in each parallel subsystem

Then, for the series configurations, the product of component availabilities must meet or exceed the required system availability threshold:

$$A_{System} = \prod_{i=1}^n (A_{Subsystem,i}) \geq A_{Required} \quad (19)$$

Where:

n: number of series subsystems (asset condition states)

These availability thresholds serve as hard constraints within the optimization framework, ensuring that the selected maintenance strategies align with the required service-level expectations for DC operations. These constraints guarantee that the system availability remains at or above the minimum level specified for each Tier classification, thereby preserving operational reliability and resilience.

Additionally, the number of components selected for maintenance at each time step must adhere to the condition-state-based decision variable. Therefore, the component selection bound & integrality constraints are as follows:

$$x_{i,t}(\min) \leq x_{i,t} \leq x_{i,t}(\max) \quad (20)$$

This constraint ensures that at least one unit in each subsystem per each state is selected for maintenance and the number of selected components per each subsystem should not exceed the total number of components per each subsystem.

- Total component selection bounds:

$$X_{i,t}(\min) \leq \sum_{i=1}^{10} x_{i,t} \leq X_{i,t}(\max) \quad (21)$$

This constraint ensures the total minimum and maximum selected components for the whole Series-Parallel system.

- Integrality constraint:

$$x_{i,t} \in \mathbf{Z}, \quad \forall i = 1, \dots, 10 \quad (22)$$

Finally, the total maintenance costs constraint ensures that the sum of maintenance costs over the planning horizon does not exceed the predefined budget:

$$\sum_{t=1}^T c_{i,t} * x_{i,t} \leq \text{Total budget} \quad (23)$$

These constraints collectively ensure that the optimal maintenance strategy remains both technically effective and economically viable.

It is important to note that all the model parameters—such as system reliability and availability metrics, definitions of MTBF, MTTR, and failure rates, and the asset condition grading system are the same used for the two previous models presented in subsection 3.1. and in Table 2.

The comprehensive maintenance cost categories ($C_{F(i,t)}$, $C_{PM(i,t)}$, $C_{CM(i,t)}$, $C_{PC(i,t)}$, $C_{CR(i,t)}$, $C_{I(i,t)}$) are consistent with those introduced in Subsection 3.1 and are similarly applied in this model formulation to ensure continuity and methodological coherence.

3.3.1.2. Model's Implementation

The optimization model was implemented using the Excel Solver add-in, employing the Evolutionary engine due to the non-linear and integer-constrained nature of the problem (Frontline Systems, n.d.; Jain, 2024). The choice of the Evolutionary algorithm is justified by its ability to handle complex, non-smooth functions, discrete decision variables, and multiple interacting constraints, characteristics inherent to the DC maintenance optimization problem.

- Rationale for Using the Evolutionary Engine
 - Non-smooth objective and constraints: The system availability function is non-linear and involves products of parallel subsystem availabilities, which may include discontinuities.
 - Integer decision variables: Each represents a discrete number of units selected for maintenance, requiring integer optimization.
 - Complex constraints: The model includes per-subsystem bounds, total selection bounds, budget limitations, and system-level availability requirements, which are efficiently managed by the Evolutionary solver.
- Advantages and Limitations
 - The Evolutionary engine provides feasible, cost-minimizing maintenance schedules for complex, discrete, and non-linear problems.
 - As a stochastic search method, it does not guarantee a global optimum, although multiple runs can improve solution quality.

- The obtained solution can be further refined by employing GRG (Generalized Reduced Gradient) optimization, starting from the best solution identified by the Evolutionary solver, enhancing local optimality.

The analysis and results of this model are presented in Chapter 4 (Subsection 4.4: Results and Discussion – Availability-Constrained Maintenance Cost Optimization Model for Series-Parallel Systems).

Chapter 4: Case studies and Results

This chapter presents the selected case study and the corresponding outcomes derived from the application of the developed optimization models. The results from the implementation of each model are explained in detail as follows:

- **Dynamic Availability-Based Maintenance Prioritization Model:** The outcomes of applying this model to the case study are discussed, focusing on how it prioritizes maintenance tasks in DCs based on availability considerations.
- **Dynamic Availability-Based Maintenance Cost Optimization Model for K-out-of-N Systems:** The results derived from this model are analyzed, emphasizing how it optimizes maintenance costs while accounting for DC system availability in K-out-of-N systems.
- **Availability-Constrained Maintenance Cost Optimization Model for Series-Parallel Systems:** The outcomes from this model are explored, illustrating how it optimizes maintenance costs in systems with availability constraints, specifically for series-parallel configurations in DCs.

The chosen case study serves as a practical validation of the proposed methodologies. The findings from running the optimization models on the case study are visually illustrated and explained, demonstrating the models' effectiveness in prioritizing maintenance, minimizing costs, and ensuring system availability under real-world operational constraints.

4.1. Case Study Implementation

4.1.1. System and Component Description

For the implementation and execution of the proposed models, as outlined in the previous chapter, a collection of UPS units within a DC has been selected as the focal point of investigation. These units operate collectively as an integral subsystem of the DC's power infrastructure.

Maintaining continuous operation and minimizing downtime are paramount for DCs, emphasizing the indispensable role of UPS in their functionality. UPS systems supply power to equipment during maintenance or unexpected power outages when the primary source fails. It is crucial for DCs to invest in equipment that aligns with their requirements and to diligently monitor Key Performance Indicators (KPIs) to ensure seamless operations (MCIM by Fulcrum Collaborations, 2023).

Various UPS types and configurations are employed across diverse facilities based on their specific operational needs and demands. UPS systems are broadly categorized into static and rotary types, further classified into single-conversion or double-conversion topologies. The static UPS, a fundamental variant, typically integrates a battery as its primary emergency power source in the DC. This system incorporates electronic switching components to convert DC voltage from the battery into AC voltage, facilitating its utilization by the connected IT Equipment (ITE). Additionally, a switch, whether electronic or electromechanical, is incorporated within the static UPS to manage the transition between primary power and battery backup during power outages (de Jonge et al., 2015), (Geng, 2015a), (Heising, 2007b). The Schematic Block Diagram of a UPS system is shown in Figure 8.

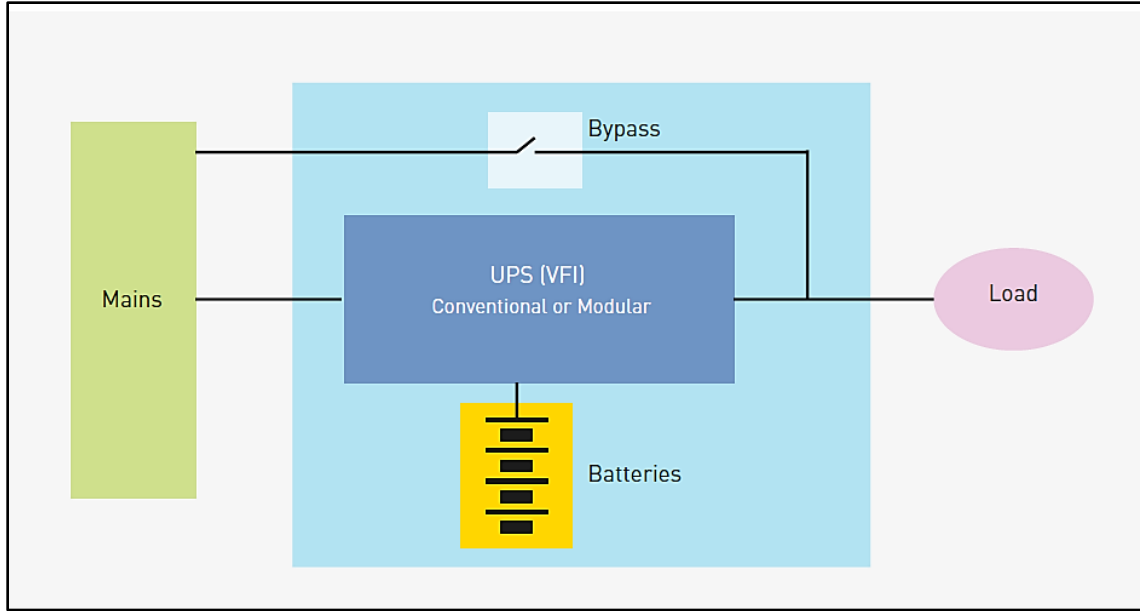


Figure 8. Schematic block diagram of a UPS system (Legrand, 2021)

To simplify the maintenance cost optimization model and have consistency in the results of this study, a single type of UPS system (APC Symmetra PX 500kW with Right Mounted Maintenance Bypass and Distribution) has been chosen to conduct the calculations and analysis (APC - Schneider Electric, 2021) (CDW LLC., 2021b). This UPS is 3-phase, modular and scalable, having high performance and industry-leading efficiency and capacity, which makes it an ideal power protection solution for medium to large DCs and mission-critical environments (APC - Schneider Electric, 2021). Notably, this UPS system is based on a real-world implementation currently in use at the Cologix MTL3 Data Center in Montréal, Québec, Canada (Cologix, 2019), further demonstrating its practical applicability in a live DC environment.

4.1.2. Failure Modes, Condition States and Maintenance Actions

Building upon the condition state rankings and descriptions outlined earlier in Chapter 3, this subsection delves into the specific details and potential failure modes associated with a UPS system within the DC infrastructure.

Various methods and approaches have been employed by researchers to determine the reliability parameters of components. Failure Modes, Effects, and Criticality Analysis (FMECA) has been utilized to investigate the causes and impacts of component failures. For UPS systems, manufacturers typically use field data measurement methods to estimate reliability parameters. Additionally, some studies have employed RBD and Monte Carlo simulations to calculate UPS failure rates, MTBF, availability, and unavailability (Rahmat et al., 2013b). Therefore, the reliability data in this study have been derived from these pertinent sources.

Figure 9 shows the top 10 failures in UPS components, which were collected from various manufacturers by Fulcrum Collaborations (MCIM by Fulcrum Collaborations, 2023).

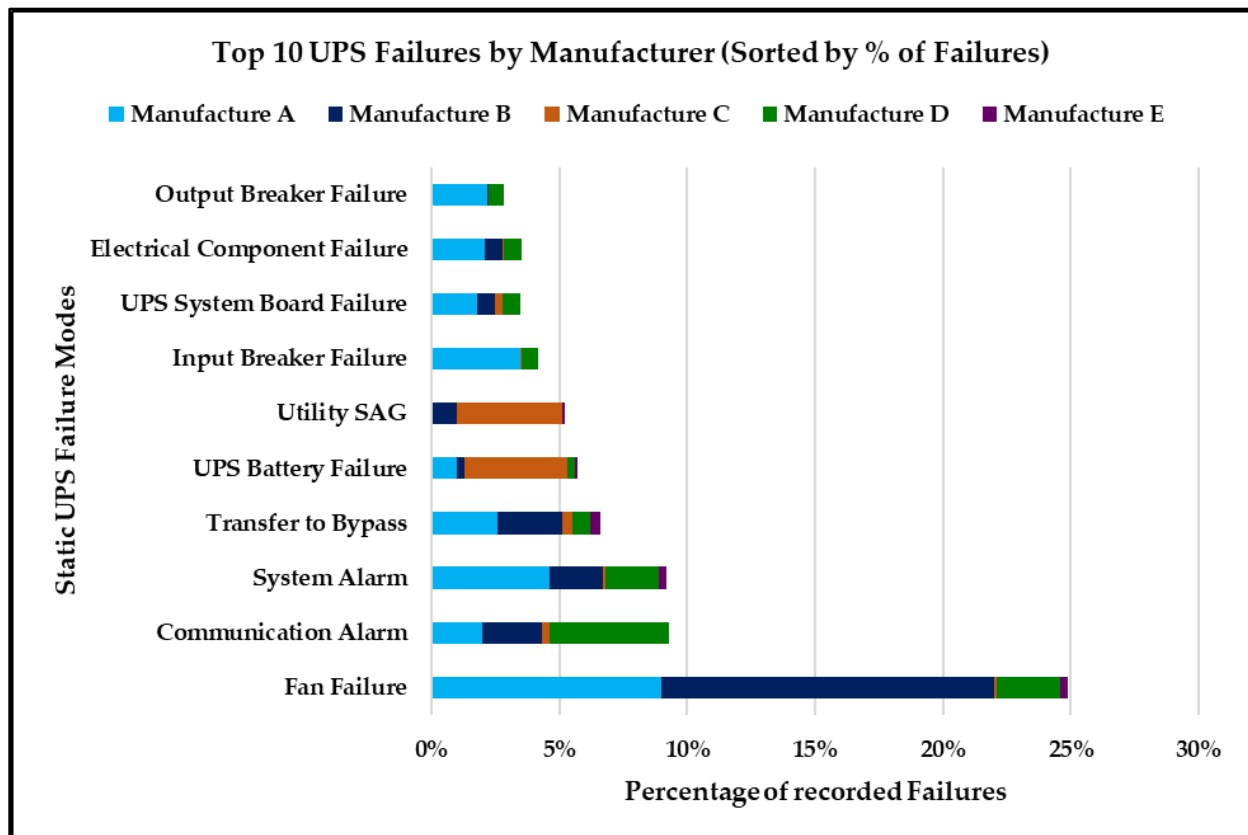


Figure 9. Top 10 failures in UPS systems (MCIM by Fulcrum Collaborations, 2023)

To operationalize the proposed maintenance optimization models, as described earlier in Chapter 3 and presented in Table 3, a discrete scale of 1 to 5 was employed to represent the varying physical and functional condition states of the UPS units. This ranking system facilitates the integration of these condition states into the model, enabling the selection of appropriate maintenance actions.

4.1.3. Reliability and Availability information

As mentioned in the previous section, variable failure rates for the UPS units based on their conditions are employed to derive dynamic maintenance costs and deploy them into the maintenance cost optimization model.

Regarding the asset condition grading system presented earlier in Chapter 3 (Table 3), a ten-point classification scheme, with 10 representing the best and 1 the worst condition, was established for the UPS systems based on their failure rates and availability percentages. The MTBF and MTTR data were sourced from the IEEE 493-2007 standard, specifically for UPS systems in small computer rooms (Heising, 2007b). This data served as the baseline for the best asset condition (State 10). To comprehensively represent the reliability profile for the remaining condition states (from 1 to 9), additional parameters were incorporated through informed assumptions. The mentioned categories and parameters are shown in the table below (Table 4) (Heising, 2007b) for a static UPS system. The available UPS units in the case study system are named UPS_DC_1 to UPS_DC_10 (for conditions 1 to 10, respectively).

Table 4: UPS system's reliability and availability data (Fadaeefath Abadi, Haghghat, et al., 2025; Heising, 2007b)

Asset Condition State	Asset Condition Description	MTBF (hrs.)	MTTR (hrs.)	Failure Rate (per year)	Asset Availability (percentage)
10	Brand new device or near new condition	933,708	2	0.009382	99.999%
9	Brand new device or near new condition	930,000	4	0.009419	99.999%
8	Fully operational device	850,000	8	0.010306	99.999%
7	Partially operational device with some failures	500,000	12	0.017520	99.997%
6	Partially operational device with some failures	300,000	14	0.029200	99.995%
5	Fair condition	100,000	18	0.087600	99.982%
4	Poor condition and needs component renewal (battery or other parts)	50,000	25	0.175200	99.950%
3	Poor condition and needs component renewal (battery or other parts)	30,000	27	0.292000	99.910%
2	Critical condition and near end-of-life	20,000	29	0.438000	99.855%
1	Critical condition and near end-of-life	10,000	30	0.876000	99.701%

The following subsections of this chapter present, analyze, and discuss the detailed results of the three models: (1) Dynamic Availability-Based Maintenance Prioritization, (2) Dynamic Availability-Based Maintenance Cost Optimization Model for K-out-of-N Systems, and (3) Availability-Constrained Maintenance Cost Optimization Model for Series-Parallel Systems.

4.2. Results and Discussion: Dynamic Availability-Based Maintenance Prioritization Model

Building on the information provided in the previous subsections, the reliability and availability parameters, condition states, and relevant maintenance actions for assumed UPS units located in a DC have been identified and quantified. These inputs were then used to develop and implement the Dynamic Availability-Based Maintenance Prioritization Model.

To run the model and generate results, an availability threshold consistent with Tier 3 DC standards was adopted as a constraint. According to the Uptime Institute DC (Uptime Institute, 2021a), a Tier 3 DC not only supports the basic capacity requirements for IT infrastructure but must also meet several key criteria, including the deployment of UPS systems to mitigate power sags, outages, and spikes, as well as the provision of dedicated spaces for IT systems. Additionally, Tier 3 facilities require redundant power and cooling components to improve maintenance flexibility and enhance operational resilience during disruptions.

The results of the model are presented in the following subsection and analyzed with respect to these operational and availability constraints.

4.2.1. Maintenance Costs Information

In the next step, the relevant maintenance costs have been collected and indicated (CDW LLC., 2021a; Hummingbird Networks, 2021a) for the UPS system to calculate the total costs for each maintenance action according to each condition state. Table 5 indicates the list of available maintenance services provided by the manufacturer and the corresponding costs for the selected UPS model. The information in Table 5 is essential for understanding the different types of available maintenance services and their costs. It provides the basis for calculating the total maintenance costs associated with each maintenance action in the study.

Table 5: Available maintenance services for the APC Symmetra PX 500kW UPS system (CDW LLC., 2021b; Fadaeefath Abadi, Haghighat, et al., 2025; Hummingbird Networks, 2021b)

APC Symmetra PX 500kW Scalable to 500kW with Right Mounted Maintenance Bypass and Distribution - SY500K500DR-PD	
Type of maintenance service offered by the manufacturer	Cost per year (USD)
New device (APC Symmetra PX 500kW)	\$261,464
Electric Critical Power and Cooling Services Advantage Ultra Service Plan - On-site	\$44,269
APC Modular Battery Replacement Service - Installation and configuration - On-site - Includes Installation, maintenance, replacement, or removal of one UPS battery during business hours.	\$9,049
APC On-Site Service On-Site Warranty Extension - Extended Service Agreement - Parts and Labour (for UPS 300-500 KVA) - 1 Year - On-site - Business Hours	\$6,660
On-Site Service Upgrade to Factory Warranty or Existing On-Site Service Contract - 4-Hour Response	\$2,704
APC Modular Battery Replacement Service Scheduling Upgrade to 7*24 (7 days a week and 24 hours a day) - Installation/configuration (for UPS battery) - On-site	\$2,073
APC 7*24 Scheduling Upgrade from Existing Preventive Maintenance Service - 1 incident - On-site	\$1,027

Table 6 presents the cost calculation details of each individual maintenance action. According to the six distinct maintenance cost categories presented in Chapter 3, this table breaks down the costs associated with different maintenance actions, allowing for a detailed understanding of how maintenance costs contribute to overall maintenance planning and budgeting.

Table 6: Combined and categorized maintenance costs for the APC Symmetra PX 500kW UPS system (CDW LLC., 2021b; Fadaeefath Abadi, Haghighat, et al., 2025; Hummingbird Networks, 2021b)

Type of maintenance action	Cost per year (USD)
Service for each incident/failure	\$1,026.99*(yearly failure rate)
Preventive maintenance (inspection)	\$6,659.6
Corrective maintenance	$\$6,659.6 + \$2,703.99 = \$9,363.59$
Battery replacement service	$\$9,048.99 + \$2,072.99 = \$11,121.98$
Electric critical power and cooling services	\$44,268.99
Component renewal (30% - 40% of purchasing a new device)	$0.35 * \$261,463.99 = \$91,500$
Investment (new device purchase)	\$261,463.99

According to the data in Table 6, the pie chart provided in Figure 10 illustrates the distribution of various lifecycle and maintenance costs of the APC Symmetra PX 500kW UPS system over a given timeframe. The initial investment in the new device accounts for a significant portion of the overall cost (approximately 62%). Component renewal, Cooling and Power services also form substantial shares (22%, 10%), while other services contribute less.

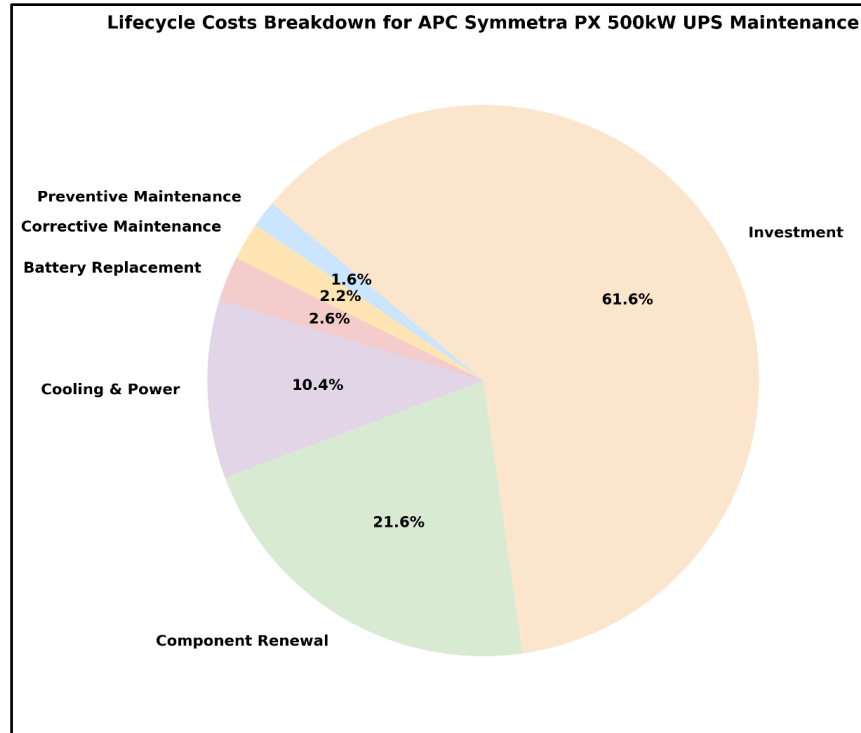


Figure 10. Lifecycle and maintenance costs distribution for the APC Symmetra PX 500kW UPS system

4.2.2. Maintenance Prioritization Model (0/1 Multiple Knapsack Problem) Results

As mentioned previously, the objective is to obtain the maximum monthly number of UPS systems which can be improved by conducting proper maintenance actions to reach the minimum availability requirement (99.982% for Tier 3 DC) considering a yearly fixed budget for the DC company. The UPS systems in condition state from 5 to 10 are excluded from the model since their availability percentages are already within the required range (above 99.982% for Tier 3 DC). Hence, the components in condition states 1 to 4 are included in the knapsack model and their availability needs to be increased. In this scenario, it is assumed that the DC company has 24 UPS devices in operation (from state 1 to state 4 and 6 devices per each condition state) and has the plan to improve them to condition states 5 or higher to meet the availability requirement of Tier 3 DC (99.982% availability) within a limited monthly and yearly maintenance budget. Table 7 shows

the corresponding maintenance costs for each UPS device regarding its availability improvement. The information presented in Table 7 is crucial for demonstrating the financial implications of maintaining and improving the availability of UPS devices in the DC. It shows the relationship between maintenance costs and the resulting availability improvement.

Table 7: UPS system’s maintenance costs for its availability improvement

UPS ID	Current condition state	Current availability (%)	Yearly maintenance costs for availability improvement (USD)	Condition state after improvement	Availability after improvement (%)	Availability improvement (%)
UPS_APC500_DC_1	1	99.701%	\$261,463.99	10	99.999%	0.29889%
UPS_APC500_DC_2	2	99.855%	\$261,463.99	10	99.999%	0.14458%
UPS_APC500_DC_3	3	99.910%	\$156,566.84	7	99.997%	0.08752%
UPS_APC500_DC_4	4	99.950%	\$156,446.89	7	99.997%	0.04758%

It should be noted that due to the nature of maintenance actions and the importance of DCs and the criticality of UPS devices operating in the DC, the “Yearly maintenance costs for availability improvement” have been converted to monthly costs so that our model could be more realistic and to meet the DC company’s maintenance prioritization goals.

Therefore, the corresponding yearly maintenance costs from Table 7 are converted into monthly costs for a more realistic budgetary application and shown in Table 8. This conversion allows

maintenance planning to align with monthly budgeting cycles, making it easier for DC companies to manage their finances and plan maintenance actions within a fixed monthly budget.

Table 8: UPS system's monthly maintenance costs for its availability improvement

UPS ID	Current condition state	Current availability (%)	Monthly maintenance costs for availability improvement (USD)	Condition state after improvement	Availability after improvement (%)	Availability improvement (%)
UPS_APC500_DC_1	1	99.701%	\$21,789	10	99.999%	0.29889%
UPS_APC500_DC_2	2	99.855%	\$21,789	10	99.999%	0.14458%
UPS_APC500_DC_3	3	99.910%	\$13,047	7	99.997%	0.08752%
UPS_APC500_DC_4	4	99.950%	\$13,047	7	99.997%	0.04758%

Based on the data obtained from Table 7, a correlation analysis between the Current Availability, Yearly Maintenance Costs, and Availability Improvement has been performed to provide a comprehensive view of how these variables relate to each other in the context of the UPS availability and maintenance costs for DCs. The heatmap in Figure 9 presents this correlation.

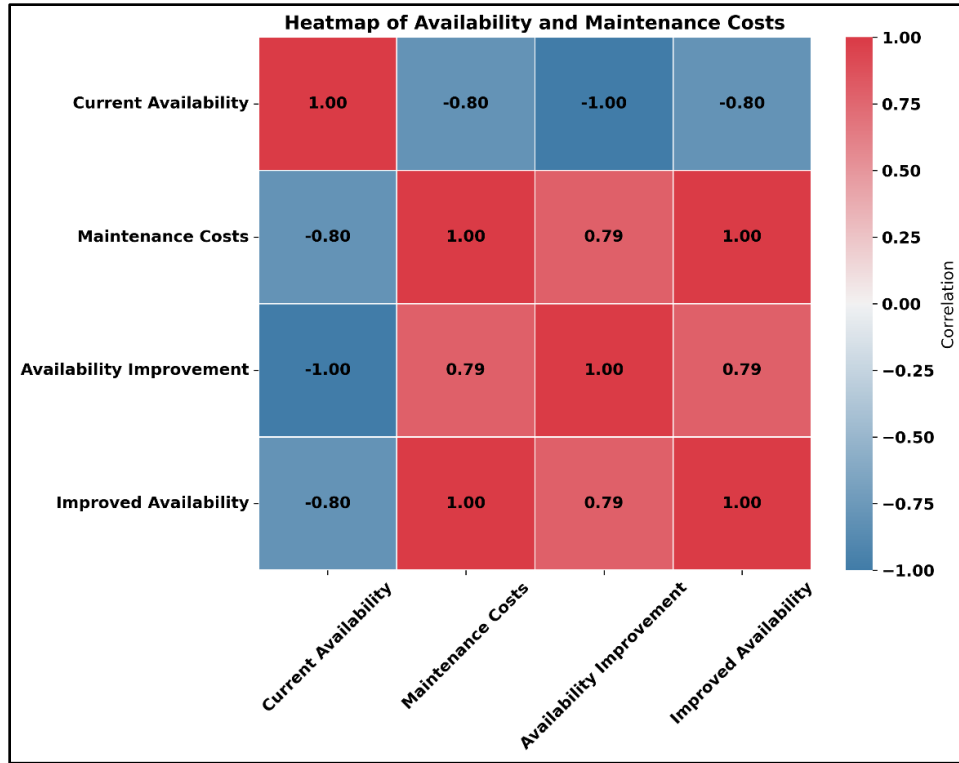


Figure 11. Correlation heatmap between the current availability, yearly maintenance costs, and availability improvement parameters

As illustrated in Figure 11, the colour scale ranges from cool (blue) to warm (red), with darker shades indicating stronger correlations. The numbers in each cell represent the correlation coefficients between the variables. A strong negative correlation (-1.00) is observed between Availability Improvement and Current Availability. Similarly, Current Availability shows strong negative correlations (-0.80) with both Maintenance Costs and Improved Availability. In contrast, Availability Improvement exhibits strong positive correlations (0.79) with both Maintenance Costs and Improved Availability. Finally, a perfect positive correlation (1.00) exists between Maintenance Costs and Improved Availability.

In addition, the 3D scatter plot presented in Figure 12 effectively illustrates the relationships between the three key variables for each UPS component which allows for easy comparison of the

different UPS components across all three variables simultaneously, providing a comprehensive view of their performance and potential for improvement.

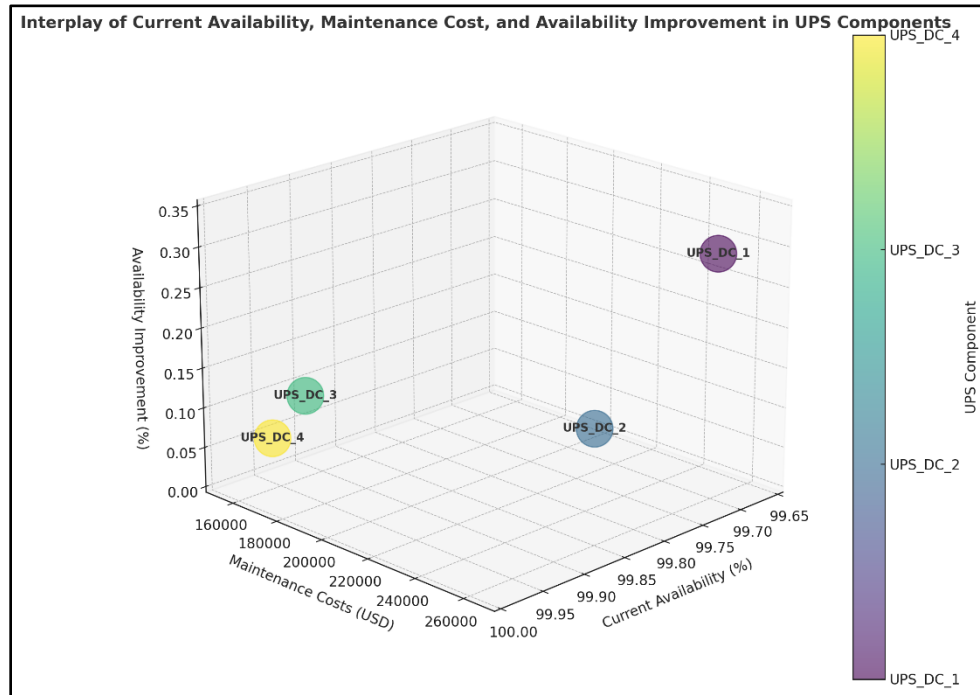


Figure 12. The relationships between the three key variables for each UPS component

According to the knapsack problem's features, the parameters involved in this scenario are as follows:

- UPS ID: The items which should be included (only 0 or 1 item can be selected).
- Availability improvement parameter: The value of each item included in the knapsack.
- Maintenance costs: The weight of each item in the knapsack.
- DC company's allocated budget: The maximum weight of the knapsack, which should not be exceeded while including different items.

The availability improvement of each UPS has been converted to a novel ranking system so that the summation of all improvement parameters is 1. Thus, the knapsack model aims to include

the maximum items with the highest values while not exceeding the maximum allocated financial resources for the maintenance actions of the DC company.

This model has been created and developed according to DP. Based on references and other studies, the 0/1 or integer knapsack problem, known as a discrete optimization problem, can be modelled and solved by applying DP. In this knapsack problem, the optimal solution is a set of integer numbers (Shehab et al., 2021). DP is a very efficient approach for solving these types of problems since it reduces the duration of repeated iterations and decreases the computing process by solving a minor central area of the problem as a principal solution (Shehab et al., 2021).

In the DP approach for modelling and solving the knapsack problem, different methods could be used. Based on the Memorization technique, which is an extension of the recursive approach, the issues of computing redundant cases can be solved and thus, the problem's complexity can be reduced, and the algorithm's running time is decreased (GeeksforGeeks, 2021). Moreover, although a separate code should be written for each specific DP problem, the approach will always lead to a global optimum solution after the algorithm termination if the problem has been correctly formulated (Jensen & Bard, 2003).

4.2.2.1. Model's Assumptions

This model operates under the following assumptions:

- System Configuration
 - The system comprises 24 UPS devices, grouped into 4 types with 6 units each.
 - Each UPS has an associated monthly maintenance cost and expected availability improvement percentage (Table 8).

- Devices are assumed to be independent in terms of availability improvement contribution.
- Availability Constraint
 - The minimum required system availability is 99.982%, corresponding to the Uptime Institute Tier III standard.
 - Components in states 1 to 4 (Table 7), which fall short of this threshold, must be selected for maintenance to ensure compliance.
 - Each selected device contributes a fixed availability improvement value when maintained, as specified in Table 8.
- Budget Constraint
 - The total yearly maintenance budget is \$1,500,000 USD, distributed across 12 months (Table 9).
 - Monthly budgets are treated as fixed, limiting the number and selection of devices for maintenance each month.
- Component Selection Constraint
 - Each UPS can be selected only once for maintenance within the one-year timeframe.
 - The maximum number of components that can be maintained per month is 4, ensuring feasible scheduling and operational continuity.
- System-Level Constraints
 - Total maintenance actions are constrained by the monthly budget and the maximum number of components per month.

- Optimization selects the combination of UPS units that maximizes overall availability improvement while respecting these constraints.

These assumptions provide the boundary conditions for simulating the Knapsack-based prioritization model, allowing an assessment of trade-offs between maintenance cost and system availability improvements under realistic operational and financial constraints.

Table 9 defines the four UPS types (24 components) with their costs and availability improvements as inputs for the optimization model. The yearly budget of \$1,500,000 USD, distributed monthly (Table 10), constrains the selection, with each UPS maintained only once and a maximum of 4 components per month allowed.

Table 9: Knapsack problem's parameters for the maintenance prioritization model

UPS ID (Item)	Number of available components	Monthly maintenance costs for availability improvement (USD)	Availability improvement (%)	Availability improvement parameter (Value)
UPS_APC500_DC_1	6	\$21,789	0.29889%	0.52
UPS_APC500_DC_2	6	\$21,789	0.14458%	0.25
UPS_APC500_DC_3	6	\$13,047	0.08752%	0.15
UPS_APC500_DC_4	6	\$13,047	0.04758%	0.08
Total	24	-	-	1

Table 10: Monthly available maintenance budget for the maintenance prioritization model

Month	Monthly fixed available budget (USD)	Month	Monthly fixed available budget (USD)
1	\$122,000	7	\$110,000
2	\$130,000	8	\$131,000
3	\$151,000	9	\$105,000
4	\$144,000	10	\$132,000
5	\$112,000	11	\$124,000
6	\$137,000	12	\$102,000
Total yearly available maintenance budget (USD)		\$1,500,000	

Finally, after running the Multiple 0-1 knapsack model based on the DP approach, the results including the quantity of UPS devices selected for maintenance each month, the budget used, and the monthly fixed available budget are obtained and shown in Table 11. This table provides the outcome of the optimization model, showing how the maintenance actions are prioritized and scheduled to maximize availability within the budget constraints.

Table 11: Knapsack problem's results for the maintenance prioritization model

Month	Quantity of UPS devices selected for maintenance action based on their condition state				Budget used for maintenance (USD)	Monthly fixed available budget (USD)	Value obtained
	UPS_APC500 _DC_1	UPS_APC500 _DC_2	UPS_APC500 _DC_3	UPS_APC500 _DC_4			
1	0	0	0	0	-	\$122,000	0
2	0	0	0	0	-	\$130,000	0
3	0	0	0	0	-	\$151,000	0
4	0	0	0	0	-	\$144,000	0
5	0	0	0	0	-	\$112,000	0
6	0	0	0	0	-	\$137,000	0
7	4	0	0	0	\$87,156	\$110,000	2.08
8	0	0	4	0	\$52,188	\$131,000	0.6
9	0	0	0	0	-	\$105,000	0
10	0	4	0	0	\$87,156	\$132,000	1.0
11	0	0	0	0	-	\$124,000	0
12	0	0	0	0	-	\$102,000	0

Hence, as seen in Tables 11 and 12, 12 UPS devices (out of 24) having the highest total value (availability improvement) while meeting the DC company's budget constraint are selected for maintenance. In addition, the total obtained value is 3.68 (out of 6) which means that about 61% of availability improvement value has been obtained.

Table 12: Summary and interpretation of the knapsack problem's results

Selected UPS devices for maintenance action(s)	UPS_APC500_DC_1, UPS_APC500_DC_2 and UPS_APC500_DC_3
Total number of selected UPS devices for maintenance action	12 of 24 (50%)
The maximum value of selected UPS devices for maintenance action	3.68 of 6 (61%)

It should also be noted that this model was created in the Spyder open-source scientific environment with Python 3.9 (Python Software, 2021a; Spyder Website Contributors, 2021a; Tutorialspoint.dev, 2019).

4.2.3. Managerial Implications

This section presents how DC managers can use the approach and findings outlined for the Dynamic Availability-Based Maintenance Prioritization Model to improve their maintenance strategies, optimize resource utilization, enhance decision-making, and achieve better operational efficiency. The proposed Availability-based maintenance prioritization approach has significant

implications for managerial decision-making and operational efficiency in DCs. Managers and decision-makers can leverage this approach in the following ways:

- Optimized Resource Allocation:

By applying DP, managers can efficiently allocate maintenance resources, ensuring that critical components receive the necessary attention while optimizing the use of available budgets. This leads to a reduction in unnecessary maintenance activities and cost savings in DCs.

- Enhanced Decision-Making:

The approach provides a structured framework for maintenance scheduling, allowing DC managers to make informed decisions based on comprehensive reliability, failure, and availability analyses. This data-driven decision-making process helps prioritize maintenance tasks that have the most significant impact on system availability and performance.

- Improved Operational Efficiency:

Implementing this approach can lead to a more streamlined and efficient maintenance process. By minimizing unexpected downtimes and optimizing maintenance schedules, DC operations can run more smoothly, leading to increased productivity and reduced operational disruptions.

- Strategic Planning

The integration of dynamic programming with maintenance management allows for long-term strategic planning. Managers can use predictive insights to plan for future maintenance needs, ensuring that the DC infrastructure remains robust and reliable over time.

- Risk Management:

By focusing on reliability and availability, managers can better manage risks associated with equipment failures. The approach helps in identifying and addressing potential failure points before they lead to significant operational issues, thus enhancing the overall resilience of the DC.

- Sustainability and Environmental Impact:

Efficient maintenance management contributes to the sustainability of DC operations. By reducing unnecessary maintenance activities and optimizing resource usage, the approach supports environmentally sustainable practices, aligning with organizational goals for sustainability.

- Competitive Advantage:

DCs that follow more developed operating strategies like the one proposed in this article can have a competitive advantage in the market. It was pointed out that high availability and reliability are crucial for customer satisfaction and business continuity, and the suggested approach helps in hitting these goals.

4.3. Results and Discussion: Dynamic Availability-Based Maintenance Cost Optimization Model for K-out-of-N Systems

4.3.1. Model's Assumptions

Although the model's assumptions will be explained in detail throughout the model description, they are consolidated here to provide a clear and comprehensive summary for clarity in the following subsections.

Maintenance actions are scheduled on a monthly basis, with decision-making guided by operational thresholds aligned with Tier I DC requirements. Accordingly, the minimum system availability is set at 99.671%, consistent with the Uptime Institute Tier I classification (Uptime

Institute, 2021b). In addition, at least $k = 5$ UPS units must remain operational at all times to satisfy the DC's power, reliability and operational requirements

This model operates under the following assumptions:

- System Configuration

- The system is modelled as a k -out-of- n UPS configuration, reflecting redundancy in DC power systems.
- A total of 10 UPS units are considered in the case study, each with defined condition states and associated failure/maintenance characteristics.

UPS devices are categorized into three age-based condition groups:

- Group 1: New (0–2 years; states 9–10)
- Group 2: Middle-aged (2–18 years; states 3–8)
- Group 3: End-of-life (18–20 years; states 1–2)

- Availability Constraint

- System availability must remain at or above 99.671% (Tier I requirement).
- At least five units ($k = 5$) must remain operational at any time to satisfy DC power requirements.
- Components with condition states below the threshold are prioritized for maintenance.

- Budget Constraint

- Maintenance costs vary dynamically by condition group and month, based on failure rates and service costs (Table 6).

- Monthly maintenance decisions must account for these costs while ensuring compliance with the availability requirement.
- Component Selection Constraint
 - Each UPS unit may be selected for maintenance depending on its condition category and associated failure rate function.
 - Maintenance costs are defined as follows:
 - Group 1 (states 9–10): Preventive inspections + corrective failure costs.
 - Group 2 (states 3–8): Preventive + corrective + battery replacement + failure costs.
 - Group 3 (states 1–2): Renewal + cooling/power services + failure costs.
 - Monthly costs for each group are calculated according to equations (24) to (26).
- System-Level Constraints
 - The optimization ensures that the selected subset of k UPS units from the n available meets or exceeds the Tier I availability requirement.
 - Dynamic programming is applied monthly to minimize maintenance costs while satisfying both availability and redundancy (k -out-of- n) constraints.

Collectively, these assumptions establish the boundary conditions for implementing the K -out-of- N optimization model, enabling a rigorous evaluation of the trade-offs between maintenance cost efficiency, redundancy management, and compliance with Tier I DC availability standards.

The subsequent analysis evaluates the model results with respect to the defined operational parameters and availability constraints, highlighting their impact on system performance and maintenance decision-making.

4.3.2. Dynamic Failure Rates and Maintenance Costs

Before presenting the model results, this subsection details how failure rates and asset conditions are integrated to categorize the UPS units and assign a failure rate function to each asset group, enabling the calculation of variable monthly failure rates and maintenance costs for each UPS unit.

These maintenance costs underpin the model's ability to simulate realistic operational scenarios, particularly for k-out-of-n configurations in DC systems.

In the Fulcrum Collaborations report (MCIM by Fulcrum Collaborations, 2023), firsthand and real-time data sourced from users of Mission Critical Information Management (MCIM) systems have been collected for Static UPS brands on a global scale which offers valuable insights into the operational dependability. As Figure 13 presents, crucial benchmarks for over 3,750 static UPS systems are documented by MCIM. This dataset includes products from leading manufacturers such as Eaton, Schneider Electric, Vertiv Group Corp., and other top companies within the MCIM database. The data offers valuable insights into the following key metrics for assessing the reliability of static UPS systems and their manufacturers: Failures per Asset, Age of Failure by Lifecycle Stage, MTBF, and Failure Modes. MCIM's analysis underscores the most prominent static UPS brands currently utilized in the global market.

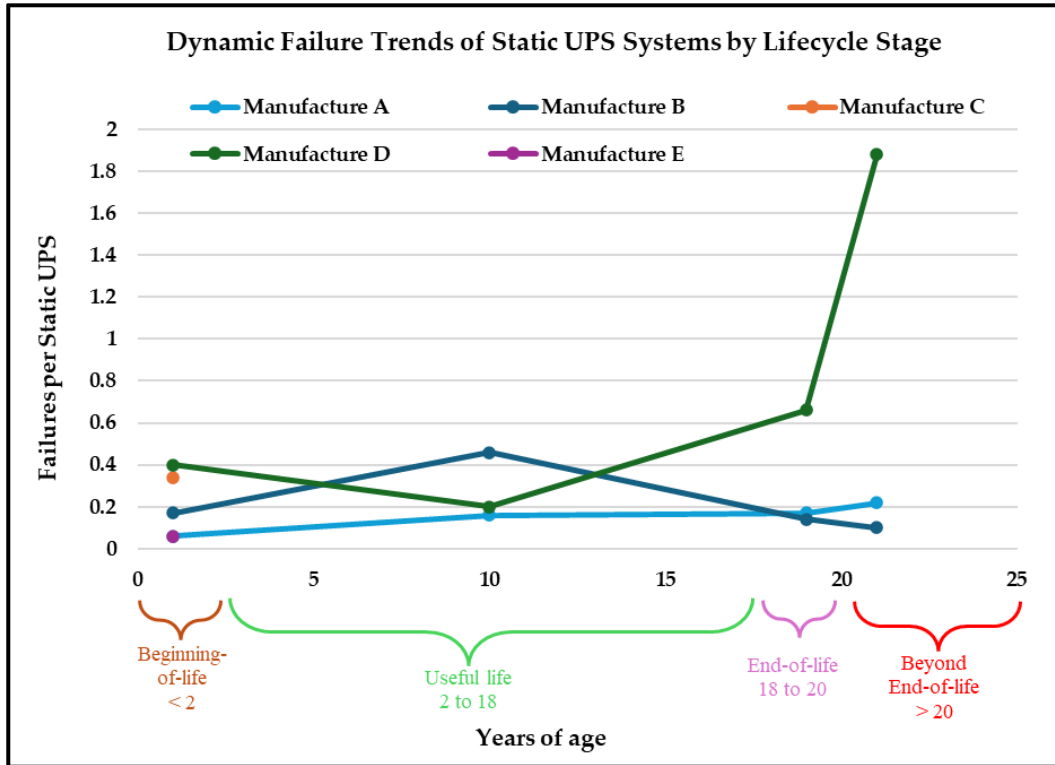


Figure 13. Number of failures of static UPS systems by their lifecycle stage (MCIM by Fulcrum Collaborations, 2023)

Therefore, by gathering the relevant information from different references, as mentioned in the “4.3.1. Model’s Assumptions” subsection, three condition categories have been selected to simplify the model implementation. These three asset condition categories are assumed based on the UPS unit’s age. Therefore, the first category represents the new UPS systems or units (UPS_DC_10 and UPS_DC_9) having an age between 0 and 2 years (beginning of their lifecycle). Then, the Middle-Aged UPS components (from 2 to 18 years old and during their useful lifecycle) were grouped having the condition states 3 to 8 (UPS_DC_8 to UPS_DC_3). Finally, the third category belongs to the UPS units in their end-of-lifecycle (between 18 and 20 years in operation) which are conditions 1 and 2.

Figure 14 presents a heatmap visualization of the yearly failure rates for UPS systems, derived from the data presented in Table 3. The heatmap effectively illustrates the relationship between a UPS system's condition state (ranging from 10, representing optimal condition, to 1, representing the worst) and its age group (categorized as Group 1, Group 2, or Group 3). The visualization clearly demonstrates the trend of increasing failure rates with declining condition state and older age group, highlighting the importance of both factors in UPS reliability.

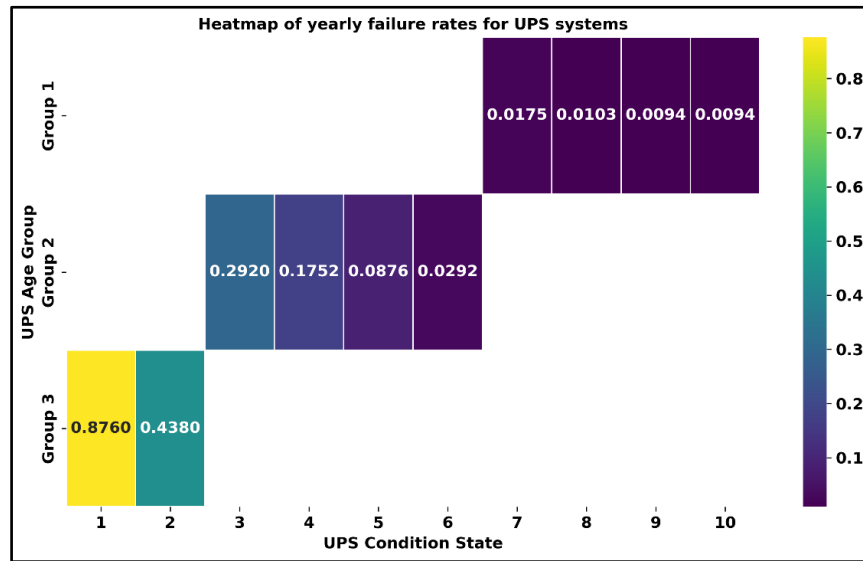


Figure 14. Heatmap visualization of the UPS yearly failure rates

In the next step, the corresponding failure rates are obtained from resources (MCIM by Fulcrum Collaborations, 2023) and the failure rate function ($\lambda(t)$) which represents the probability of failure per unit of time in a one-year time horizon has been derived for each of these three categories as follows.

- Group 1 - New UPS components (0-2 years old) including condition states 9 and 10:

The failure rate function for this group is:

$$\lambda(t)=0.2+0.8*e^{(-0.5x)} \quad (24)$$

Where:

x: Represents the time of the year (month or hours)

Figure 15 shows the failure rate function plot for this group of UPS components in a one-year time horizon.

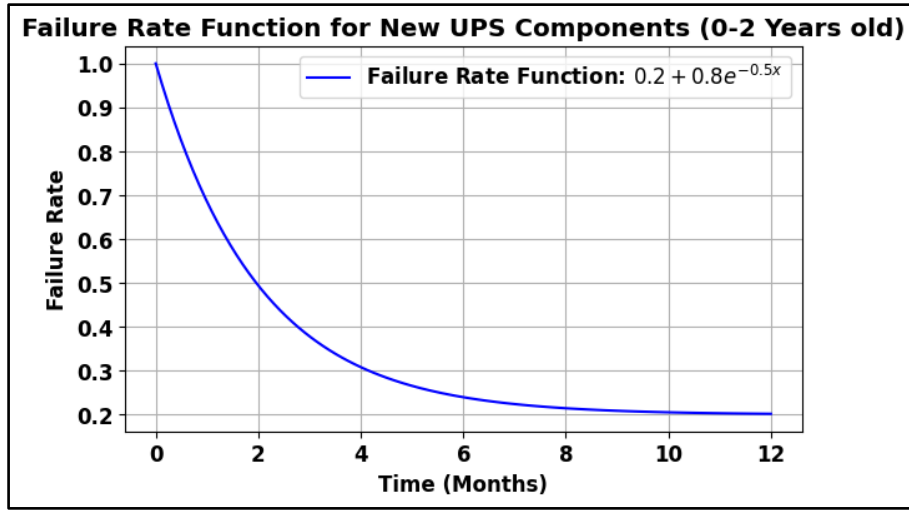


Figure 15. Failure rate function for the UPS components of Group 1 in one year

- Group 2 - Middle-Aged UPS components (2-18 years old), including condition states 3 to 8:

It is important to highlight that the data pertaining to this asset group spans a 16-year duration, corresponding to the typical useful life of UPS systems. Based on the insights gleaned from Figure 5, the failure rate function has been recalibrated to align with a one-year timeframe.

The Weibull continuous random variable distribution is a versatile tool for modelling various physical phenomena. Its flexibility lies in the ability to adjust parameters within its reliability functions, allowing for the representation of diverse distributions. By characterizing failure modes

with a slope parameter (b) and considering the associated age and probability of failure for a component, the Weibull distribution becomes instrumental in statistical analyses of experimental data (Fadaeefath Abadi et al., 2022).

Therefore, the Weibull distribution has been assumed and used for this group of UPS systems which is more appropriate due to its flexibility in modelling different types of failure behaviours, including early-life failures, random failures during the useful life, and wear-out failures as the system ages. The equation for the normalized failure rate function for Group 2 is given below.

$$\lambda(t)=0.16+F(t)*(0.46-0.16) \quad (25)$$

Where:

F(t): Represents the Weibull Cumulative Distribution Function (CDF) evaluated at the time 't' (each month)

- Group 3 - End-of-Life UPS components (18-20 years old) including condition states 1 and 2:

The failure rate function for this group is:

$$\lambda(t)=0.14*e^{0.1551x} \quad (26)$$

Where:

x: Represents the time of the year (month or hours)

Figures 16 and 17 show the failure rate function plots and the failure rate changes over the 12 months, for groups 2 and 3 of UPS components.

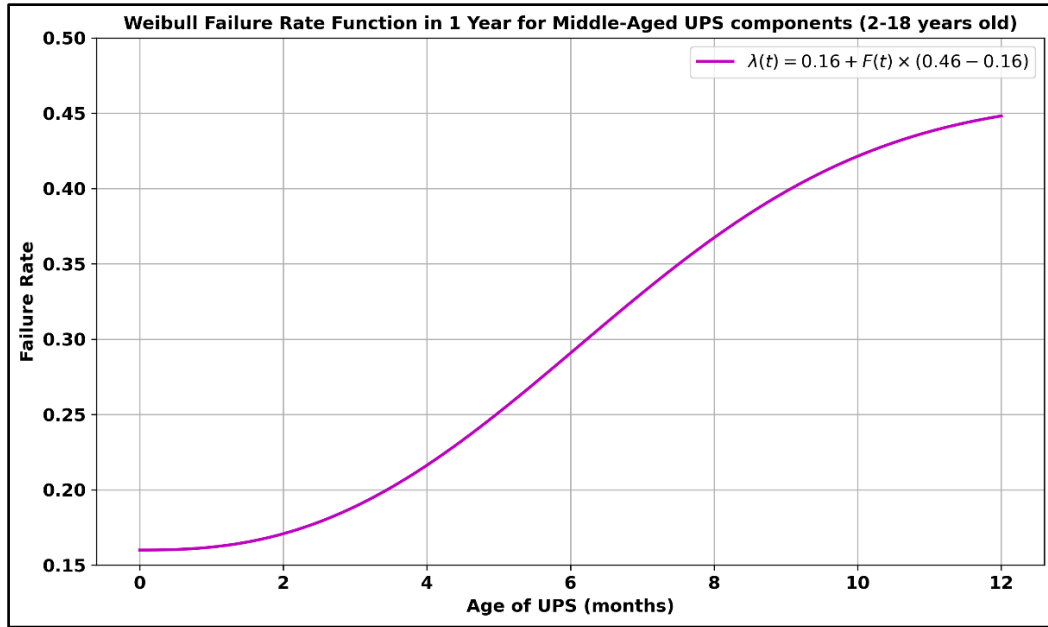


Figure 16. Failure rate function (Weibull distribution) for the UPS components of Group 2 in one year

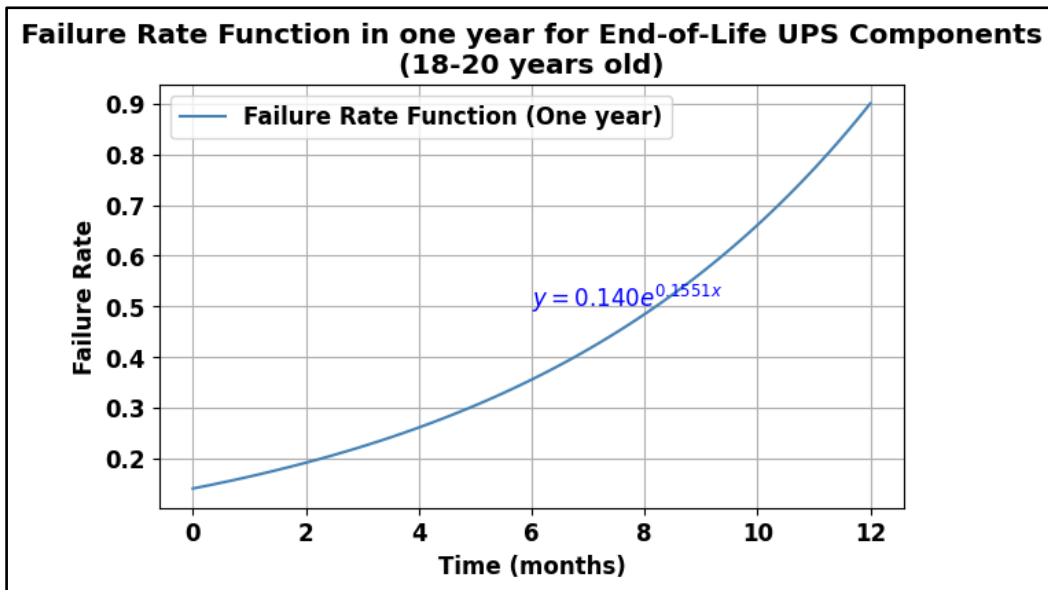


Figure 17. Failure rate function for the UPS components of Group 3 in one year

Therefore, by obtaining the failure rate functions for each month and for each group of asset conditions for the available UPS components in the case study system, the failure rates are integrated into the corresponding monthly maintenance costs. Hence, the dynamic maintenance

costs for each month depending on the type of UPS components are available and these maintenance costs are presented further.

The maintenance cost information used in this model is consistent with the data gathered from various sources and applied in the Dynamic Availability-Based Maintenance Prioritization Model, as detailed in Section 4.2.1. Therefore, the relevant maintenance costs for the APC Symmetra PX 500kW UPS system were utilized to calculate the total cost associated with each maintenance action under different condition states. The available maintenance services offered by the manufacturer for the selected UPS model, along with their respective annual costs which were presented in Tables 4 and 5 form the basis for cost estimation in our case study.

Now that the yearly categorized and combined maintenance costs are defined, the monthly dynamic maintenance costs which are based on variable failure rates for each group of UPS systems are calculated.

For Group 1, which are the new UPS components (0-2 years old), we assume that only the preventive maintenance (inspection) (C_{PM}) costs and the costs of each incident/failure (C_F) are applicable. Therefore, the total monthly maintenance costs of this group of assets (conditions 9 and 10) are calculated as follows:

Monthly maintenance costs of Group 1 assets =

$$(C_{PM(i,t)} / 12) + C_{F(i,t)} * (\text{monthly failures})] \quad (27)$$

For Group 2, which are the Middle-Aged UPS components (2-18 years old), the costs of preventive maintenance (inspection) actions (C_{PM}), corrective maintenance actions (C^{CM}), the costs of each incident/failure (C_F) and the costs of battery replacement service (C_{BR}) have been

considered and added together. Therefore, the total monthly maintenance costs of this group of assets (conditions 3, 4, 5, 6, 7 and 8) are calculated as follows:

Monthly maintenance costs of Group 2 assets =

$$[(C_{PM(i,t)} + C_{CM(i,t)} + C_{BR(i,t)})/12] + C_{F(i,t)} * (\text{monthly failures}) \quad (28)$$

Finally, for the third group which are End-of-Life UPS components (18-20 years old), the costs of electric critical power and cooling services (C_{PC}), the component renewal costs (C_{CR}), and the costs of each incident/failure (C_F) are added together and calculated as follows:

Monthly maintenance costs of Group 3 assets =

$$[(C_{PC(i,t)} + C_{CR(i,t)})/12] + C_{F(i,t)} * (\text{monthly failures}) \quad (29)$$

The monthly maintenance costs of all three groups are presented in Table 13.

Table 13: Monthly dynamic failure rates and maintenance costs for the UPS units based on their state of condition

Asset Group →	Group 1 (UPS_DC_10 and UPS_DC_9)		Group 2 (UPS_DC_3 to UPS_DC_8)		Group 3 (UPS_DC_1 and UPS_DC_2)	
Month ↓	Monthly Failures	Monthly Maintenance costs (USD)	Monthly Failures	Monthly Maintenance Costs (USD)	Monthly Failures	Monthly Maintenance Costs (USD)
1	0.68522	\$1,344	0.16190	\$2,428	0.16349	\$12,410
2	0.49430	\$1,148	0.17080	\$2,438	0.19092	\$12,438
3	0.37850	\$1,029	0.18890	\$2,456	0.22295	\$12,471
4	0.30827	\$957	0.21630	\$2,484	0.26035	\$12,509

5	0.26567	\$913	0.25130	\$2,520	0.30403	\$12,554
6	0.23983	\$887	0.29080	\$2,561	0.35504	\$12,607
7	0.22416	\$871	0.33070	\$2,602	0.41461	\$12,668
8	0.21465	\$861	0.36740	\$2,639	0.48417	\$12,739
9	0.20889	\$855	0.39800	\$2,671	0.56541	\$12,823
10	0.20539	\$851	0.42150	\$2,695	0.66027	\$12,920
11	0.20327	\$849	0.43780	\$2,712	0.77104	\$13,034
12	0.20198	\$848	0.44820	\$2,722	0.90040	\$13,167

Table 13 provides data that is visually represented in Figure 18 to illustrate the monthly dynamic maintenance costs for three UPS groups: New, Mid-life, and End-of-life. The costs for new UPS systems (Group 1) show a decreasing trend, stabilizing around \$850 per month. For mid-life UPS systems (Group 2), costs gradually increase, reaching approximately \$2,720 per month by the end of the year. In contrast, end-of-life UPS systems (Group 3) exhibit a significant and consistent rise, reaching about \$13,200 per month by year's end.

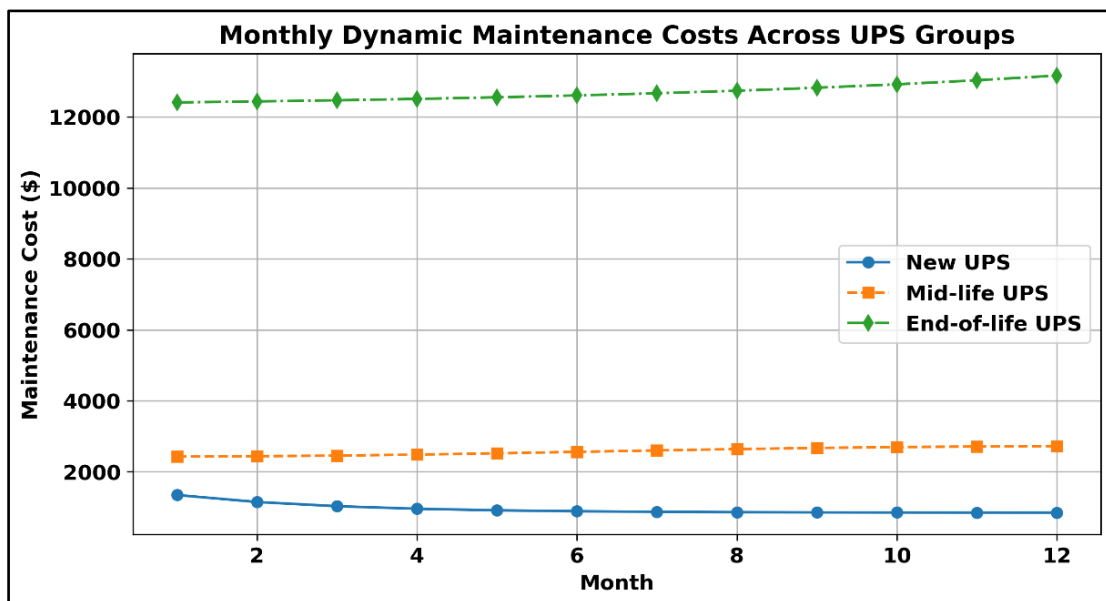


Figure 18. Monthly dynamic maintenance costs for the three groups of UPS systems

4.3.3. Model's Results

This section presents the detailed results and analysis of the maintenance optimization model for a k-out-of-n configuration in a DC.

As mentioned in the previous sections, by running this cost and availability-based DP optimization model, we aim to find the optimal number or combinations of UPS units (k) out of all available UPS units (n) in the parallel system, while having the minimum monthly maintenance costs, and meeting the required total system availability.

Hence, the model is executed by using the DP algorithm and by having the following input data for the first month provided in Table 13. As an assumption, the total minimum required parallel system availability is 99.671% for the Tier 1 DC (Uptime Institute, 2021a). Similarly, the input data for the other 11 months (from month 2 to month 12) are derived from Table 13 and used to run the optimization model for the whole year. Table 14 summarizes the first month's input data for UPS assets, showing MTBF, MTTR, expected failures, and availability across condition states. Higher condition states exhibit longer MTBF, shorter MTTR, and higher availability, while degraded states have reduced reliability and lower availability.

Table 14: Model input data for the first month of operation

Condition State	Asset Group	MTBF (hrs.)	MTTR (hrs.)	Failures (per month)	UPS Availability (percentage)
10	Group 1	933,708	2	0.68522	99.999%
9		930,000	4		99.999%
8	Group 2	850,000	8	0.16190	99.999%
7		500,000	12		99.998%

6		300,000	14		99.995%
5		100,000	18		99.982%
4		50,000	25		99.950%
3		30,000	27		99.910%
2	Group 3	20,000	29	0.16349	99.855%
1		10,000	30		99.701%

By running the optimization algorithm for the first month of operation, the optimal combination of UPS components in the DC power system configured as a k-out-of-n parallel system was determined. The results, presented in Table 15, detail the selected components and their characteristics. A 3D visualization of this optimal combination is depicted in Figure 19, illustrating the selected components alongside their respective availabilities and monthly maintenance costs. In addition, the selected UPS components and their availabilities are shown in the column chart in Figure 20.

Table 15: Optimized combination of UPS components in the k-out-of-n system in one month

Component	Asset Condition State	Available components for maintenance	Selected Components for maintenance	Monthly maintenance costs for available (n) components (USD)	Monthly maintenance costs for selected (k) components (USD)
UPS_DC_10	10	1	1	\$1,344	\$1,344
UPS_DC_9	9	1	1	\$1,344	\$1,344
UPS_DC_8	8	1	1	\$2,428	\$2,428
UPS_DC_7	7	1	1	\$2,428	\$2,428
UPS_DC_6	6	1	1	\$2,428	\$2,428
UPS_DC_5	5	1	0	\$2,428	0

UPS_DC_4	4	1	0	\$2,428	0
UPS_DC_3	3	1	0	\$2,428	0
UPS_DC_2	2	1	0	\$12,410	0
UPS_DC_1	1	1	0	\$12,410	0
Total:		10	5	Total Monthly Maintenance Costs:	\$9,973
Total System Availability = 99.991% $\geq$ 99.671% (Tier 1 DC)					

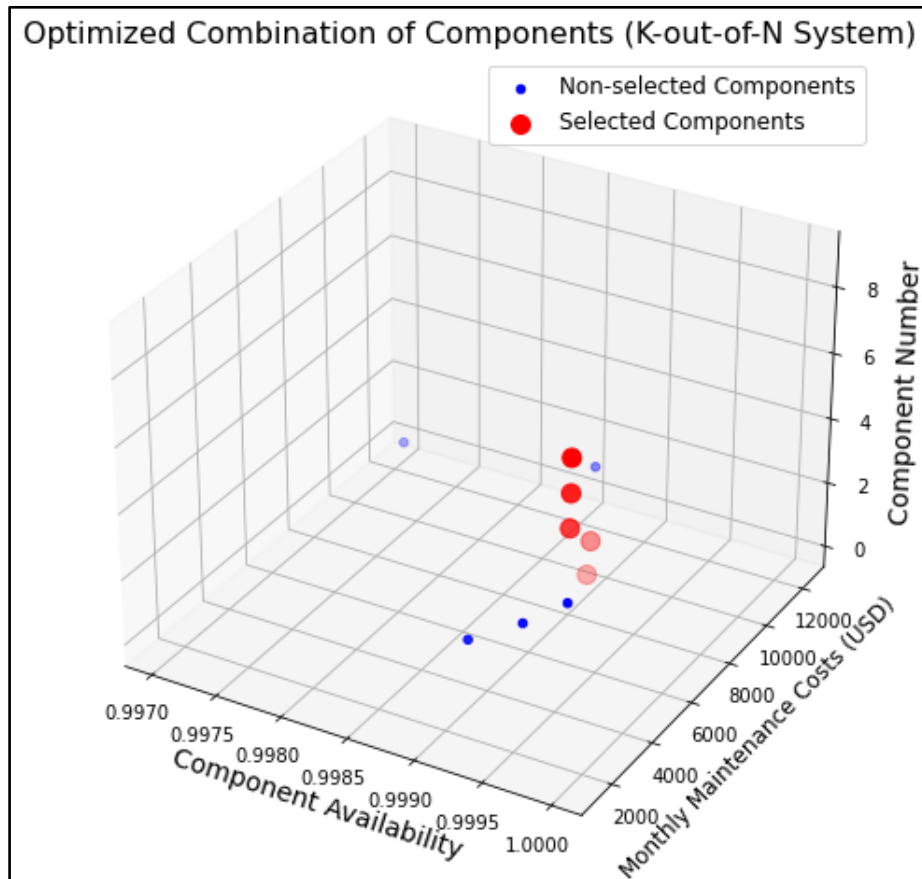


Figure 19. 3D visualization of the optimal combination of UPS components in one month of operation

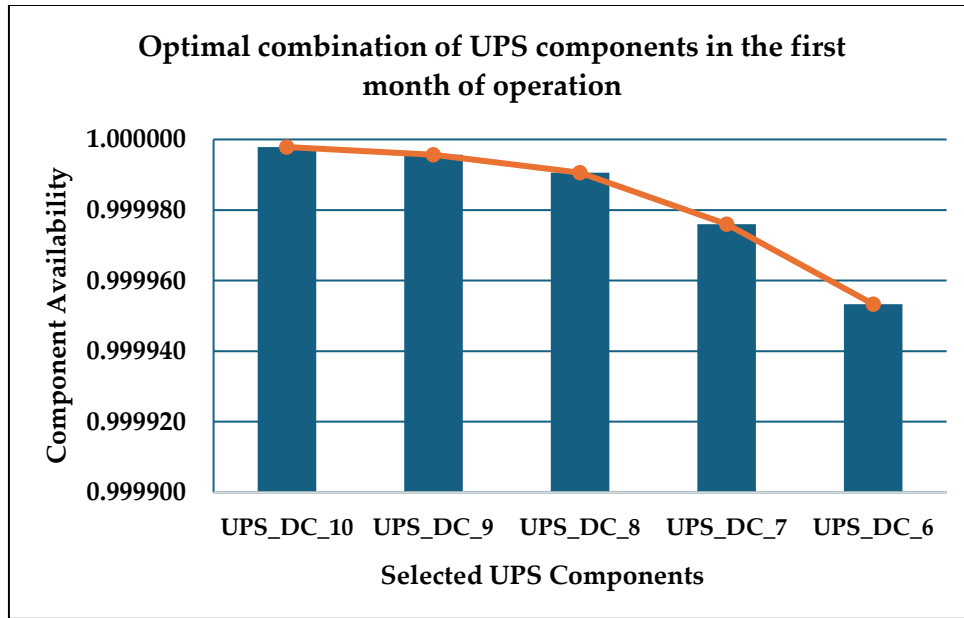


Figure 20. Optimal combination of UPS components in one month of operation

Table 15 demonstrates the outcome of the optimization process applied to the DC power system's UPS components. Specifically, a subset of 5 UPS units—namely, UPS_DC_10, UPS_DC_9, UPS_DC_8, UPS_DC_7, and UPS_DC_6—has been selected for maintenance actions out of the total 10 available UPS systems or units. This selection optimizes the system's availability and maintenance costs, highlighting the efficacy of the k-out-of-n redundancy approach. Also, as illustrated in Table 14, the total monthly maintenance budget required amounts to \$9,973 USD. Furthermore, the combined system availability achieved with the optimal configuration of UPS components is 99.991%, surpassing the minimum system availability requirement for a Tier 1 DC, which is 99.671%. This allocation is essential for conducting various maintenance procedures on the optimal combination of UPS components throughout one month of operation.

In addition to running the DP optimization model, further investigation has been conducted to assess the robustness and applicability of the proposed optimization model and enhance the value

of this study by performing a comprehensive sensitivity analysis. This analysis focused on key parameters such as MTBF, MTTR, failure rates, maintenance costs, and system availability thresholds.

Specifically, the first part of the sensitivity analysis explored the impact of $\pm 10\%$ variations in key parameters, including MTBF, MTTR, and maintenance costs. The analysis examined how these changes influenced the total system availability and total maintenance costs, highlighting the interdependence of these factors and their effect on the optimization outcomes (OpenAI, 2024).

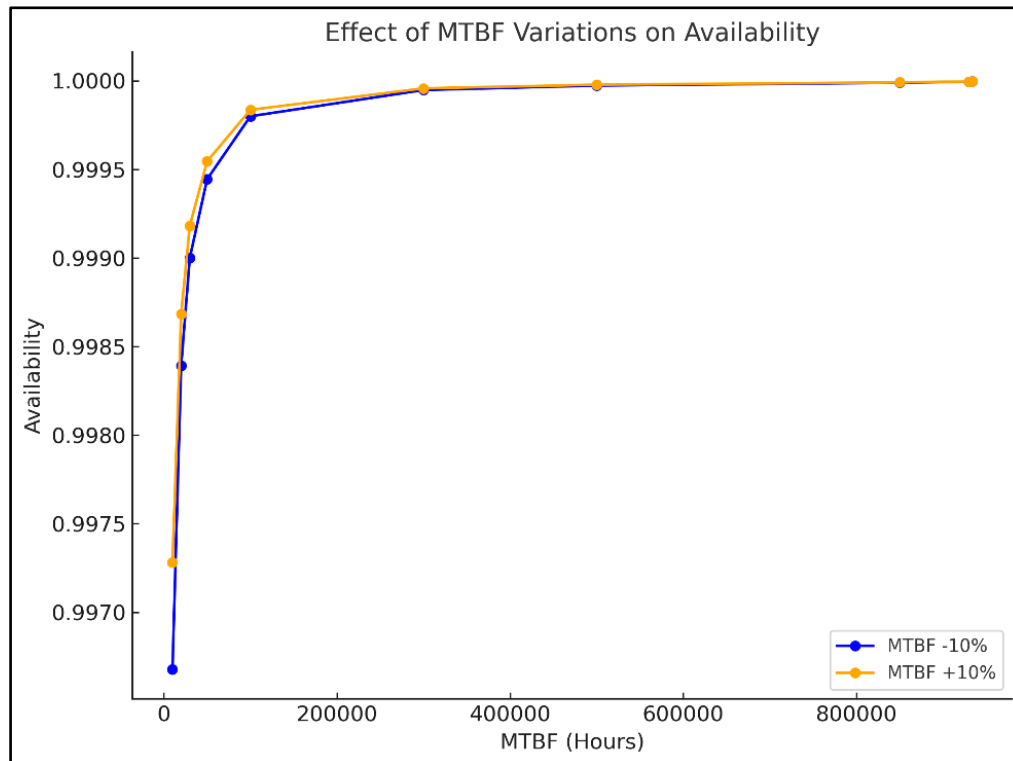


Figure 21. Sensitivity Analysis: Impact of $\pm 10\%$ variations in MTBF on availability (Python Software, 2021b)

As observed in Figure 21, decreasing MTBF by 10% slightly reduces total system availability, while a 10% increase results in marginal improvement. The availability remains high across the range, indicating robustness to MTBF variations.

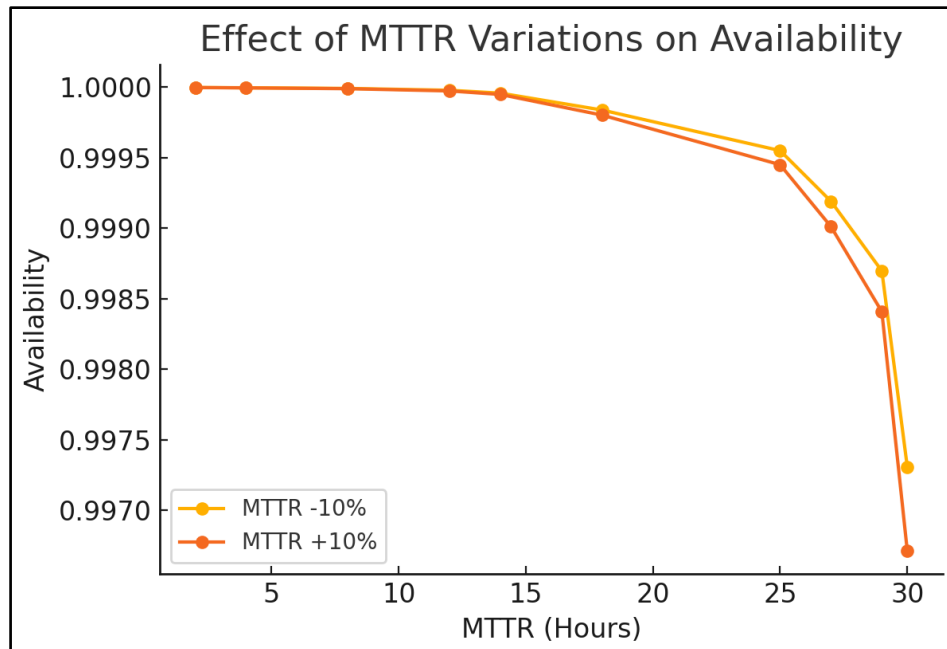


Figure 22. Sensitivity Analysis: Impact of $\pm 10\%$ variations in MTTR on availability (Python Software, 2021b)

According to the sensitivity analysis presented in Figure 22, a 10% increase in MTTR results in a significant reduction in system availability, whereas a 10% decrease in MTTR leads to a marked improvement in availability. These findings underscore the pivotal role that minimizing repair times plays in sustaining optimal system performance, highlighting the direct correlation between rapid fault resolution and enhanced operational reliability.

The analysis presented in Figure 23 demonstrates that variations in maintenance costs lead to proportional changes in the total monthly maintenance expenses, confirming the model's predictable scaling with cost fluctuations. A baseline total cost of approximately \$9,973 was observed, which increased or decreased by roughly \$1,000 under sensitivity scenarios reflecting a $\pm 10\%$ change in maintenance costs. This result highlights the robustness of the model in responding linearly to cost adjustments, ensuring its reliability for scenario analysis and financial planning.

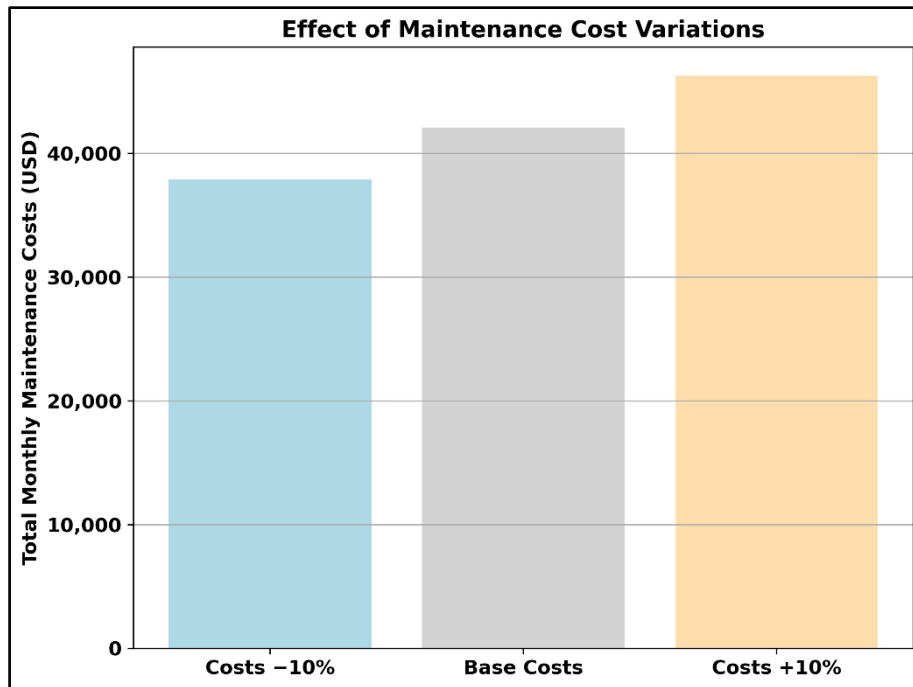


Figure 23. Sensitivity Analysis: Impact of $\pm 10\%$ variations in maintenance costs on total maintenance costs

(Python Software, 2021b)

In the second part of our sensitivity analysis, a systematic approach is conducted to assess the impact of different k-out-of-n UPS system configurations on the total system availability and maintenance costs. The analysis systematically varied the minimum required UPS units (k) from 5 to 9, identifying the lowest-cost configurations that maintained a total system availability above the required 99.671% total availability threshold for Tier 1 DC. The results presented in Figure 24 help identify the optimal number of components to maintain while meeting the Tier 1 DC availability requirement at a reasonable cost. This approach provides valuable insights for DC managers aiming to balance maintenance cost and availability in their operations.

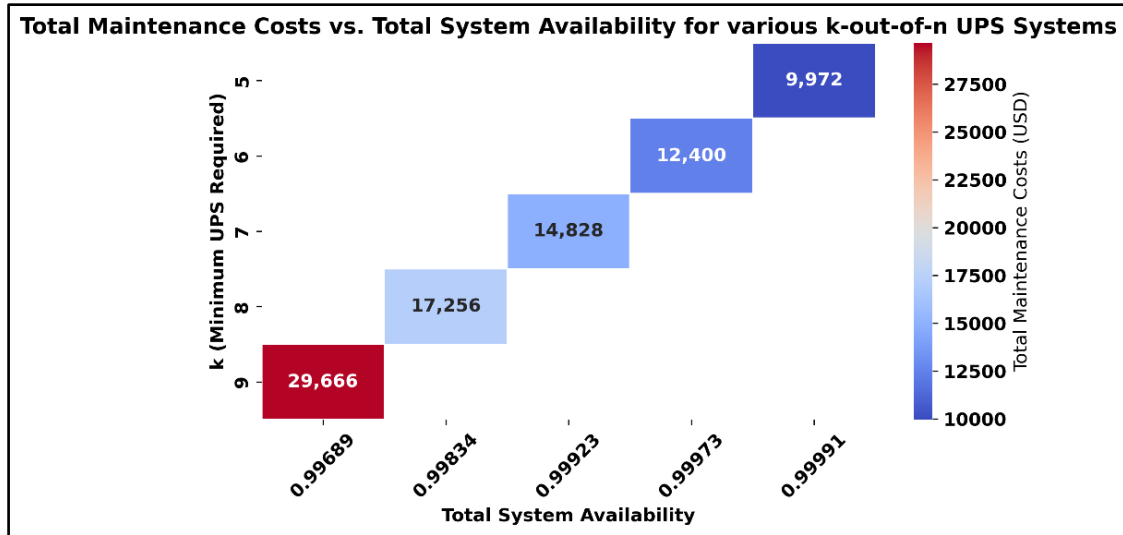


Figure 24. Sensitivity Analysis: Maintenance costs and total system availability comparison for various k-out-of-n UPS configurations from k=5 to k=9 (Python Software, 2021b)

In the third part of the sensitivity analysis, different optimal selections of UPS units under different monthly maintenance budget constraints (ranging from \$2,000 to \$10,000 per month) were found to achieve a minimum total system availability of 0.99671. The optimization process explores various k-out-of-n system configurations while considering the associated maintenance costs.

Figure 25 illustrates the feasible k-out-of-n UPS configurations across different allocated maintenance budget constraints, highlighting the number of selected UPS units (k) that meet the minimum total system availability requirement. The heatmap highlights how lower budgets significantly restrict feasible configurations, while higher budgets allow for more redundancy.

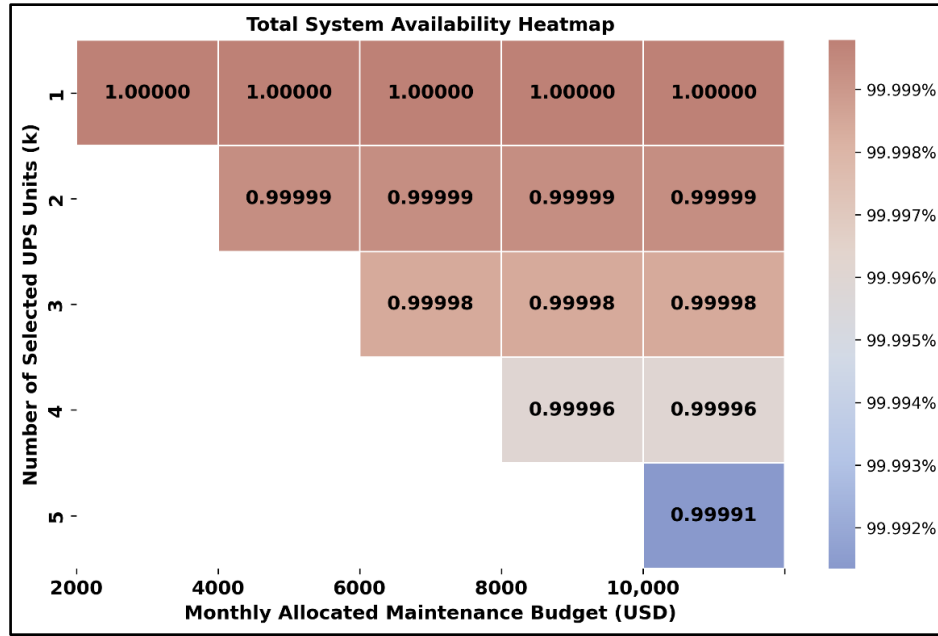


Figure 25. Sensitivity Analysis: System availability variations for different optimal k-out-of-n configurations under varying budget constraints (Python Software, 2021b)

Figure 26 presents a heatmap visualization of total maintenance cost variations for different optimal k-out-of-n configurations under different budget constraints. The total maintenance cost values are colour-coded, with darker shades representing higher costs. The results demonstrate that as the number of selected UPS units increases, the maintenance costs also increase due to the additional servicing requirements and increasing the budget doesn't necessarily lead to higher availability. A higher maintenance budget allows for a greater number of UPS units to be maintained, but beyond a certain threshold, cost efficiency diminishes.

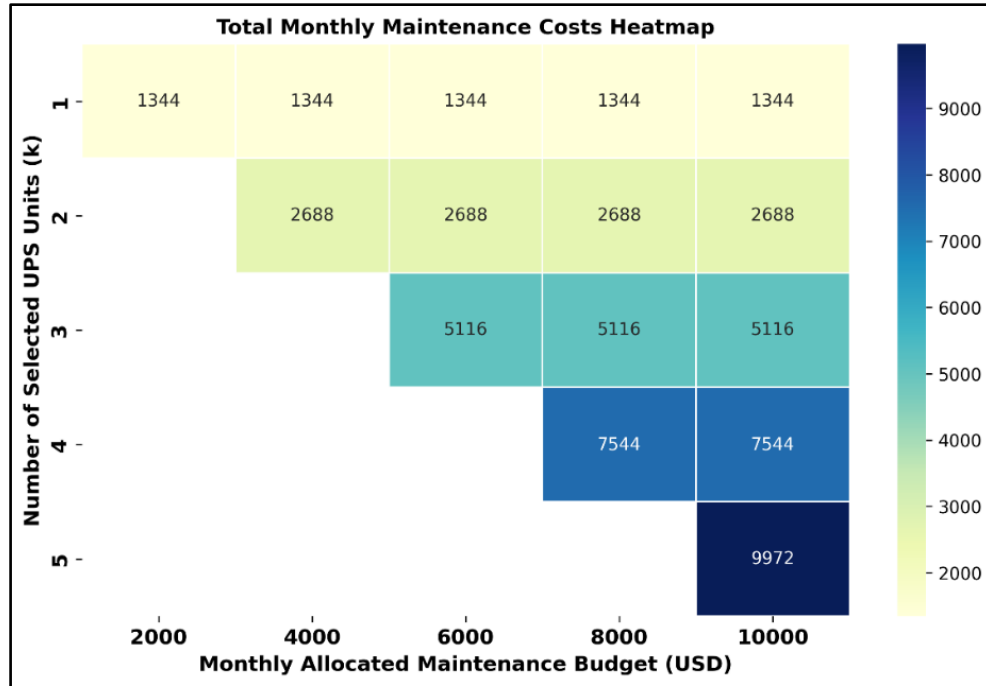


Figure 26. Sensitivity Analysis: Maintenance costs variations for different optimal k-out-of-n configurations under varying budget constraints (Python Software, 2021b)

According to the two recent heatmaps, it is observed that optimizing the number of UPS units is crucial for achieving a balance between high availability and cost-effectiveness. Increasing the maintenance budget does not always result in higher availability, as evidenced by the diminishing returns observed for larger values of k. Therefore, selecting an appropriate k-out-of-n configuration is essential to maximizing system availability while keeping operational expenses under control.

This analysis provides valuable insights into the trade-offs between budget constraints, system redundancy, and availability, offering a systematic approach for optimizing UPS maintenance strategies in mission-critical environments.

Comparing the optimal number of UPS components and their associated minimum costs across different DC tiers have been performed in the fourth and final part of our sensitivity analysis which reveals a clear relationship between redundancy requirements and operational expenses.

Figure 27 presents the optimal number of UPS components and their minimum maintenance costs across different DC tiers based on their availability requirements. As depicted, the optimal number of UPS units increases with higher tier levels, reflecting the enhanced redundancy and availability demands. Specifically, Tier I (1), with an availability requirement of 99.671%, necessitates 5 UPS units at a minimum cost of \$9,973. In contrast, Tier II (2), which requires 99.741% availability, optimally utilizes 6 UPS units, incurring a cost of \$11,417. For Tier III (3), with a stringent availability target of 99.982%, 8 UPS units are optimal, resulting in a cost of \$14,856. Finally, Tier IV (4), the highest tier with a 99.995% availability requirement, demands 10 UPS units, with the minimum cost rising to \$19,946. Table 16 provides a summarized overview for improved clarity.

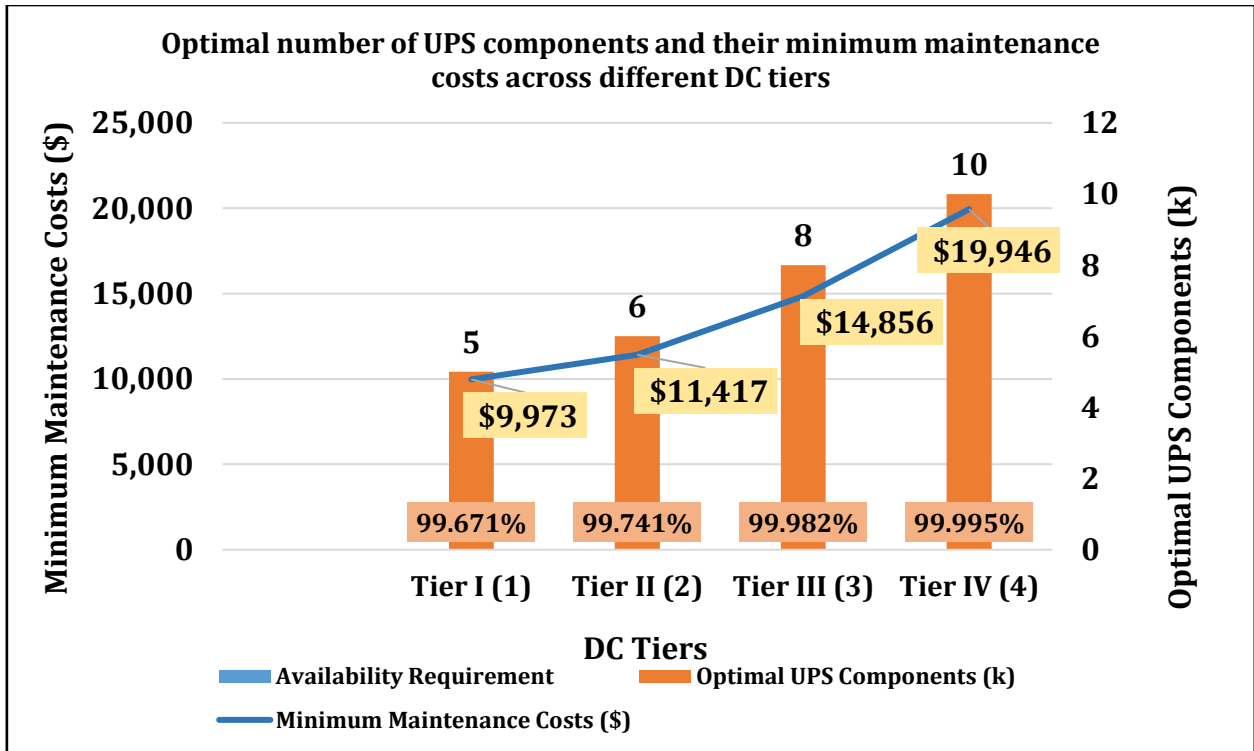


Figure 27. Sensitivity Analysis: Optimal combination of UPS components across different DC tiers (Microsoft Copilot AI, 2024; Python Software, 2021b).

Table 16: Optimal number of UPS components and maintenance costs across different DC tiers

DC Tier	Availability Requirement	Optimal Number of UPS Units	Minimum Maintenance Cost (\$)
Tier I (1)	99.671%	5	9,973
Tier II (2)	99.741%	6	11,417
Tier III (3)	99.982%	8	14,856
Tier IV (4)	99.995%	10	19,946

This progression underscores the significant impact of redundancy on both the number of components and the financial investment required to maintain high availability in DC operations.

The results of the sensitivity analysis demonstrated that the DP optimization model remains effective under varying conditions, thereby reinforcing its reliability and practical relevance.

The optimized selection of components underscores the effectiveness of the proposed DP model in balancing reliability and cost efficiency. Achieving an availability of 99.991% not only meets but surpasses the Tier 1 standard (99.671%), which demonstrates the model's capability to provide robust maintenance planning even under strict operational constraints.

The results highlight the practical utility of incorporating dynamic failure rates and variable maintenance costs into the optimization framework. By selecting fewer components while maintaining high availability, the model minimizes redundant expenses, offering a significant cost-saving advantage for DC operators.

This optimization model and algorithm was developed and implemented using the Spyder open-source scientific environment, leveraging the capabilities of Python. The scripts were executed in a Python 3.x environment with libraries such as NumPy and Matplotlib (OpenAI, 2024; Python Software, 2021b; Spyder Website Contributors, 2021b).

4.3.4. Discussions

While the proposed availability-based maintenance cost optimization model demonstrates effectiveness in optimizing maintenance strategies for UPS systems within DCs, certain limitations must be acknowledged in greater detail, along with their potential impact on the results and strategies for mitigation. This section first examines the challenges associated with implementing the model, followed by an analysis of its key limitations and constraints.

4.3.4.1. Challenges in Implementing the Proposed Model

There are several potential challenges to implementing our proposed availability-based maintenance cost optimization model in real-world scenarios. The important ones are discussed below.

One of the primary challenges in validating and refining the proposed model is the restricted access to accurate and comprehensive maintenance and reliability data for DCs. Due to security concerns and confidentiality agreements, organizations are often reluctant to share operational data related to system failures, maintenance schedules, and cost breakdowns. Despite multiple attempts to engage with various DC operators and obtain access to relevant datasets, we were unable to secure real-world records for direct validation. This limitation affects the ability to fine-tune model parameters, particularly failure rates and maintenance cost variations, which are essential for ensuring accurate predictions.

DCs operate within complex infrastructures that incorporate diverse equipment, monitoring tools, and maintenance frameworks. Integrating the proposed model into existing maintenance management systems requires compatibility with different software solutions and data processing architectures. Additionally, the model's reliance on dynamic failure rate estimations necessitates real-time data collection and analysis, which may not be readily available in all DCs.

To mitigate these challenges, future research should explore collaboration with DC operators under strict confidentiality agreements to obtain anonymized datasets for model validation. Additionally, integrating machine learning techniques to estimate missing parameters dynamically can improve prediction accuracy. Further efforts should also focus on developing user-friendly software interfaces that simplify model implementation and adoption by industry professionals.

4.3.4.2. Key Limitations and Constraints

This research is based on a specific DC configuration, with a focus on UPS systems in a k-out-of-n arrangement. Consequently, the optimization model may not be directly applicable to different system configurations or other critical DC subsystems, such as HVAC, network systems or other components. Thus, future research could explore extending the model to incorporate additional critical DC components, such as cooling systems, by integrating multi-component optimization frameworks. Additionally, developing a modular version of the model that allows for subsystem-specific parameters would enhance its adaptability to diverse DC architectures.

In addition, as discussed as one of the model's important implementation challenges, the model relies on assumed failure rates and maintenance costs due to the variability and limited availability of real-world operational data for each component across different DCs. This assumption introduces potential inaccuracies, particularly for organizations with distinct operational environments, unique maintenance policies, or varying workload intensities. In the event of a significant deviation between the actual and the assumed failure rates, the model's results for optimal maintenance strategies may require recalibration to preserve their effectiveness. Additionally, collaborations with DC operators to collect real-time operational data would improve parameter accuracy, leading to more reliable optimization results.

Also, certain assumptions were made regarding the system reliability metrics, such as MTBF and MTTR, and the availability thresholds aligned with Tier 1 standards which may not be suitable for DCs of higher or lower criticality (e.g., Tiers 2, 3, and 4) and will limit the direct applicability of the model's results beyond similar operational environments. Therefore, the model can be adjusted and modified in the future based on other DC Tiers.

To address potential uncertainty in MTBF and MTTR values, and to ensure broader applicability, the implications of such variability are discussed in Chapter 5. Specifically,

Subsection 5.2.1 highlights limitations arising from the reliance on deterministic reliability parameters, while Subsection 5.2.2 outlines actionable research directions, including sensitivity analysis, stochastic modelling, and periodic updates with field data. These strategies provide a foundation for adjusting and refining the models to accommodate different DC tiers and operational environments in future studies.

Lastly, although the model incorporates dynamic maintenance costs, it does not account for external economic factors such as inflation, supply chain disruptions, or regulatory changes that may impact long-term cost predictions. Thus, the long-term validity of cost-based optimization may decrease if external cost factors change unpredictably. To mitigate this limitation, future extension of this research could integrate economic forecasting models to adjust maintenance cost predictions dynamically. Furthermore, incorporating stochastic optimization techniques would enhance robustness in handling uncertain cost fluctuations.

Therefore, to ensure simplicity and feasibility, the model incorporated certain assumptions that were necessary for its initial implementation. Adjusting these parameters and assumptions—such as failure rates, maintenance costs, and availability thresholds—would alter the model’s outcomes and potentially expand its applicability. Thus, the model can be modified to suit other DC tiers, allowing it to adapt to varied operational environments and requirements.

Based on the discussed limitations and restrictions of the proposed model, specific methodologies, technologies, and frameworks could be explored in future studies to improve the model's precision, scalability, and real-world implementation.

The incorporation of machine learning (ML) techniques could improve failure rate predictions by dynamically analyzing historical maintenance logs. This refinement would lead to more precise

maintenance scheduling. Accurate data collection with ML, combined with predictive maintenance models leveraging supervised and unsupervised learning algorithms can analyze historical failure data, detect patterns, and predict component degradation more effectively.

Furthermore, IoT technologies can be integrated into maintenance frameworks which allow real-time monitoring and data acquisition from DC components. Thus, future research could explore the integration of IoT-based condition monitoring systems with the proposed optimization model to enhance decision-making accuracy.

The proposed model can also be enhanced by incorporating stochastic elements through Monte Carlo simulations or probabilistic risk assessment techniques. Various failure scenarios and maintenance actions under uncertain conditions can be simulated by researchers to evaluate the system's reliability and availability for different strategies and determine optimal responses to unexpected system behaviours.

Despite the discussed challenges, limitations and restrictions, the proposed model successfully identifies the optimal (minimum) number of k components to meet the minimum system availability threshold precisely using DP.

As reviewed, extant literature underscores the numerous advantages of the DP method, notably its reduced computational time and efficiency in handling complex problems. A distinguishing feature of the proposed maintenance cost optimization model, in contrast to prior scholarly work, is its explicit design for DCs. This model uniquely incorporates principal DC availability requirements as established by the Uptime Institute, dynamic monthly failure rates with corresponding maintenance costs, and the application of the DP algorithm to ascertain the optimal “ k ” out of “ n ” components within the DC's parallel k -out-of- n system.

As illustrated in the results, the sensitivity analysis confirms that the DP optimization model consistently identifies optimal maintenance strategies while maintaining high system availability and cost-efficiency. This analysis not only enhances the robustness of the research conclusions but also provides valuable guidance for DC operators in making informed, cost-effective maintenance decisions under varying operational constraints.

This tailored approach ensures practicality in real-world applications and aids DC managers in optimizing maintenance schedules, reducing downtime, and extending equipment lifecycles as hyperscale and cloud-based DCs are expanding globally. The model's ability to optimize resource utilization while maintaining high system availability addresses challenges like budget constraints and increasing energy costs. By incorporating dynamic maintenance costs, the framework adapts to real-world variations in asset performance and reliability, offering a robust tool for long-term infrastructure management. Beyond maintenance cost optimization, the model also supports sustainable infrastructure planning by improving resource utilization in DC operations. By determining the optimal number of k components, it minimizes unnecessary, energy-intensive maintenance and component replacements, indirectly reducing energy consumption and lowering the environmental footprint. Additionally, optimizing maintenance strategies ensures critical systems operate efficiently with minimal downtime, reducing reliance on redundant backup power. It sets the stage for future work on advanced optimization methods tailored to industrial challenges and underscores the model's versatility for other critical systems. Furthermore, the theoretical implications of this study extend to reliability engineering and optimization, demonstrating the applicability of DP to complex maintenance systems. This research sets the foundation for future advancements in optimization methods tailored to industrial challenges, highlighting the model's versatility for other critical systems.

4.4. Results and Discussion: Availability-Constrained Maintenance Cost Optimization Model for Series-Parallel Systems

4.4.1. Model's Assumptions

To evaluate the effectiveness of the proposed availability-constrained maintenance cost optimization model, a case study is conducted using a representative DC subsystem. The system comprises 30 UPS devices, distributed into 10 discrete condition states with 3 devices allocated to each state. Devices follow a state-transition model that captures natural degradation and performance deterioration over time. The overall system is modelled as a hybrid series-parallel structure (Figure 7; Section 3.3.1.1), reflecting realistic DC configurations where redundancy is achieved through parallel subsystems and dependencies are captured through series connections.

The model operates under the following critical assumptions:

- System Configuration
 - Each case-study system is composed of $n = 10$ series subsystems, each containing $m = 3$ parallel units, giving a total of 30 UPS devices.
 - Condition states reflect operational degradation, and devices are assumed to transition between states over time.
- Availability Constraint
 - The minimum required availability is set to $A_{Required} = 0.99671$ (99.671%), corresponding to the Tier I Uptime Institute standard.
 - This requirement is treated as a hard constraint in the optimization model.
- Budget Constraint

- A fixed monthly maintenance budget of \$20,000 is enforced: $\sum_{t=1}^T C_{i,t} * x_{i,t} \leq \$20,000$
- This ensures that optimization remains aligned with practical DC operational budgets.
- Component Selection Constraint
- For each condition state i , at least $x_{i,t}(\min) = 1$ device must be selected for maintenance, while no more than $x_{i,t}(\max) = 3$ devices (i.e., all devices in that state) can be selected.

Thus:

$$1 \leq x_{i,t} \leq 3 \quad (30)$$

This condition guarantees balanced attention across all condition categories.

- System-Level Constraints
- The total number of selected components must satisfy:

$$X_{i,t}(\min) = 10 \leq \sum_{i=1}^{10} x_{i,t} \leq X_{i,t}(\max) = 30 \quad (31)$$

- This ensures that the optimization selects enough units to meet system availability requirements while not exceeding operational or budgetary limits.

These assumptions and parameter assignments provide the boundary conditions for simulation, enabling an assessment of trade-offs between cost efficiency and system availability under realistic operational settings.

4.4.2. Sensitivity Analysis

A sensitivity analysis was conducted to evaluate how variations in MTBF, MTTR, and failure rates affect the availability of UPS components across different condition states, relative to the Tier 1 DC requirement of 99.671% availability. Table 17 presents availability results based on changes

in MTBF and MTTR values. It reveals that only components in better condition states meet or exceed the Tier 1 threshold, while those in degraded states fall significantly below. Table 18 examines the relationship between MTBF and failure rate. Similar trends are observed, with availability increasing as the failure rate decreases and the condition improves. These tables collectively underscore the critical influence of reliability parameters on system-level availability and the importance of prioritizing maintenance for components in suboptimal states to ensure compliance with availability requirements.

Table 17: Sensitivity Analysis: The effect of MTBF and MTTR on the UPS availability (%)

		MTTF (hours)					
		5	100	500	1000	1500	2000
MTBF (hours)	8.0	38.4615%	92.5926%	98.4252%	99.2063%	99.4695%	99.6016%
	4.0	55.5556%	96.1538%	99.2063%	99.6016%	99.7340%	99.8004%
	0.5	90.9091%	99.5025%	99.9001%	99.9500%	99.9667%	99.9750%
	0.4	92.5926%	99.6016%	99.9201%	99.9600%	99.9733%	99.9800%
	0.3	94.3396%	99.7009%	99.9400%	99.9700%	99.9800%	99.9850%

Table 18: Sensitivity Analysis: The effect of MTBF and failure rate on the UPS availability (%)

		MTBF (hours) = 1/Failure Rate (λ)					
		5	100	500	1000	1500	2000
Failure Rate (λ)	1.00E-04	99.8501%	99.8501%	99.8501%	99.8501%	99.8501%	99.8501%
	3.00E-04	99.5510%	99.5510%	99.5510%	99.5510%	99.5510%	99.5510%
	6.70E-04	99.0000%	99.0000%	99.0000%	99.0000%	99.0000%	99.0000%
	1.00E-03	98.5112%	98.5112%	98.5112%	98.5112%	98.5112%	98.5112%
	1.00E-02	86.0708%	86.0708%	86.0708%	86.0708%	86.0708%	86.0708%

4.4.3. Model's Results

This subsection presents the outcomes of the maintenance cost optimization model applied to a UPS system operating under a series-parallel configuration. As detailed in Table 19, 20 out of 30 available components were selected for maintenance, with individual component costs ranging from \$140.92 to \$2,650.00. This selection strategy resulted in a total monthly maintenance cost of \$19,999.75, remaining within the \$20,000 budget constraint. The model also ensures regulatory compliance by achieving a system availability of 99.974%, surpassing the Tier 1 DC requirement of 99.671%.

Table 19: Results of the availability-constrained maintenance cost optimization model for Series-Parallel systems

Component	Asset Condition State Rating	Availability of each subsystem (Parallel)	Number of available Components for maintenance	Number of Components selected for maintenance	Monthly Maintenance Costs for one component (USD)	Monthly Maintenance Costs for selected components (USD)
UPS_DC_10	10	99.9998%	3	1	140.92	140.9
UPS_DC_9	9	100.000%	3	3	141.83	425.5
UPS_DC_8	8	100.000%	3	3	143.33	430.0
UPS_DC_7	7	99.9976%	3	1	370.42	370.4
UPS_DC_6	6	99.9953%	3	1	373.50	373.5
UPS_DC_5	5	100.000%	3	2	392.75	785.5
UPS_DC_4	4	99.9500%	3	1	395.17	395.2
UPS_DC_3	3	100.000%	3	3	1,276.25	3,828.7
UPS_DC_2	2	99.9998%	3	2	2,650.00	5,300.0

UPS_DC_1	1	100.000%	3	3	2,650.00	7,950.0
Total:			30	20	Total Monthly Maintenance Costs	19,999.75

- Total Availability (Series-Parallel System):

$$\prod_{i=1}^n (A_{i,t}) \geq A_{t,Required}$$

$$99.974\% \geq 99.671\% \text{ (Tier 1 DC Requirement)} \checkmark$$

- Budget Constraint:

$$\sum_{t=1}^T C_{i,t} * x_{i,t} \leq \text{Total budget}$$

$$\$19,999.75 \leq \$20,000 \checkmark$$

These results demonstrate that the model successfully prioritizes components based on condition ratings and cost-effectiveness. The proposed optimization model effectively balances cost-efficiency and system availability in the maintenance of a UPS system configured in a series-parallel architecture.

Chapter 5: Conclusions and Future Research Directions

5.1. Summary of Contributions

This research aimed to address the growing complexity of maintenance planning in DCs, with a focus on enhancing the reliability and availability of UPS systems—critical components in ensuring continuous DC operations. Three novel maintenance optimization models were developed to support data-driven, availability-aware maintenance strategies within constrained budgets and diverse system configurations.

In the first phase, a Dynamic Availability-Based Maintenance Prioritization model was developed. This model formulates the problem as a 0/1 multiple knapsack problem within a DP framework to prioritize maintenance actions based on component condition states and their contribution to availability improvement. Unlike traditional approaches, it explicitly integrates Uptime Institute Tier-based availability thresholds, ensuring strong relevance to real-world DC operations. Results from the case study demonstrated that applying this model led to the selection of 50% of UPS units for maintenance, yielding a 61% improvement in total system availability for 12 UPS units—highlighting its efficiency in budget-constrained maintenance prioritization. Correlation analysis further highlighted that components with lower initial availability offer greater potential improvement, and higher maintenance investment directly translates into increased system availability. Accordingly, this model is most appropriate for situations where operators face strict budget limitations and must identify the most impactful subset of components to maintain.

The second phase introduced a Dynamic Availability-Based Maintenance Cost Optimization model for k-out-of-n Systems, which extends the first model by incorporating variable failure rates and dynamic maintenance costs into a dynamic programming framework. This model identifies the optimal number of active components (k) required to meet or exceed system availability thresholds while minimizing total maintenance costs. Sensitivity analyses were performed to validate the robustness of the model. The primary goal of these analyses was to identify abnormal deviations in results under varying parameter conditions. The findings confirmed that the model behaved predictably: availability was only marginally affected by MTBF changes but showed significant sensitivity to MTTR, emphasizing the importance of fast repair times. Maintenance costs responded linearly to $\pm 10\%$ adjustments, validating the model's stability and reliability under multiple scenarios. Furthermore, optimizing the k-out-of-n configuration revealed diminishing returns beyond certain budget thresholds, highlighting the need for careful redundancy planning. Tier-based comparisons also demonstrated that higher availability requirements significantly increase costs—for example, total maintenance costs rise from \$9,973 for Tier I (5 units) to \$19,946 for Tier IV (10 units)—illustrating the model's adaptability across different operational and financial conditions. Overall, the proposed optimization model represents a substantial advancement toward cost-effective and availability-driven maintenance planning. The DP-based framework successfully balances operational expenditures and reliability objectives, achieving a maximum system availability of 99.991%, well above the Tier I benchmark of 99.671%. This makes the model particularly valuable in contexts where redundancy management and dynamic cost structures significantly shape maintenance decision-making.

In the third phase, an Availability-Constrained Maintenance Cost Optimization model for Series-Parallel Systems was developed. This model addresses the complexity of real-world DC

architectures by explicitly representing UPS configurations with both series and parallel components. It incorporates availability constraints aligned with Uptime Institute Tier standards while enforcing budgetary and component selection rules. Sensitivity analyses were conducted to evaluate how variations in MTBF, MTTR, and failure rates affect system availability relative to the Tier I DC requirement of 99.671%. The results indicated that only components in better condition states consistently meet or exceed the Tier I threshold, while degraded components fall significantly below, highlighting the importance of prioritizing maintenance based on component condition and reliability parameters. Availability was observed to increase as failure rates decreased and component condition improved, emphasizing the model's capability to guide cost-effective, condition-based maintenance decisions. The case study confirmed the model's effectiveness in maintaining required availability levels while minimizing total maintenance costs, demonstrating its practical value for DCs with heterogeneous infrastructures. Compared with the Knapsack and k-out-of-n models, this approach offers the greatest flexibility, as it captures hybrid system dependencies that simpler configurations cannot. Accordingly, this model is most applicable in environments where infrastructure complexity, mixed redundancy strategies, and strict Tier-based compliance requirements necessitate a comprehensive, reliability-driven optimization framework.

Collectively, these three models offer a scalable, flexible, and theoretically grounded framework for maintenance scheduling in DCs. They enable operators to manage resources efficiently, maintain high availability, and align with industry standards under varying operational and financial conditions. Moreover, the validation through sensitivity analysis confirmed the robustness of the results under these varying conditions, reinforcing the practical reliability of the models.

5.2. Limitations and Future Research

5.2.1. *Limitations*

While this research advances the state-of-the-art in DC maintenance optimization, several limitations must be acknowledged.

From a theoretical perspective, the models assume:

- Uniform and discrete condition state transitions that may not capture the continuous and stochastic nature of component degradation.
- Static availability thresholds based on predefined Tier levels, which do not account for varying Service-Level Agreements (SLAs) or evolving operational demands.
- Deterministic failure rates and repair times, as well as maintenance cost estimates, are assumed to be known and accurate. This overlooks real-time fluctuations and uncertainties in field operations. Variability in these parameters could influence system availability predictions and optimal maintenance strategies across all three models.

From an application perspective, the models:

- Were validated using simulated or structured case studies rather than real-world datasets.
- Focused solely on UPS systems, excluding other critical DC subsystems such as HVAC, power distribution units, and networking equipment.
- Do not currently incorporate live data feeds, predictive analytics, or integration with enterprise asset management systems, limiting their adaptability in dynamic operational environments.

- Optimize maintenance primarily for cost and system availability. Other potentially important operational, environmental, or regulatory constraints such as energy consumption limits, thermal management, SLAs, interdependencies with other subsystems, or sustainability targets are not explicitly included. While sustainability metrics were beyond the scope of this study, the models indirectly support sustainability by reducing unnecessary maintenance, minimizing failure risks, and optimizing resource usage. Explicit inclusion of environmental indicators such as energy consumption, carbon footprint, or lifecycle impacts would better align the models with current DC sustainability pressures.
- Were specifically developed to model k-out-of-n and series-parallel UPS configurations. Although these configurations are widely used, exploring other DC architectures was beyond the scope of this study and thus represents a limitation of the research. Nevertheless, the proposed models are generalizable: with appropriate parameter adjustments, they can be applied to different UPS configurations and DC layouts to provide comparable insights into availability-driven maintenance planning and cost optimization.

5.2.1.1. Implications of parameter uncertainty

Given that MTBF and MTTR values may vary due to operational conditions, environmental factors, and manufacturing tolerances, the models' predictions may require recalibration when applied in different DC environments. To enhance robustness under uncertainty, future work could consider:

- Sensitivity Analysis: Evaluating how variations in MTBF, MTTR, and maintenance costs affect model outputs and optimal strategies.

- **Stochastic Modelling:** Incorporating probability distributions for uncertain parameters within the optimization frameworks.
- **Field Data Updates:** Periodically updating reliability parameters based on actual operational data to refine predictions.

By acknowledging these limitations, the research provides a foundation for further methodological enhancements and practical extensions to improve the adaptability, accuracy, and applicability of DC maintenance optimization frameworks.

5.2.2. Future Research Directions

To address these limitations and expand the scope of the research, the following future directions are proposed:

- **Integration of Real-Time Data and Predictive Analytics:** Incorporating IoT-enabled condition monitoring and AI-driven failure prediction would allow for dynamic adjustments to maintenance schedules and enable truly predictive maintenance strategies.
- **Stochastic and Multi-Objective Optimization:** Future models could introduce stochastic elements to account for uncertainty in failure rates and costs and consider multiple objectives—such as minimizing energy use or carbon footprint—in addition to system availability and cost.
- **Incorporation of Uncertain Reliability Parameters:** To address variability in MTBF, MTTR, and maintenance costs, stochastic modelling approaches and sensitivity analyses should be integrated into the optimization frameworks. This would allow the models to account for operational uncertainties and provide more resilient maintenance strategies.

- **Cross-System Optimization:** Expanding the model framework to include multiple subsystems (e.g., cooling, power distribution, network infrastructure) and their interdependencies would provide a more holistic maintenance optimization platform.
- **Exploration of Alternative DC Architectures:** Future research could extend the models to diverse UPS configurations and overall DC architectures beyond k-out-of-n and series-parallel setups, validating their applicability in a wider range of operational contexts.
- **Inclusion of Broader Operational Constraints:** Future work should extend the optimization framework to incorporate additional constraints—such as energy efficiency, thermal management, SLA requirements, and subsystem interdependencies—ensuring that maintenance strategies align with the full spectrum of operational and regulatory demands.
- **Validation Through Industry Collaboration:** Partnering with DC operators, UPS vendors, and software providers could support large-scale pilot implementations, enabling empirical validation and refinement of the models.
- **Scalable Decision-Support Tools:** Translating the models into decision-support tools with user-friendly interfaces and integration capabilities would support real-world adoption by operations teams.
- **Sustainability Metrics:** Incorporating metrics such as energy consumption, carbon emissions, and lifecycle sustainability into the optimization process would align the models with the increasing environmental expectations placed on DCs.

By addressing these directions, future research can build upon the foundational framework developed in this study and move toward more intelligent, resilient, and sustainable DC maintenance strategies.

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