UNIVERSITI TEKNOLOGI MARA

OPTIMIZING MULTI-CHILLER ENERGY EFFICIENCY USING A HYBRID GENETIC ALGORITHM-BARNACLE MATING OPTIMIZER (GA-BMO) AND DYNAMIC SCHEDULING

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MSc

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Thesis submitted in fulfilment
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CONFIRMATION BY PANEL OF EXAMINERS

I certify that a Panel of Examiners has met on 26 January 2026 to conduct the final examination of Aniq Syahmi bin Azman for his Masters of Science thesis entitled "Optimizing Chiller Energy Efficiency Through Hybrid Genetic Algorithm-Based Control and Scheduling Strategies" in accordance with Universiti Teknologi MARA Act 1976 (Akta 173). The Panel of Examiner recommends that the student be awarded the relevant degree. The Panel of Examiners was as follows:

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ABSTRACT

Energy consumption in heating, ventilation, and air conditioning (HVAC) systems, particularly chillers, represents a major portion of operating expenditure in large-scale facilities. This study proposes a hybrid optimization-based control strategy that integrates a Genetic Algorithm (GA) with the Barnacle Mating Optimizer (BMO), referred to as GA-BMO, to minimize total chiller power consumption while satisfying cooling demand constraints. The case study is a three-chiller plant inspired by the Malaysian Nuclear Agency configuration with installed capacities of 370 RT, 370 RT, and 340 RT (total 1080 RT). The research was conducted in three stages: algorithm development, comparative performance evaluation, and simulated real-time validation using a MATLAB/Simulink dynamic scheduler integrated with a cloud-synchronized monitoring dashboard. Across six operating scenarios (70%-95% of plant capacity), GA-BMO optimized the partial load ratios (PLRs) and achieved power reductions of 25.37-52.31 kW (3.55%-9.01%) relative to the default baseline operation (static schedule derived from the existing plant settings). The proposed method consistently outperformed standalone GA and BMO as well as benchmark algorithms including Improved Genetic Algorithm (I-GA), Imperialist Competitive Algorithm (ICA), Particle Swarm Optimization (PSO), and Cuckoo Search (CS). Economic analysis using the Non-Domestic Medium Voltage tariff (ToU peak rate) indicated projected annual cost savings of RM 18,587.10-RM 38,361.26 depending on load conditions. Overall, the GA-BMO strategy provides a practical and scalable solution for intelligent chiller scheduling by bridging optimization-based control and real-time-capable monitoring in HVAC energy management.

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LIST OF SYMBOLS

Symbols

a_i, b_i, c_i, d_i	These are coefficients specific to each chiller (i).
CL^t	Represents the Cooling Load at a specific time or during a specific time period
E_{WT}	Entering Water Temperature
i	Denotes a specific chiller identifier when there are multiple chillers in a cooling system.
L_i	Load for chiller i
P_i^t	Represents the electrical power consumption of the chiller at a given hour (t).
PLR_i^t	Represents Part Load Ratio is a measure of how much a chiller is operating relative to its full capacity.
P_{total}	Total system power
RT_i	Represents the Rated Capacity of the i-th chiller.
t	Refers to a specific time or time period

LIST OF ABBREVIATIONS

Abbreviations

BMO	Barnacle Mating Optimizer
CS	Cuckoo Search
CSV	Comma-Separated Values
FFD	Full Factorial Design
GA	Genetic Algorithm
GA-BMO	Genetic Algorithm – Barnacle Mating Optimizer
HVAC	Heating, Ventilation, and Air Conditioning
ICA	Imperialist Competitive Algorithm
I-GA	Improved Genetic Algorithm
KPI	Key Performance Indicator
kWh	Kilowatt-Hour
MATLAB	Matrix Laboratory (Software)
M-File	MATLAB Script File
PLR	Part Load Ratio
PSO	Particle Swarm Optimization
RT	Refrigeration Ton
UI	User Interface

LIST OF NOMENCLATURE

Nomenclatures

C	Operational cost, (RM)
COP	Coefficient of Performance, (unitless)
E	Amplitude Ratio, (No Units)
f (x)	Objective function
i	Index for chiller unit
L	Cooling Load, (RT)
m	Mass flow rate of chilled water, (kg/s)
N	Number of iterations / population size
P	Power Consumption, (kW)
pl	Spermcast Probability
PLRi	Partial Load Ratio of chiller i, (unitless)
Q	Cooling capacity, (kW)
T	Time, (hour)
Tchwr	Chilled water return temperature, (°C)
Tchws	Chilled water supply temperature, (°C)
η	Efficiency, (%)

CHAPTER 1
INTRODUCTION

1.1 Research Background

The drive for enhancing the performance and efficiency of chiller systems has led to significant research and development in optimization techniques. The critical role of chillers in industrial and commercial cooling systems, consuming a substantial part of energy usage, underscores the urgency of optimizing their performance [1]. Recent advancements in optimization algorithms offer promising pathways to achieve this goal. Among these, the application of Genetic Algorithms (GA) has been a pivotal approach due to its ability to efficiently search large solution spaces for optimal configurations, thus improving chiller performance significantly [2].

Building on the foundational work of Genetic Algorithms, the incorporation of Barnacle Mating Optimization (BMO) based control strategies presents an innovative hybrid approach. The BMO, inspired by the unique mating behaviour of barnacles, introduces a novel paradigm in optimization techniques, focusing on enhancing chiller performance by leveraging both genetic diversity and precision mating strategies. While Genetic Algorithms (GAs) are effective for exploring diverse solutions in chiller performance optimization due to their flexibility and ability to handle complex variables, they often fall short in terms of convergence speed and local optima entrapment [2]. This limitation hampers their effectiveness in dynamic environments where rapid adaptation to changing conditions is crucial. To overcome these challenges, this research proposes a hybrid approach that incorporates the robustness and adaptability of Barnacle Mating Optimization (BMO). BMO enhances the search capabilities of GAs by providing a more structured exploration of the solution space, thus accelerating the convergence rate and improving the algorithm's ability to escape from local optima. This hybrid strategy leverages the strengths of both algorithms, offering a powerful tool for addressing the multifaceted challenges of optimizing chiller performance.

One pivotal study by [3] exemplifies the potential of integrating BMO in chiller optimization. This research highlights the effectiveness of BMO algorithms in achieving significant energy conservation, which is a crucial aspect of optimizing chiller systems for enhanced performance and sustainability. Furthermore, another relevant study by M. Sulaiman [4] underscores the versatility and efficiency of BMO algorithms in optimizing power systems, showcasing their broad applicability in industrial optimization tasks. These studies provide compelling evidence supporting the effectiveness of BMO, reinforcing the belief that its hybridization with Genetic Algorithms (GA) could yield even greater efficiency. By combining the strengths of GA in navigating complex problem spaces with the robust optimization capabilities of BMO, this hybrid approach is anticipated to enhance adaptability and improve overall system performance in chiller optimization.

These studies underscore the burgeoning interest in hybrid optimization methods that blend traditional algorithms with innovative strategies inspired by natural processes, such as barnacle mating behaviours. Such hybrid approaches, particularly when applied to the optimization of chiller systems, promise not only enhanced performance and energy efficiency but also a roadmap for future research in the field of industrial system optimization. The exploration of hybrid Genetic Algorithms with Barnacle Mating Optimization based control strategies represents a cutting-edge frontier in the quest for optimizing chiller performance, offering a blend of theoretical innovation and practical utility in tackling the energy and efficiency challenges faced by contemporary cooling systems. [3] [6] [7]

1.2 Motivation for This Work

The increasing demand for energy efficiency in large-scale facilities has placed significant pressure on building management systems, particularly in commercial buildings where chillers are responsible for up to 40% of the total energy consumption. As environmental and economic concerns grow, optimizing the operation of chiller systems is no longer optional—it is essential for reducing operational costs and minimizing carbon emissions. While existing optimization strategies using standalone Genetic Algorithms (GA) or other evolutionary techniques such as PSO, ICA, and CS have shown promise, they still face challenges such as premature convergence, limited adaptability to real-time changes, and suboptimal load distribution under dynamic environmental conditions [5]. This gap presents a strong motivation to explore novel hybrid algorithms that can address these shortcomings more effectively.

This research is motivated by the opportunity to contribute a hybrid GA-BMO strategy that integrates the global search capabilities of GA with the local precision of Barnacle Mating Optimizer (BMO). This approach is not only technically innovative but also practically impactful. The proposed algorithm is implemented in a dynamic scheduler supported by a real-time dashboard monitoring system, ensuring the optimization strategy is both theoretically sound and practically deployable.

Furthermore, this work builds upon earlier undergraduate research where an Improved Genetic Algorithm (I-GA) produced encouraging chiller-loading results, but the approach still exhibited limitations that are typical of single-method metaheuristics, such as sensitivity to parameter tuning, premature convergence in some operating regions, and reduced adaptability when cooling demand changes over time. To address these weaknesses, this master's study integrates BMO as an embedded operator within GA, enhancing exploration without sacrificing the structured exploitation provided by GA selection and crossover. This hybridization is motivated by the need for a more robust optimizer that can sustain performance across diverse load levels and support dynamic scheduling, periodic PLR update for real-time-capable chiller management.

1.3 Problem Statement

In contemporary commercial and industrial facilities, optimizing chiller operation is a critical challenge for both energy efficiency and operating cost reduction. Chillers can account for a substantial fraction of a building's electricity use, which motivates control strategies that minimize total chiller power while meeting cooling demand under nonlinear equipment constraints. However, chiller plants operate under time-varying loads and environmental conditions, and fixed or heuristic setpoints often lead to suboptimal partial load ratio (PLR) allocation and avoidable energy consumption.

Although advanced controllers such as model predictive control (MPC) have been applied in HVAC contexts, MPC typically requires an accurate plant model, careful constraint tuning, and sufficient computation and sensor reliability for online optimization. These practical requirements can limit MPC feasibility when model uncertainty is high or when rapid commissioning and low-maintenance operation are required. Consequently, there remains a research gap for robust, computation-efficient metaheuristic-based schedulers that can adapt PLRs across operating conditions while maintaining feasibility and stability. This thesis addresses that gap by proposing and validating a hybrid GA-BMO strategy with embedded operators for improved exploration-exploitation balance and dynamic scheduling compatibility.

1.4 Research Questions

a) How can a hybrid GA-BMO optimizer be designed to allocate chiller partial load ratios (PLRs) under nonlinear plant constraints to minimize total power consumption while satisfying cooling demand?
b) How does the proposed GA-BMO strategy compare with established metaheuristics (GA, BMO, PSO, ICA, CS, and I-GA) in terms of power reduction, convergence behaviour, and robustness across multiple load scenarios?
c) How can GA-BMO be validated within a dynamic scheduling and monitoring framework (simulated real-time operation) to ensure consistent performance under time-varying cooling demand?

1.5 Research Objective

Based on the existing scenario and the problems that have been identified, this study will focus on the following objectives:

i) To design and develop a hybrid GA-BMO optimization strategy to enhance chiller energy efficiency and minimize operational power consumption.
ii) To evaluate the performance of GA-BMO against benchmark optimization algorithms in terms of power savings, convergence performance, and robustness across multiple cooling-load scenarios.
iii) To validate the GA-BMO strategy within a dynamic scheduling and dashboard monitoring framework for simulated real-time adaptability under variable operating conditions.

1.6 Scope of Study

This research focuses on developing and evaluating a hybrid Genetic Algorithm-Barnacle Mating Optimizer (GA-BMO) strategy to optimize a three-chiller plant using operational data inspired by the Malaysian Nuclear Agency configuration. The study evaluates six steady-state cooling load scenarios (70%-95% of total plant capacity, in 5% increments) and uses consistent constraint enforcement to ensure feasible PLR schedules.

For dynamic scheduling validation, a representative working-day demand profile is applied over standard operating hours, for example 08:00-17:00, where the cooling demand is sampled at a fixed interval (hourly updates in the scheduler) and PLRs are updated at each time step. The default baseline operation represents a static schedule derived from the existing plant settings (without GA-BMO optimization), enabling fair power and cost comparisons.

Environmental impact is assessed at a screening level by translating the achieved electrical energy reduction (kWh) into potential avoided emissions using an appropriate grid emission factor; detailed life-cycle assessment is outside the scope of this thesis.

1.7 Limitation of Study

The study, while pioneering in its approach to optimizing chiller performance through a Hybrid Genetic Algorithm with Barnacle Mating Optimization (GA-BMO) control strategy, encounters several limitations inherent to its scope and methodology. A primary limitation is the study's focus on commercial buildings, significant energy consumers due to chiller usage, yet representing just one segment of a broader potential application spectrum. This specificity might restrict the generalizability of the findings to other types of facilities such as industrial plants or residential complexes, where chiller usage patterns and optimization needs differ substantially. It is also important to note that this study does not encompass full HVAC system integration; rather, it focuses solely on the chiller module as the primary target for optimization. As such, ventilation and air distribution systems are beyond the scope of this research, which may limit the broader applicability of the findings to complete HVAC infrastructures.

The complexity and novelty of the proposed hybrid optimization strategy itself present unique challenges, including the calibration of algorithm parameters and adaptation to diverse operational scenarios within commercial settings. The effectiveness of the strategy depends heavily on the accurate modelling of chiller system dynamics, which may not capture all real-world operational nuances, potentially limiting its applicability under certain unrepresented conditions. External factors such as technological advancements in chiller systems could also impact the relevance and feasibility of the proposed optimization strategy. As new technologies emerge, the algorithms' effectiveness and applicability may require adjustments to remain relevant.

Data limitations pose another significant constraint, with data availability or quality potentially affecting the accuracy and reliability of findings. Inadequate data could lead to biased conclusions and limit the strategy's effectiveness in broader applications. Resource constraints, including time, access to specialized equipment, and expertise, also limit the scope of the study. These constraints may affect the depth of research and the extent of real-world testing and simulations performed. Furthermore, the study's comparative analysis, aimed at benchmarking the Hybrid GA-BMO against traditional and evolutionary-based optimization methods, may face limitations due to variability in performance metrics and evaluation criteria. Differences in the setup, scale, and specific objectives of comparative algorithms could pose challenges in establishing a fair and comprehensive basis for comparison.

The dual approach of simulation and real-world testing introduces limitations in terms of scalability and practical implementation. While simulations are useful for preliminary evaluations, they may not account for all physical and environmental variables affecting chiller performance. Conversely, real-world testing is constrained by the availability of suitable test environments, the willingness of commercial building operators to participate, and potential operational disruptions.

Lastly, the environmental impact assessment component of the study, focusing on energy consumption reduction and greenhouse gas emissions, might not capture the full spectrum of environmental benefits or drawbacks associated with implementing the Hybrid GA-BMO strategy. This aspect is limited by the availability of accurate and comprehensive environmental data, as well as by the methodologies used to estimate impacts. Potential biases, such as selection biases in data collection or sampling and biases in the interpretation of results, further challenge the study's validity.

Despite the benefits of dynamic scheduling with dashboards, several limitations are acknowledged. First, advanced optimal controllers, MPC-style schedulers can demand accurate plant models, trustworthy forecasts, and non-trivial tuning and computation; these requirements can limit portability across sites and seasons [37]. Second, EMIS/MBCx programs frequently face data quality and integration challenges such as meter gaps, sensor drift, time sync, which can affect real-time visualizations and any analytics depending on them [36]. Third, reported field studies show that realized savings from optimal chiller dispatch depend strongly on local tariffs, system configurations for example TES, and operational constraints, results may not generalize without site specific adaptation [38]. Finally, organizational adoption and operator workflow integration mediate the value captured from dashboards, even when the technology functions as intended [34], [35].

1.8 Significance of Study

This study introduces a novel approach to enhancing the efficiency and performance of chiller systems in commercial buildings through a Hybrid Genetic Algorithm with Barnacle Mating Optimization (GA-BMO) control strategy. It innovatively addresses a critical area of energy consumption by combining the robust searching capabilities of Genetic Algorithms (GAs) with the adaptive mating strategies of Barnacle Mating Optimization (BMO). This hybridization presents a cutting-edge solution to complex optimization problems in the HVAC domain, which are often challenging due to the dynamic nature of environmental and operational variables. This energy-saving solution is especially timely and relevant given the recent increases in electricity tariffs, which are expected to rise further, placing greater economic pressure on commercial building operators to improve energy efficiency.

The integration of GA and BMO into a single framework is particularly innovative, representing a significant departure from traditional single-algorithm approaches. By leveraging the strengths of both algorithms, the GA-BMO strategy effectively balances exploration and exploitation phases in the search space, leading to more efficient and reliable optimization outcomes. This novel integration makes the study stand out from previous efforts, offering a unique contribution to the field of building management systems.

Moreover, the environmental impact of this study is profound, aligning with global efforts to combat climate change by reducing the carbon footprint of commercial buildings. The practical implications of this research, validated through simulation and real-world testing, ensure its findings are directly applicable to improving current practices in chiller system management. This bridges the gap between theoretical research and practical application, offering actionable insights that could lead to widespread adoption and enhancements in energy efficiency.

Consequently, the significance of this study is multifaceted, promising not only economic and environmental benefits but also paving the way for future innovations in the optimization of complex systems within commercial settings. The hybrid GA-BMO approach has the potential to serve as a benchmark for future advancements, inspiring further research and development in energy optimization technologies.

Situating the GA-BMO dynamic scheduler within an EMIS style monitoring stack is significant because it enables continuous commissioning. Optimization decisions are tracked by persistent feedback loops for verification and operator action. Large, EMIS campaigns report median annual energy savings on the order of 7% with cost savings that accrue over time, largely by surfacing and correcting issues quickly via dashboards [34], [35]. Parallel field work on optimal chiller dispatch under real tariffs demonstrates that combining optimization with real-time monitoring yields practical, measurable reductions in both energy and demand charges, reinforcing the approach adopted here [38], [39].

1.9 Thesis Structure

This thesis is structured into five chapters, each addressing specific components of the research in a logical and coherent manner:

Chapter 1: Introduction

This chapter introduces the background and context of the study, outlines the problem statement, formulates the research questions and objectives, and defines the scope, limitations, significance, and motivation for the work. It sets the foundation for understanding the need for optimization in chiller systems and the development of the proposed hybrid strategy.

Chapter 2: Literature Review

This chapter provides a comprehensive review of existing strategies for chiller system optimization, including traditional control methods and modern metaheuristic algorithms. It highlights the limitations of current approaches and establishes the theoretical foundation for the proposed GA-BMO hybrid. Comparisons between various algorithms are presented to justify the need for hybridization.

Chapter 3: Research Methodology

This chapter describes the methodology used to achieve the research objectives, including the mathematical modelling of the chiller system, formulation of the optimization problem, and the design of the GA-BMO algorithm. It also details the simulation setup, parameter tuning, system constraints, and implementation of the real-time dynamic scheduler and dashboard monitoring system.

Chapter 4: Results and Discussion

This chapter presents the outcomes of the research, including the performance of the proposed GA-BMO algorithm across different cooling load scenarios. Comparative analyses with GA, I-GA, BMO, PSO, ICA, CS, and default settings are discussed. The chapter also covers the implementation of the dynamic scheduler and real-time dashboard, highlighting the system's ability to adapt to environmental variations.

Chapter 5: Conclusion and Recommendations

This chapter summarizes the key findings, outlines the contributions and practical implications of the study, and discusses its limitations. It also provides recommendations for future research directions to further improve chiller optimization and extend the framework to other industrial applications.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Optimization of chiller systems is crucial for achieving energy efficiency and cost minimization in HVAC applications. Traditional strategies like PID control, fuzzy logic, and MPC have been used but often fall short due to the complex, non-linear nature of chiller operations. This chapter reviews advanced optimization techniques, emphasizing their effectiveness in improving chiller performance.

This chapter will explore the application of advanced optimization techniques, specifically the Genetic Algorithm (GA) and Barnacle Mating Optimizer (BMO), to achieve superior energy efficiency in chiller operations. A discussion of existing strategies, their strengths, and limitations will provide the foundation for understanding the potential enhancements offered by GA and BMO. Additionally, emerging trends in hybrid optimization approaches, dynamic scheduling, and dashboarding will be examined as complementary strategies to support a holistic solution to managing chiller system efficiency.

2.2 Comprehensive Understanding of Chillers

Chillers are essential for precise temperature control in various industries. Two main types are water-cooled and air-cooled chillers, each with specific operational and cost implications.

Figure 2.1 shows there are two main types of chillers commonly used in commercial buildings: water-cooled chillers and air-cooled chillers. Water-cooled chillers operate by circulating chilled water through a network of pipes to absorb heat from the building's interior. The heated water is then transported back to the chiller, where the heat is released through a cooling tower. On the other hand, air-cooled chillers use fans to extract heat directly from the refrigerant, which is then dissipated into the ambient air

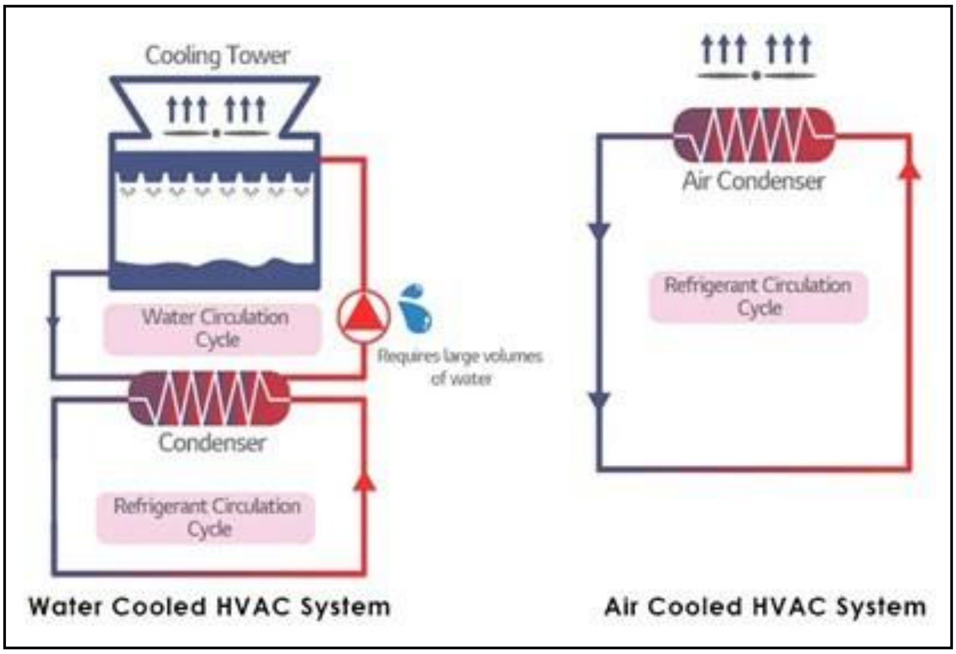

Figure 2.1:Water-Cooled vs Air-Cooled HVAC System [8]

While it may seem apparent that water-cooled chillers are more efficient due to their use of water, the choice between water-cooled and air-cooled chillers depends on various factors. Water-cooled chillers are typically more energy-efficient and can provide higher cooling capacities. However, they require additional infrastructure, such as cooling towers and water circulation systems, which can increase installation and maintenance costs. Air-cooled chillers, on the other hand, offer a more straightforward installation process and do not necessitate a separate water system. They are commonly employed in areas with limited space or in retrofit projects where the infrastructure for a water-cooled system is not feasible.

2.2.1 Water-Cooled Chiller

The main focus is on water-cooled chillers, shown in Figure 2.2, which are typically used in large commercial properties with high cooling loads. The chiller produces chilled water and pushes this around the building's air handling units and fan cool units. Their purpose is to distribute air around defined areas within the building. The air is then forced across the heat exchangers containing the chilled water, which extracts the unwanted heat before the air is distributed throughout the building. The unwanted heat that is extracted from the air collects in the chilled water loop, which is pumped back to the chiller, where it will transfer over the chiller's condenser via a refrigerant loop. The condenser absorbs this heat and then dumps this into the condenser water loop, and this runs between the chiller's condenser and the cooling tower up on the roof. The cooling tower will force ambient air across the condenser water to extract the unwanted heat and reject this heat out of the building and into the atmosphere. in this instance, the condenser of the chiller has been cooled by water, so it is now a water-cooled chiller.

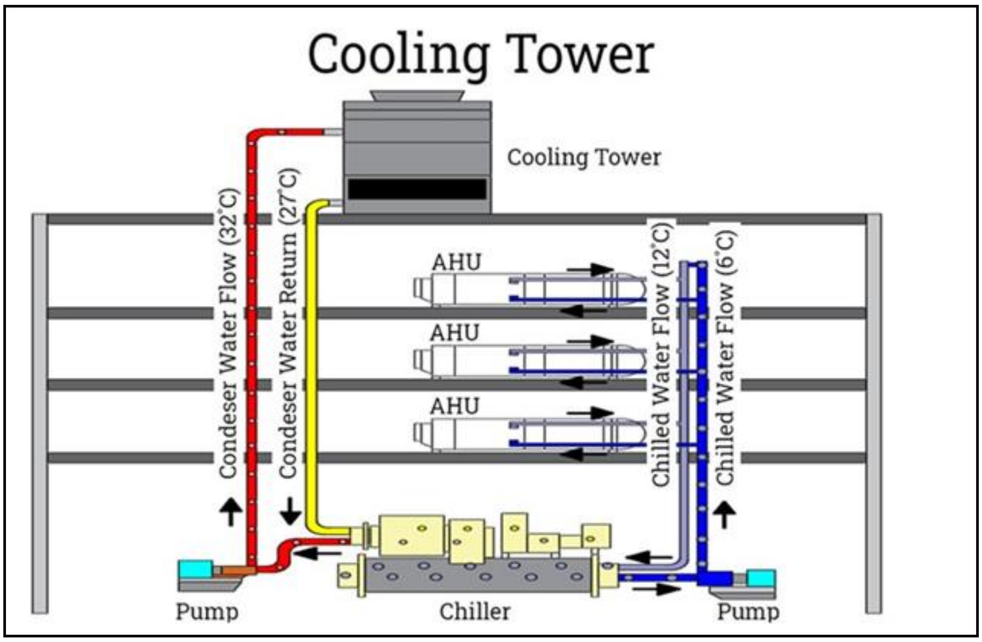

Figure 2.2: Water Cooled Chiller Diagram [9]

2.3 Existing Strategy for Chiller System Optimization

Section 2.3 provides only background context on prior operational frameworks and comparison practices. The detailed operational framework and comparative evaluation setup were relocated to Chapter 3 (Research Methodology), particularly in the performance-evaluation and dynamic-scheduling method sections, to improve chapter flow and methodological coherence.

2.4 Metaheuristic Algorithm

Metaheuristic algorithms have emerged as powerful and versatile tools for addressing complex optimization problems in diverse domains. These algorithms are particularly well suited for scenarios where traditional optimization techniques may face challenges due to high- dimensional search spaces, non-linearity, and lack of continuous differentiability. Metaheuristic algorithms operate through iterative processes that emulate natural or human-inspired behaviours to navigate the solution space efficiently. By harnessing the strengths of exploration and exploitation, these algorithms offer flexible and effective solutions to tackle optimization challenges, including those encountered in chiller loading operations.

There are several methods that have been proposed to solve the Optimization of the Chiller Loading problem, aiming to optimize energy consumption and improve the efficiency of chiller systems. In this context, researchers have explored various approaches to tackle this optimization problem, including the application of adaptive neuro-fuzzy inference systems and genetic algorithms for optimizing chiller loading [5]. Among these approaches, metaheuristic algorithms have emerged as powerful tools for addressing complex optimization problems in different domains, such as electric energy consumption prediction [15], cloud computing [16], smart homes [17], and wireless sensor networks [18]. These algorithms offer flexible and efficient solutions by leveraging iterative search processes inspired by different principles.

In the realm of chiller loading optimization, metaheuristic algorithms have demonstrated promising results in achieving energy conservation and optimal performance, as evidenced by the use of an improved invasive weed optimization algorithm for reducing energy consumption in chiller systems [19]. Metaheuristic algorithms can be broadly categorized into four types: swarm-based, physics-based, human-based algorithms, and evolutionary-based. Each type exhibits distinct characteristics and mechanisms for solving optimization problems, including the optimal placement of FACTS devices in power network systems [20]. Metaheuristic algorithms can be broadly categorized into four types: evolutionary-based, swarm-based, physics-based, and human-based algorithms. Each type exhibits distinct characteristics and mechanisms for solving optimization problems.

2.5 Evolutionary Base Algorithm

Evolutionary-based algorithms (EAs) offer a robust approach to optimization, drawing inspiration from the principles of biological evolution. These algorithms iteratively refine a population of potential solutions using processes that mimic natural selection, reproduction, and mutation. The goal is to guide the population towards optimal or near-optimal solutions for complex problems that might be difficult to address with traditional optimization techniques. Key concepts underpinning most EAs include a population of candidate solutions, a fitness function to evaluate the quality of each solution, a selection mechanism to favour higher-fitness solutions for the next generation, a crossover operator to combine elements from parent solutions, and a mutation operator to introduce diversity. Evolutionary Algorithms excel due to their robustness in handling complex and noisy problems, their ability to perform global searches, their lack of reliance on gradient information, and their suitability for parallel computation. They have proven effective in fields like engineering design, machine learning, resource scheduling, financial modelling, robotics, and image processing.

Table 2.1
Summary of Metaheuristic Algorithms Applied in Chiller Loading Optimization

Algorithm	Inspiration	Solution Representation	Key Operators/Behaviours
Genetic Algorithm (GA) [21]	Natural selection, genetics	Chromosomes (often binary)	Crossover, mutation
Particle Swarm Optimization (PSO) [22]	Bird flocking, fish schooling	Particles in search space	Velocity updates based on personal and swarm best positions
Imperialist Competitive Algorithm (ICA) [23]	Socio-political imperialistic competition	Countries (solutions) grouped into empires	Assimilation, revolution, and competition among empires
Cuckoo Search (CS) [24]	Brood parasitism of cuckoo birds	Cuckoo eggs	New eggs (solutions) replacing less optimal ones
Barnacle Mating Optimizer (BMO) [3]	Barnacle mating behaviour	Individual barnacles	Mating selection based on reproductive organ lengths

2.6 Genetic Algorithm (GA)

Genetic Algorithms (GAs) are a subset of evolutionary algorithms used in computational science to find optimized solutions to search and optimization problems. These algorithms mimic the process of natural selection, where the fittest individuals are selected for reproduction to produce offspring of the next generation[30], [31].

Genetic algorithms operate through a cycle of stages that simulate the evolutionary process of natural selection, drawing inspiration from Charles Darwin's theory. The algorithm begins by generating an initial population of candidate solutions to a problem, each represented by a set of parameters or configurations. This population undergoes evaluation where each individual's fitness, or how well it solves the problem, is assessed using a predefined fitness function. The core of the algorithm lies in selecting the fittest individuals to produce offspring for the next generation. This selection process ensures that the traits of the best solutions are more likely to be passed on. Offspring are generated through crossover (or recombination), where segments of the genetic information from two or more parents are combined, and through mutation, where random changes are introduced to individual offspring to maintain genetic diversity within the population.

A new generation is formed, often by replacing some or all of the older generation with new offspring, although some algorithms retain a mix of both, to prevent loss of potentially good solutions. This process of selection, crossover, and mutation repeats for a specified number of generations or until a satisfactory solution emerges.

2.6.1 Parameters use for Genetic Algorithm

Table 2.2
Parameter for Genetic Algorithm

Parameter	Description
Population Size	The total number of individual solutions in each generation. It impacts on the algorithm's exploration and exploitation capabilities.
Fitness Function	A function that evaluates the quality or fitness of a solution. It guides the selection of individuals for reproduction.
Selection Method	The strategy used to choose individuals for reproduction based on their fitness. Common methods include roulette wheel selection and tournament selection.

Crossover Rate	The proportion of the population that will undergo crossover to produce offspring. It affects the introduction of new genetic combinations.
Mutation Rate	The probability of altering each gene during mutation. It maintains genetic diversity and helps prevent premature convergence.
Termination Criteria	Conditions under which the genetic algorithm stops running. This could be after a set number of generations or once a satisfactory fitness level is achieved.

The table above outlines key parameters that influence the operation and effectiveness of genetic algorithms (GAs). Each parameter plays a vital role in the evolutionary process, impacting how solutions evolve over generations towards an optimal or satisfactory outcome

2.6.2 Pseudocode for Genetic Algorithm

Table 2.3
GA Pseudocode

Algorithm 1 Pseudocode for Genetic Algorithm

```
Initialize population
Evaluate fitness of population

While termination condition not met:
    Select parents
    Perform crossover on parents to create offspring
    Perform mutation on offspring
    Evaluate fitness of offspring
    Select individuals for the next generation
    Update population with the new generation

Output the best solution found
```

This pseudocode outlines the fundamental steps of a Genetic Algorithm (GA). It begins by initializing a population of candidate solutions, usually encoded as chromosomes. The fitness of each solution is then evaluated using a fitness function. To evolve the population, the algorithm enters a loop that continues until a termination condition is met (for example, a maximum number of generations or a satisfactory solution is found). Within the loop, parent solutions are selected based on their fitness. Crossover and mutation operators are applied to these parents to create new offspring. The fitness of the offspring is evaluated, and the best individuals from the combined pool of parents and offspring are chosen to form the next generation. Finally, the best solution discovered during the entire process is presented as the output.

2.6.3 Chiller-Specific GA Implementation

Genetic Algorithms (GAs) have shown significant success across a broad spectrum of optimization problems due to their robust and versatile nature. Unlike traditional optimization methods that may require assumptions about the problem's statistical distributions, GAs thrive without such prerequisites, making them particularly effective in scenarios where problem spaces are large, rugged, or otherwise complex. Their flexibility in model specification and effectiveness with non-stationary data allows for the exploration of solutions that might be inaccessible to other methods. One of the areas where GAs have been particularly impactful is in the optimization of Heating, Ventilation, and Air Conditioning (HVAC) systems, where they have been used to optimize the operations of chiller units, among other components.

A notable application of GAs in the optimization of HVAC systems is their use in chiller loading operations. In a study focused on optimal chiller loading (OCL) by GAs, the traditional method using the Lagrangian method was outperformed by GAs, especially at low demand levels where the former might not converge [27]. The study involved encoding the Part Load Ratios (PLR) of chiller units into binary code chromosomes and executing reproduction, crossover, and mutation operations. The results indicated not only a solution to the convergence issue but also the achievement of high accuracy and rapid results, making GA a highly recommendable method for such applications. This application underscores the GA's strength in handling complex, non-linear optimization problems, offering significant improvements in energy efficiency and operational effectiveness.

Despite these strengths, the implementation of GAs is not without challenges. GAs can be computationally intensive and time-consuming, which might limit their practicality in real-time systems or environments where computational resources are constrained. Additionally, they may sometimes only achieve modest gains in prediction accuracy, especially when used in conjunction with other methods such as neural networks. These weaknesses highlight the importance of ongoing research into making GAs more efficient and effective, particularly through improved selection methods, exploitation of parallelism, and better parameter configuration.

2.7 Barnacle Mating Optimizer

The Barnacle Mating Optimizer (BMO) draws inspiration from the unique mating behaviour of barnacles, which are sessile creatures with a distinctive reproductive strategy. Barnacles, being fixed in one place for the majority of their life, have developed a remarkable mating mechanism where they utilize long penises, up to eight times their body length, to reach out to nearby mates. This biological phenomenon has been abstracted into an algorithmic form to solve optimization problems by mimicking the barnacles' method of finding and selecting mates based on the distance, which correlates to the exploration and exploitation phases in optimization terms [4].

BMO incorporates concepts such as the *pl* to determine the reach or the scope of solution exploration within the search space, effectively balancing between exploring new potential solutions (global search) and exploiting the current promising areas of the search space (local search). The algorithm initiates with a population of solutions, iteratively updating this population by mimicking the mating process. Solutions are selected as parents based on their fitness and the distance criteria, leading to the generation of offspring solutions. The iterative process aims at enhancing the quality of solutions with each generation, moving towards optimal solutions for the given optimization problem.

2.7.1 Parameter Use for Barnacle Mating Optimizer

Table 2.4
Parameter for Barnacle Mating Optimizer

Parameter	Description
Population size (N)	The number of candidate solutions in the population.
Max generations (Gmax)	The maximum number of generations (iterations) the algorithm runs for.
Spermcasting Probability *(pl)*	The probability of direct sperm transfer to nearby barnacles, enhancing local search capability.

2.7.2 Pseudocode for Barnacle Mating Optimizer

The provided pseudocode outlines the process for the Barnacle Mating Optimizer (BMO), an algorithm that mimics barnacle reproduction to solve optimization problems. Initially, a population of barnacles is created with random solutions, and their fitness is evaluated. The algorithm iterates, where each barnacle's probability of mating is determined by its fitness, akin to how barnacles use the length of their reproductive organ. Mating pairs are chosen based on these probabilities, prioritizing those with higher fitness. Offspring are produced using crossover, combining features from both parents, and mutation, introducing variability. These offspring are then added to the population, and their fitness is evaluated. The algorithm applies the principle of survival of the fittest to select the top individuals for the next generation, and it may include elitism to retain the best solution found so far. This process repeats until a termination condition is met, and the algorithm outputs the best solution discovered.

Table 2.5
Pseudocode for Barnacle Mating Optimizer

Algorithm 2 Pseudocode for Barnacle Mating Optimizer

```
Initialize population of barnacles with random solutions
Evaluate fitness of each barnacle

While termination condition not met:
    For each barnacle in the population:
        Calculate mating probability based on fitness (reproductive organ len
analogy)

    Perform mating selection based on probabilities:
        Select pairs of barnacles for mating with a preference for those wit
higher fitness (longer "reproductive organ lengths")
        Generate offspring through:
            - Crossover: Combine features of parents to create new solutions
            - Mutation: Introduce small random changes to offspring for dive

    Place offspring in the population
    Evaluate fitness of the entire population including offspring

    Apply survival of the fittest:
        Select the best fit individuals from the current population to form
new generation

    Optionally, apply elitism to ensure the best solution is carried over

Output the best solution found
```

2.7.3 Key Contributions of BMO in Solving Optimization in Chiller Loading problem

The paper on the Barnacles Mating Optimizer (BMO) algorithm presents an innovative approach to solving the optimal chiller loading (OCL) problem [3], which is crucial for minimizing energy consumption in multi-chiller systems. The BMO algorithm is inspired by the unique mating behaviour of barnacles in nature, specifically their capacity to stretch their penises several times their body length to reach mates. This biological phenomenon is modelled to optimize the partial load ratios (PLRs) of chillers in a way that minimizes total power consumption. The algorithm employs a mix of exploitation (direct mating) and exploration (sperm-cast or broadcasting sperm to the water) strategies to navigate the solution space effectively, which mirrors the two modes of barnacle reproduction.

The significance of this research lies in its application to a practical and highly relevant problem in building management systems—energy-efficient chiller operation. The paper demonstrates that the BMO algorithm can outperform existing methods like the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in terms of energy efficiency. The results of the study show that BMO can achieve significant energy savings by optimizing chiller loads more effectively compared to traditional methods. The ability of BMO to adapt its search strategy dynamically, mimicking the dual reproductive strategies of barnacles, provides it with a robust mechanism for finding optimal or near-optimal solutions to complex optimization problems in real-world applications. This makes it a noteworthy contribution to the field of evolutionary computation and its application in engineering optimization problems.

To ensure that reported improvements are comparable across studies, performance should be assessed using explicit, quantitative metrics such as total power consumption (kW), specific energy (kW/RT or kW/ton), coefficient of performance (COP), daily/annual energy (kWh), and cost impact (RM) under the stated tariff structure. When discussing algorithm superiority, convergence metrics best/mean/std over multiple runs, iteration-to-threshold and feasibility rate constraint satisfaction frequency should also be reported to avoid conclusions based solely on single-run best cases.

2.8 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution regarding a given measure of quality. It solves a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity [22]. Each particle's movement is influenced by its local best-known position but is also guided toward the best-known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions. PSO is inspired by the social behaviour of birds within a flock or fish within a school. Just as birds might fly in somewhat coordinated ways when migrating or foraging, the PSO algorithm simulates this kind of social behaviour to solve optimization problems. The algorithm was developed in 1995 by James Kennedy and Russell Eberhart and was initially intended to simulate the graceful but unpredictable choreography of a bird flock

2.8.1 Parameter use for Particle Swarm Optimization

Table 2.6
Parameter for Particle Swarm Optimization

Parameter	Description
Population Size	The number of particles in the swarm.
Dimensions	The number of variables to be optimized in the problem.
c1 (Cognitive Component)	Acceleration coefficient that represents the particle's cognition toward its personal best.
c2 (Social Component)	Acceleration coefficient that represents the particle's social behaviour toward the global best.
w (Inertia Weight)	A factor that determines the contribution of the particle's previous velocity to its current one.
Max Velocity	The maximum allowed velocity for particles, which prevents them from flying too fast
Position Limits	The upper and lower bounds for the particle's position in the search space.

Max Iterations	The maximum number of iterations before the algorithm terminates

The table above outlines key parameters that influence the operation and effectiveness of Particle Swarm Optimization (PSO). Each parameter plays a crucial role in guiding the swarm behaviour, impacting how solutions are explored and exploited in the search space towards an optimal or satisfactory outcome

2.8.2 Pseudocode for Particle Swarm Optimization

The pseudocode represents the process of a Particle Swarm Optimization (PSO) algorithm. It begins by initializing a swarm of particles with random positions and velocities and evaluating the fitness of each particle. The algorithm then enters a loop where it updates the personal best positions if the current positions are superior and identifies a global best from all personal bests. Within a termination loop, it repeatedly updates the velocity and position of each particle based on both personal and global bests, evaluates their fitness, and updates the personal and global bests as needed. This process continues until a termination condition is met, after which it outputs the best solution found.

Table 2.7
PSO Pseudocode

Algorithm 3 Pseudocode for Particle Swarm Optimization

```
Initialize swarm of particles with random positions and velocities
Evaluate fitness of each particle

For each particle in the swarm:
    Update personal best if current position is better

Update global best from all personal bests

While termination condition not met:
    For each particle:
        Update velocity based on personal best and global best
        Update position based on velocity
        Evaluate fitness
        Update personal best if current position is better
        Update global best if required

    Output the best solution found
```

2.8.3 Particle Swarm Optimization Applied to Optimization in Chiller Loading Problem

The paper "A Novel Approach for Optimal Chiller Loading Using Particle Swarm Optimization"[25] explores new methodologies for solving the Optimal Chiller Loading (OCL) problem, crucial in large, air-conditioned buildings where chillers are significant energy consumers. The study introduces continuous Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) as alternatives to conventional optimization methods, which struggle with precision and computational intensity due to the continuous nature of chiller system variables.

The research employs the Partial Load Ratio (PLR) of chillers as the optimization variable, with the power consumption of chillers serving as the fitness function. Both PSO and continuous GA methods have been shown to efficiently determine the optimal solution while precisely satisfying the equality constraint of the cooling load demand. The main advantages of these approaches over traditional methods include rapid convergence, avoidance of local optima, ease of implementation, and solution independence from the initial problem setup.

The paper presents a detailed analysis of these methods, with a specific focus on the PSO process. The PSO algorithm is lauded for its robustness and efficiency in dealing with real-valued optimization problems and is shown to be particularly suitable for the continuous nature of the OCL problem. The PSO technique is applied to a case study, revealing its capacity for quick convergence and high precision in finding the optimum chiller load distribution with minimal error.

2.9 Cuckoo Search

The Cuckoo Search (CS) algorithm, another bio-inspired optimization technique, draws its inspiration from the brood parasitism behaviour of some cuckoo species. This algorithm's ability to efficiently navigate complex solution spaces using Lévy flights—a mathematical representation of the irregular flight patterns of birds—makes it particularly relevant to this research [24]. As the development of a novel optimization approach combining Genetic Algorithms with Barnacle Mating Optimization (BMO), it is insightful to compare these methodologies with CS. Both CS and BMO employ unique strategies derived from natural behaviours which is they are both bio-inspired algorithm to solve optimization problems, which offers valuable perspectives on the adaptability and efficiency of bio-inspired algorithms in optimizing chiller system operations.

2.9.1 Parameter use for Cuckoo Search

Table 2.8
Parameter use for Cuckoo Search

Parameter	Description
Population Size, *n*	The number of solutions (nests) in the population.
Discovery Rate, *pa*	The probability of discovering an alien egg. This represents the fraction of the worst nests to be abandoned and new ones built
Lévy Flights	This is a mechanism for generating new solutions, modelling the cuckoo's flight behaviour. It allows the algorithm to make long jumps across the solution space for efficient exploration.

Cuckoo Search utilizes these parameters to balance exploration and exploitation, ensuring efficient navigation through the solution space to find global optima for various optimization problems.

2.9.2 Pseudocode for Cuckoo Search

Table 2.9
Cuckoo Search Pseudocode [24]

Algorithm 4 Pseudocode for Cuckoo Search

```
Initialize a population of cuckoo nests with random solutions
Evaluate the fitness of the nests

While termination condition not met:
    For each cuckoo:
        Generate new solution (egg) by performing Lévy flights
        Choose a random nest to lay the egg
        If the new solution is better than the worst solution in
            Replace the worst solution in the nest with the new

    Perform a fraction (pa) of the worse nests with new solution
    Evaluate the fitness of all new solutions and nests

    Apply a greedy selection strategy to keep the best solutions

Output the best solution found
```

Upon the generation of new solutions, their fitness is assessed, and a Darwinian selection process ensues. Superior solutions are retained, effectively replacing the less viable ones, akin to a cuckoo's egg usurping the place of a host's egg. To further enhance the algorithm's exploratory capabilities, a fixed proportion of the least fit solutions are periodically abandoned—reflecting the scenario where host birds detect and eliminate the foreign eggs. New solutions are then introduced to these vacated spots, simulating the cuckoo's relentless quest for unguarded nests.

A particularly critical parameter in this algorithm is the discovery rate (pa), dictating the frequency at which nests are abandoned and new ones are established. This parameter plays a pivotal role in balancing the exploration and exploitation phases within the algorithm, ensuring a dynamic adaptation to the problem landscape. A higher discovery rate promotes exploration, encouraging the algorithm to scout new areas of the search space, while a lower rate favours exploitation, intensifying the search around the currently promising areas.

2.9.3 Cuckoo Search Applied to Optimization in Chiller Loading Problem

In the paper "Optimal Chiller Loading for Energy Conservation Using a New Differential Cuckoo Search Approach,"[24] the authors address the challenge of optimizing the operation of multi-chiller systems in heating, ventilation, and air-conditioning (HVAC) systems to minimize energy consumption while satisfying cooling demands. The paper introduces a novel approach utilizing an improved cuckoo search algorithm (CSA) enhanced by a differential operator, termed Differential CSA (DCSA), to solve the optimal chiller loading problem. This approach is motivated by the need for efficient energy management in HVAC systems, particularly in multi-chiller configurations, which are among the primary energy consumers in such setups.

The authors begin by outlining the significant energy consumption attributed to improperly managed multi-chiller systems and the potential for energy savings through optimized chiller operations. The cuckoo search algorithm, inspired by the brood parasitism of some cuckoo species and the Levy flight behaviour of certain birds and fruit flies, is initially described. The classical CSA has shown promise in solving various optimization problems, but it faces challenges like premature convergence and insufficient local exploration capabilities.

To address these issues, the authors propose the DCSA, incorporating a differential operator to enhance the algorithm's local search abilities and prevent premature convergence. This novel approach aims to find the optimal partial load ratios (PLRs) for chillers to minimize total energy consumption under operational constraints, ensuring the cooling demand is met. The effectiveness of the DCSA is validated through three case studies involving different numbers of chillers and cooling load scenarios. The performance of the DCSA is benchmarked against classical CSA and other optimization techniques from the literature, demonstrating its superior capability in finding more energy-efficient chiller loading configurations.

The results from these case studies illustrate the DCSA's efficiency and effectiveness in reducing energy consumption for multi-chiller systems, outperforming existing methods, including the classical CSA, in terms of energy savings and optimization performance. The authors conclude by highlighting the promising results of the DCSA approach for optimal chiller loading problems and suggest future work to explore multi-objective versions of the CSA and DCSA with diversity control mechanisms.

In comparison to DCSA (Dynamic Cuckoo Search Algorithm), BMO offers a distinct exploration-exploitation mechanism driven by local normal-copulation for exploitation and long-range sperm-cast events for exploration. This dual-mode search can improve robustness against premature convergence by injecting global-search moves when the population stagnates, while still retaining strong local refinement. In the thesis, explicitly define DCSA, state the common evaluation metric (kW or kW/RT), and explain under which operating conditions BMO/GA-BMO provides an advantage (mid-load regimes with higher PLR flexibility).

The difficulty in directly hybridizing Cuckoo Search (CS) with GA in this study arises from differences in how the two methods generate new candidate solutions and maintain population structure. GA relies on selection and recombination (crossover/mutation) across a population, whereas CS heavily depends on Levy-flight-based sampling and nest replacement controlled by discovery probability (p_a). Without careful operator design, combining both can either disrupt GA exploitation by overwriting offspring too aggressively (excessive nest abandonment) or reduce CS exploration if GA operators dominate. Therefore, a hybrid requires a clearly defined integration point (for example, CS as a mutation-like operator or a secondary exploration phase) and consistent constraint-repair handling; this study instead selected

BMO as the embedded operator because its mating mechanisms map more naturally to GA-style population updates.

2.10 Imperialistic Competitive Algorithm

The Imperialist Competitive Algorithm (ICA) is a socio-politically inspired metaheuristic algorithm introduced by Atashpaz-Gargari and Lucas in 2007 [23]. Unlike bio-inspired algorithms such as GA or PSO, ICA simulates the process of imperialistic competition, where a number of countries (candidate solutions) compete to form the most dominant empire. Stronger countries act as imperialists and attract weaker ones (colonies) through assimilation and revolution processes. Over time, empires compete, and weaker ones collapse while stronger ones expand, leading the population toward global optimum convergence.

In the context of optimization, ICA has gained attention due to its structured balance between exploration (via revolution and randomization) and exploitation (through assimilation). It is particularly useful for problems where local optima are abundant, as its revolution mechanism allows for regular diversification of the solution space.

2.10.1 Parameters Used for Imperialist Competitive Algorithm

Table 2.10
Parameters use for Imperialist Competitive Algorithm

Parameter	Description
Number of Countries	The number of particles in the swarm.
Number of Imperialists	The number of variables to be optimized in the problem.
Max Iterations	Acceleration coefficient that represents the particle's cognition toward its personal best.
Assimilation Coefficient	Acceleration coefficient that represents the particle's social behaviour toward the global best.
Assimilation Angle Coefficient	A factor that determines the contribution of the particle's previous velocity to its current one.
Revolution Rate	The maximum allowed velocity for particles, which prevents them from flying too fast

These parameters were carefully selected based on convergence behaviour and constraint adherence for dynamic chiller load optimization.

2.10.2 Pseudocode for Imperialist Competitive Algorithm

Table 2.11
Pseudocode for Imperialist Competitive Algorithm

Algorithm 5 Pseudocode for Imperialist Competitive Algorithm

```
Initialize population of countries (candidate solutions) randomly
Evaluate fitness of each country (solution)
Select top countries as imperialists; assign others as colonies

While stopping condition not met:
    # Assimilation
    For each colony:
        Move colony toward its imperialist
        Apply random deviation (assimilation angle)
        Adjust solution to meet PLR bounds and load constraints

    # Revolution
    For each colony:
        With certain probability, replace with random solution

    # Imperialist Update
    For each empire:
        If a colony performs better than imperialist, exchange roles

    # Imperialistic Competition
    Evaluate total empire powers
    Transfer weakest colony from weakest empire to strongest one
    Remove collapsed empires (those with no colonies)

Return the best imperialist as the optimal solution
```

The study by Jabari et al. (2020) [23] applied the Imperialist Competitive Algorithm to the Optimal Chiller Loading (OCL) problem in multi-chiller plants. The goal was to minimize hourly electrical power consumption by optimizing the on/off status and Partial Load Ratios (PLRs) of chillers under varying cooling demands. The ICA-based approach modelled each potential chiller operation scenario as a "country," with imperialists representing promising solutions and colonies representing alternatives.

The optimization was conducted on three benchmark systems with 3, 4, and 6 electric chillers, respectively. The ICA algorithm showed faster convergence and superior energy savings compared to other methods such as GA, PSO, ES, DE, DCSA, and IWO. For example, under a 5717 RT cooling load, the ICA strategy reduced power consumption from 3840.05 kW (found by DCSA) to 3789.99 kW, translating to an annual energy saving of over 438,000 kWh.

Additionally, the ICA approach balanced refrigeration production more effectively by considering the unique power coefficients of each chiller. It identified favourable PLR combinations that respected all operating constraints while reducing total energy use. The results affirmed ICA's effectiveness in identifying energy-efficient chiller dispatch strategies under both deterministic and uncertain conditions.

2.11 Parameter Settings Used in This Study for Algorithm Benchmarking

The algorithms evaluated in this study are listed in Table 2.12. Each of these metaheuristic optimization techniques was applied to optimize chiller load distribution in a multi-chiller system. The Genetic Algorithm (GA) [21] and Particle Swarm Optimization (PSO) [22] are widely adopted in HVAC energy optimization tasks due to their strong global search capabilities. The Imperialist Competitive Algorithm (ICA) [23] and Cuckoo Search (CS) [24] offer alternative evolutionary and exploratory strategies, particularly for constrained engineering problems. The Barnacle Mating Optimizer (BMO) [3], a more recent nature-inspired algorithm, was included for its proven efficiency in exploitation and local refinement. These references serve as the foundational studies for the algorithm configurations and implementations used throughout this researc

Table 2.12
Parameter Settings for Compared Algorithms

Algorithm	Parameter(s)	Value(s)
Genetic Algorithm (GA) [21]	Population Size	50
	Crossover Fraction	0.8
Barnacle Mating Optimizer (BMO) [3]	Population Size	30
	Max Iterations	50
	Spermcast Probability (pl)	0.5
Particle Swarm Optimization (PSO) [22]	Swarm Size	50
	Max iterations	400
	Inertia Weight (w_{max}, w_{min})	0.9, 0.4
	Cognitive & Social Coefficients (c1, c2)	2, 2
Imperialist Competitive Algorithm (ICA) [23]	Number of Countries	75
	Number of Imperialists	10
	Max Iterations	200
	Assimilation Coefficient	2
	Revolution Rate	0.1
Cuckoo Search (CS) [24]	Number of Nests	30
	Max iterations	50
	Discovery Rate (pa)	0.25
	Levy Flight Parameter (β)	1.5

2.12 Summary

Table 2.13
Comparison Review between Algorithms

Area of Study	Method	Finding	Advantages	Disadvantages	Overcoming Weaknesses with GA-BMO
Optimal Chiller Loading with ICA [26]	Imperialist Competitive Algorithm (ICA)	Demonstrates superior energy savings and convergence compared to GA, PSO, SA, ES, DE, DCSA, and IWO in multi-chiller systems across various cooling load levels	Fast convergence; strong local search due to empire competition; well-balanced exploration and exploitation; effective for mixed-integer nonlinear problems	May stagnate if diversity is lost early; performance sensitive to parameter tuning; lacks adaptive evolution over generations	While ICA effectively balances exploration and exploitation, it may stagnate in later iterations due to reduced diversity. GA-BMO addresses this by using GA's crossover and mutation to reintroduce diversity and BMO's sperm casting for local refinement, ensuring convergence continues toward global optima under dynamic chiller load scenarios.
Optimal Chiller Loading by Genetic Algorithm[27]	Genetic Algorithm (GA)	Highly accurate and fast results in optimal chiller loading	Overcomes non-convergence issues at low demand; fast execution speed	Requires careful setup of parameters and initial conditions	Genetic Algorithms (GAs) require careful parameter setup and initial conditions, which can be a limitation. The GA-BMO method incorporates adaptive parameter tuning mechanisms where parameters such as mutation rates and crossover probabilities are dynamically adjusted based on the current state of the search process. This reduces the sensitivity to initial

					parameter settings and improves overall robustness.
Optimal Chiller Loading by Cuckoo Search Approach[28]	Cuckoo Search Algorithm	Superior performance in energy optimization for chillers compared to AVL, SA, PSO and ES	Efficiently handles multiple types and characteristics of chillers; versatile in application	Potentially slower convergence compared to other methods	The Cuckoo Search (CS) algorithm, although efficient in handling complex problems, has a slower convergence speed. The hybrid nature of GA-BMO leverages the fast convergence of GAs with the precision of BMO. The initial population generated by GA undergoes rapid convergence towards promising regions, which BMO then exploits and refines, thus speeding up the overall convergence process.
Optimal Chiller Loading by BMO Algorithm[3]	Barnacle Mating Optimization (BMO) Algorithm	Superior performance in energy optimization for chillers compared to PSO, ICA, AGSO,	High efficiency in handling complex variables and operational settings	Complexity in understanding and implementing the mating mechanism	Barnacle Mating Optimization can be complex to understand and implement due to its unique mating mechanism. GA-BMO simplifies this by using GA to handle broad exploration and applying BMO's mating mechanisms only in the latter stages of the optimization. This phased approach reduces the complexity of implementation while retaining the benefits of BMO's precision.
Optimal Chiller Loading with PSO [25]	Particle Swarm Optimization (PSO)	Superior performance in energy optimization for chillers compared to	Based on social behaviours of bird flocks, simple to implement; effective in diverse settings	Less effective than newer algorithms in some complex optimization tasks	Particle Swarm Optimization (PSO) tends to get trapped in local optima and faces challenges in parameter tuning. GA-BMO addresses this by initializing with a diverse population using GA's crossover and mutation operators, preventing premature convergence. The hybrid approach also means that the parameter tuning of PSO can be

	Binary GA and Continuous GA	mitigated by the adaptive nature of the GA- BMO framework, which adjusts strategies dynamically.

Table 2.13 presents a comparative review of various optimization algorithms including bio-inspired and evolutionary-based techniques applied to chiller loading systems. The proposed GA-BMO method aims to combine the strengths of Genetic Algorithms (GA) and Barnacle Mating Optimization (BMO) while addressing their individual weaknesses as well as those of other methods. Compared to standalone approaches, GA-BMO offers improved convergence speed, enhanced robustness against premature convergence, and dynamic adaptability under varying operational loads. Its hybrid nature allows efficient initial global search via GA and precise local refinement via BMO, making it particularly well-suited for optimizing multi-chiller systems that operate under dynamic and non-linear conditions. These advantages make GA-BMO the most appropriate and effective strategy for achieving high energy efficiency, stable control, and cost reduction in this study.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Introduction

Chapter 3 of this proposal, 'Research Methodology', is a deep dive into the systematic processes employed to pursue the objectives laid out in this study. It encapsulates the blueprint of our research design, data collection methods, sampling strategies, and the analytical tools that will be employed. The methodology is underpinned by a hybrid genetic algorithm, integrated with a barnacle mating optimization approach, aimed at enhancing the energy efficiency of chiller systems. This chapter will elaborate on the rationale behind the choice of methods, the implementation of the dynamic scheduling system, and how data will be gathered and analysed to test the hypotheses. It will also discuss the protocols for ensuring the accuracy, reliability, and ethical compliance of the research, setting the stage for empirical validation of the proposed optimization strategies.

3.2 Objective Summary

Figure 3.1 outlines a structured project flow that starts with a comprehensive literature review and background study, followed by an investigation into the factors influencing chiller performance. This initial phase paves the way for the development of a novel Hybrid Genetic Algorithm enhanced by Barnacle Mating Optimization, with the goal of optimizing chiller performance as its first major milestone. As the project advances into the second phase, this innovative algorithm is implemented, creating a practical application for the theoretical work completed in phase one. The implementation's efficacy is then thoroughly evaluated to ensure it meets the second objective, which focuses on the algorithm's performance and potential improvements.

In the final phase, the project shifts towards the creation of a dynamic scheduler and dashboard designed for real-time monitoring, indicating a move from theoretical development to applied technology. This phase involves an in-depth performance study, after which the system undergoes rigorous testing, evaluation, and analysis to assess its efficiency and effectiveness, thus addressing the third and final objective. The culmination of this project is marked by the documentation of the entire process and the publication of a paper, summarizing the research, development, and evaluations conducted throughout the project's lifecycle. Each phase is methodically designed to build upon the previous work, leading to a systematic and goal-oriented progression towards enhancing the performance of chiller systems through advanced optimization techniques.

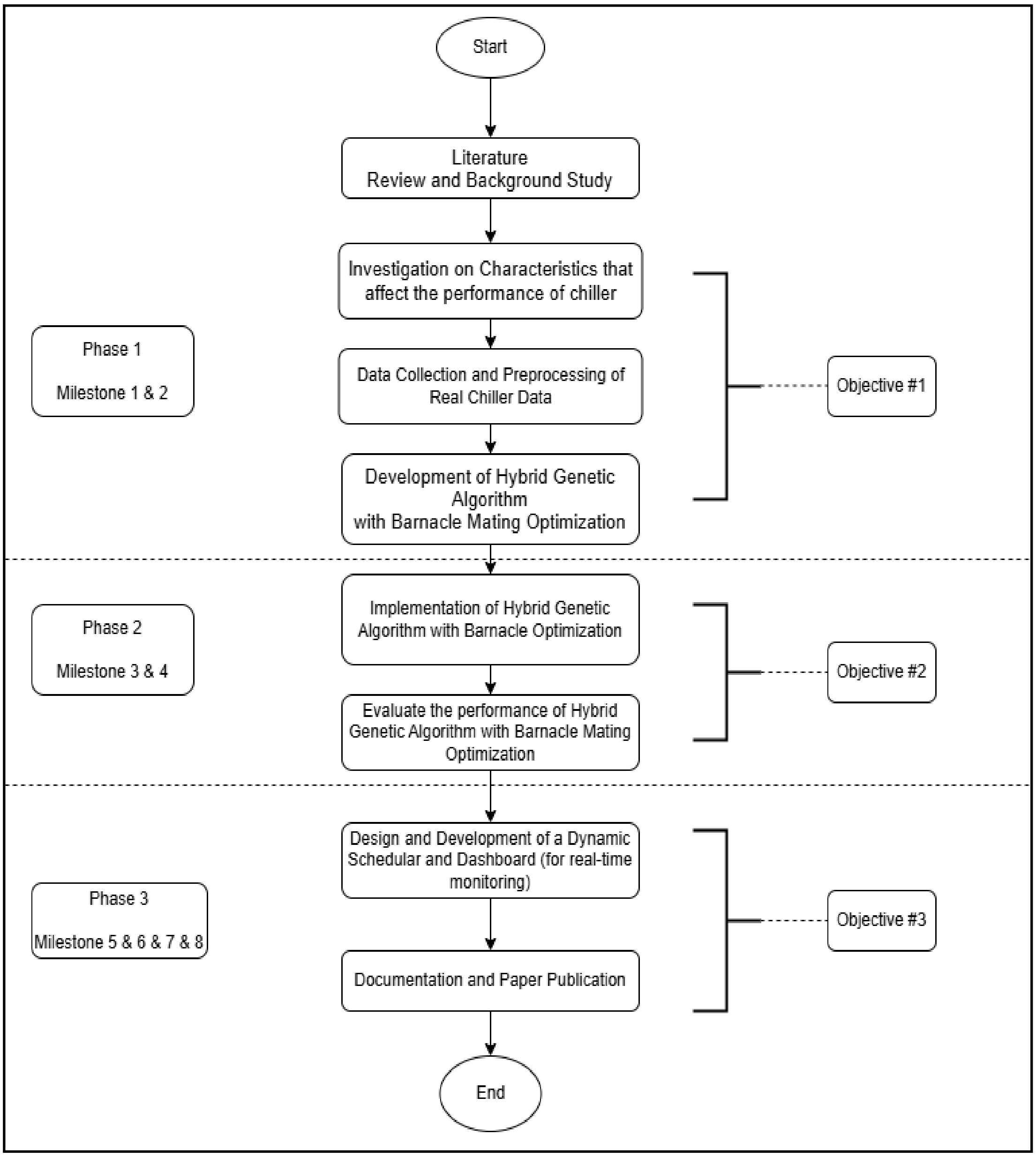

Figure 3.1: Overview of Research Framework

3.3 Conceptual Diagram

Having reviewed the operational principles and components of the chiller system in the previous section, this section presents the conceptual diagram of the system architecture used in this study. This diagram provides a structural overview of the multi-chiller configuration, highlighting how the primary and secondary loops operate to deliver chilled water efficiently across the distribution network.

The multi-chiller system shown in Figure 3.2 consists of more than one chiller connected by series or parallel piping to a distribution system. In the primary cycle, electrical power is consumed by the pump to increase the pressure of water flowing in the chiller, resulting in efficiency improvement of the refrigeration cycle. The pressure of chilled water flow is controlled by the secondary cycle pump. The chilled water then enters the cooling coils, and the heat is absorbed before returning to the primary cycle pumps. The best performance of the chiller system can be obtained by minimizing the sum of energy consumption.

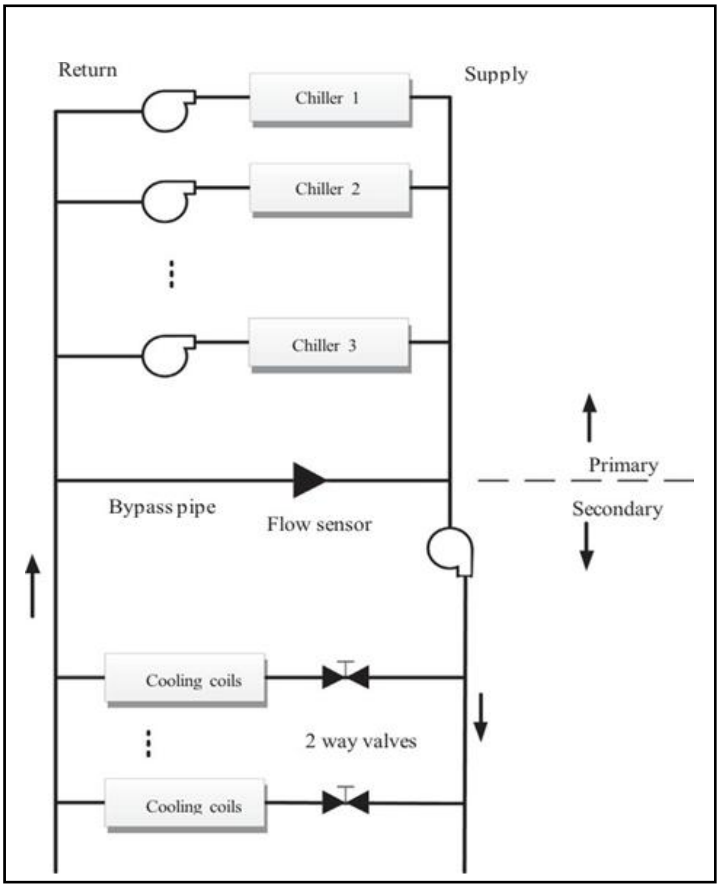

Figure 3.2: A simplified illustration of a standard multiple-chiller plant with water cooling

The current study investigates the cooled chiller system installed at the Nuclear Agency Malaysia in Bangi, Selangor. The Nuclear Agency Malaysia utilizes three TRANE water-cooled chillers, namely chiller 1, chiller 2, and chiller 3, for its cooling requirements. These chillers, with model number RTHC-IOM-1C, have capacities of 370 tons, 370 tons, and 340 tons, respectively. The operation schedule for the chillers follows a weekly pattern from Monday to Friday.

Table 3.1
Chiller Operation Schedule at Nuclear Agency Malaysia

Chiller	Model Number	Capacity (tons)	Monday	Tuesday	Wednesday	Thursday	Friday
Ch 1	RTHC-IOM-1C	370	On	Off	On	Off	On
Ch 2	RTHC-IOM-1C	370	Off	On	Off	On	Off
Ch 3	RTHC-IOM-1C	340	On	On	On	On	On

Table 3.1 illustrates a predefined operational pattern that has been implemented to ensure cooling reliability and energy management across the facility. This schedule plays a significant role in supporting the current study, as it provides a real-world baseline for evaluating the effectiveness of optimization strategies using GA-BMO. The fixed schedule reveals a pattern where only two out of the three chillers are active on any given day. While this strategy may be intended to save energy and facilitate maintenance planning, it does not necessarily ensure optimal utilization of the system.

From an operational standpoint, this kind of static scheduling introduces a trade-off. On one end, limiting operation to only two chillers at a time conserves energy and extends equipment lifespan. On the other hand, it risks underutilizing available capacity and may compromise system efficiency during peak demand periods. Conversely, running all chillers simultaneously can maximize cooling capacity but may lead to unnecessary energy consumption. Therefore, this research aims to explore an optimized scheduling strategy that intelligently balances three key objectives: energy efficiency, chiller utilization, and thermal comfort. By addressing this trade-off through the GA-BMO optimization approach, the study seeks to enhance the adaptability and sustainability of multi-chiller operations under varying load conditions.

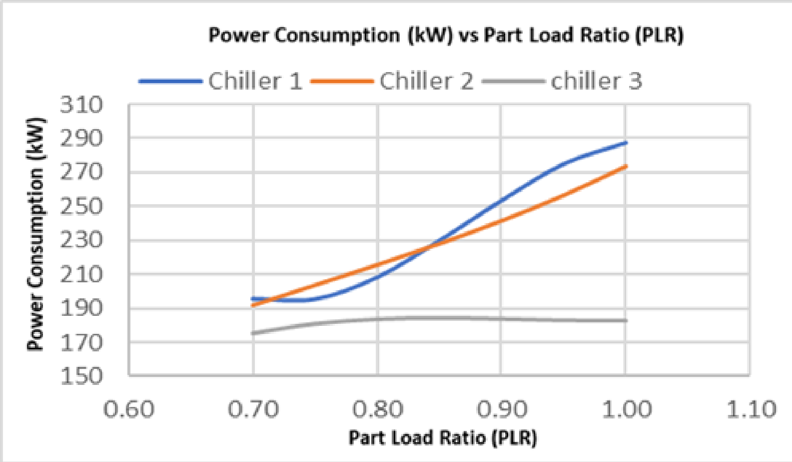

Figure 3.3: Power Consumption (kW) vs Part Load Ratio (PLR)

The analysis of the relationship between Power Consumption and Part Load Ratio (PLR) provides valuable insights into the power consumption variations at different PLR values, as depicted in Figure 3.3. The graph showcases the results obtained from the study, where the x-axis represents the PLR values ranging from 0.70 to 1.00, and the y-axis represents the corresponding Power Consumption (P) values in kilowatts (kW). By analysing the specific data points from the table, we can see the actual values of power consumption at different PLR levels. For example, at a PLR of 0.70, the power consumption is 195.81 kW, whereas at a PLR of 1.00, the power consumption reduces to 287.09 kW. These values provide concrete evidence of the power consumption variations and can be utilized to improve the energy efficiency and performance of the multi-chiller system under different operating conditions.

It is also noteworthy that the power consumption for Chiller 3 remains relatively lower than Chiller 1 and Chiller 2, even at higher PLR values. This behavior can be attributed to the inherent efficiency characteristics of Chiller 3, which may be due to differences in model design, compressor performance, or its rated cooling capacity being slightly lower (340 RT) compared to Chiller 1 and 2 (370 RT each). Additionally, load distribution strategies in the scheduling may prioritize Chiller 3 for partial load scenarios, thus limiting its operation at full capacity.

Table 3.2
Coefficients and Capacity of Respected Chiller

Chiller	a_i	b_i	c_i	d_i	RT
1	4671.5	-16164	19040	-7259	370
2	-257.88	1375.6	-1521.1	677.2	370
3	-658.25	2784.4	-3051.5	1108.1	340

Table 3.2 presents the coefficients and capacity of each chiller, providing a detailed overview of their specifications. The coefficients (,,,) in the table represent the mathematical parameters used to model the chiller performance. These coefficients define the relationship between the cooling capacity, power consumption, and operating conditions of the chillers. Each chiller model may have its unique design, construction, or technology, which can result in variations in the coefficients. Even though chiller 1 and chiller 2 have the same cooling capacity (RT) of 370. This variation in coefficients can be attributed to various factors, such as operating conditions referring Table 3.1 and maintenance practices implemented at Nuclear Agency Malaysia. These factors can impact the internal components, design, and efficiency of the chillers, resulting in differences in their coefficients. Therefore, while the cooling capacity may be the same, the variations in coefficients highlight the influence of specific operational and maintenance practices on the performance and energy efficiency of the chillers.$a_i b_i c_i d_i$

3.4 Data Collection Parameters Validation Techniques

This section outlines the procedures used to collect, structure, and validate the simulation and optimization data generated throughout the implementation of the GA-BMO-based dynamic scheduler. Since this study is primarily simulation-based, data collection focuses on output parameters from MATLAB Simulink, optimization algorithm results, and real-time monitoring logs exported for dashboard visualization. Validation methods were employed shown in Table 3.3 to ensure output consistency, constraint compliance, and the integrity of comparative benchmarking between optimization algorithms.

Table 3.3
Summary of Data Collection Parameters and Validation Techniques

Data Source	Collected Parameters	Collection Method	Validation Method
MATLAB Simulink (Chiller Model)	PLRs, Cooling Load (RT), Power (kW), Total Power, EEWT, ELWT	Logged via updateSimulationData block	Checked against expected value ranges; PLR bounds (0.55–1.00); load match
GA-BMO Optimization Algorithm	Optimized PLRs, Best Fitness, Power Consumption	Stored in MATLAB workspace and CSV export	Full Factorial Design (FFD); Constraint penalties applied
Benchmark Algorithms (GA, PSO, etc.)	Fitness values, PLRs, Total Power for same cooling load scenarios	MATLAB runs using fixed parameters	Identical simulation conditions and cooling demand input
Automation Script Output	Hourly simulation results, Time-stamped logs, Cooling demand mapping	Exported to .csv per hour loop	Manual checks; script debug output; data completeness
Android & Web Dashboards	Displayed KPIs, Load Distribution, System Status, Time-based Graphs	Read from Google Drive CSV files	Manual cross-validation with MATLAB CSV files; Sync timing tests

3.5 Chiller System Configuration Flowchart

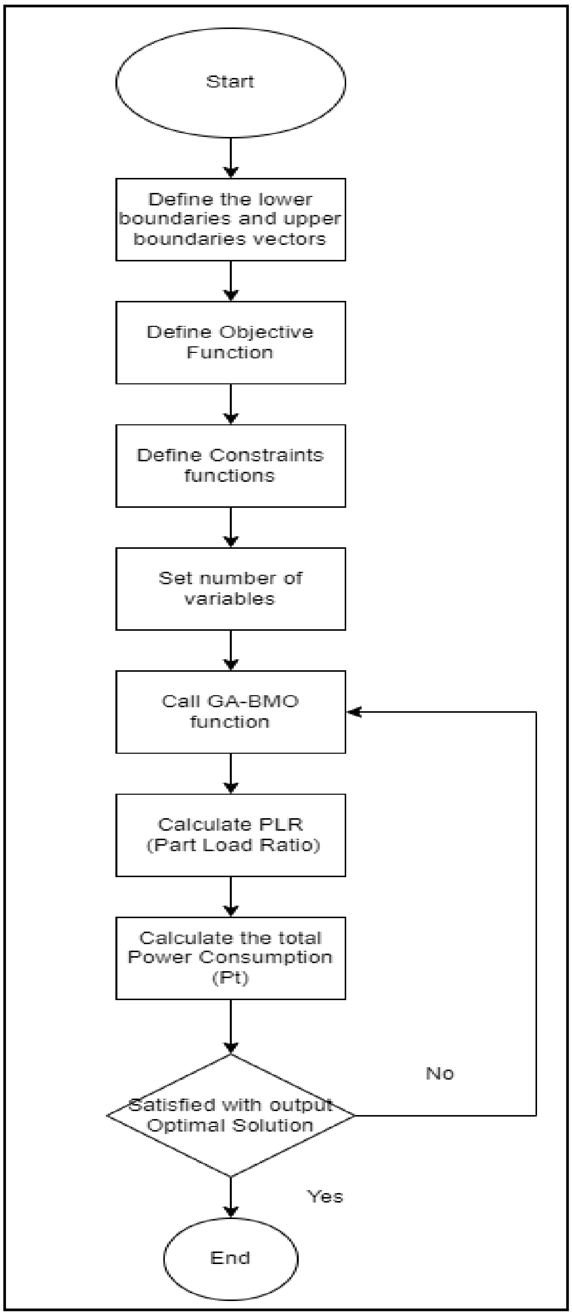

Figure 3.4: Chiller System Configuration Flowchart

Figure 3.4 illustrates the flow chart of the steps for the proposed chiller loading operation optimization investigation. These processes will pre- configure the chiller system for GA-BMO optimization setup. The first step is to define the lower and upper boundary vectors, which set the acceptable range of values for each decision variable in the optimization problem. These boundaries guide the search space of the genetic algorithm hybrid with barnacle mating optimizer.

$$P_i^t = a_i + b_i(PLR_i^t) + c_i(PLR_i^t)^2 + d_i\left(PLR_i^t\right)^3 \tag{1}$$

Next, the objective function (Equation 1) is defined, representing the optimization goal of the problem. The objective function evaluates the fitness of the solution. The P_i^t represents the electrical power consumption of the chiller at a given hour (t). It is the output of the objective function and what we want to minimize. Where a_i, b_i, c_i, d_i These are coefficients specific to each chiller (i). They determine the relationship between the PLR and the power consumption of the chiller. Each chiller may have different coefficients depending on its characteristics and efficiency.

PLR_i^t stands for Partial Load Ratio, where PLR is the fraction of full capacity, 0.00–1.00. A PLR of 1 indicates that the chiller is operating at full capacity, while a PLR of 0.00 means the chiller is not operating at all. The variable represents a particular chiller within a collection of chillers. The variable "t" is associated with time and represents various time periods. It is used to identify the hour at which the cooling capacity of a specific chiller is being calculated. By optimizing the values of the PLR (the variables to be optimized), the objective function aims to minimize the total energy consumption required to meet the cooling load. This optimization process involves finding the PLR values that result in the lowest power consumption for each chiller at each hour.

$$PLR_i^t \times RT_i = CL^t \tag{2}$$

The constraints' function is then defined, representing the limitations or restrictions on the values of the decision variables. The equation provided is used to ensure that the sum of the cooling loads of each chiller in a system satisfies the overall system load. CLt represents the total cooling load required by the system. This is the amount of cooling that the system needs to provide to maintain the desired temperature or meet the cooling requirements of the space.

PLR (Part Load Ratio) is a dimensionless value that represents the operating capacity of the chiller. It is the ratio of the actual cooling load to the chiller's full capacity. For example, if a chiller is operating at 50% of its full capacity, the PLR would be 0.5. RT (Cooling Capacity of Chiller) refers to the cooling capacity of an individual chiller. It is the maximum amount of cooling that a chiller can provide when operating at full capacity. The equation ($PLR \times RT$) = CL expresses the equality constraint that must be satisfied for each chiller in the system. It states that the cooling load of each chiller, calculated by multiplying its part load ratio (PLR) by its cooling capacity (RT), must equal the total cooling load required by the system (CLt).

$$\begin{cases} 0.55 \leq PLR \leq 1 & Chiller\ is\ on \\ 0 & Chiller\ is\ off \end{cases} \tag{3}$$

Chiller ON condition: If a chiller is operating (considered ON), its PLR must be between 0.55 and 1. This means that the chiller should be operating at a capacity utilization level ranging from 55% to 100%. Operating within this range ensures that the chiller is functioning optimally and efficiently. Chiller OFF condition: If the chiller's PLR falls below 0.55, it will be considered OFF. This implies that the chiller is not operating or is operating at a very low-capacity utilization level (less than 55%). When the PLR is below the threshold, the chiller is either shut down or not providing significant cooling capacity.

The variable vars is set to 3. This indicates that the optimization problem has three decision variables. The main genetic algorithm function is then called, which generates a set of candidate solutions based on the objective and constraints functions, as well as the boundaries and integer constraints. The utilization of the GA-BMO function will subsequently be elucidated comprehensively. Following that, the flow moves to the calculation of the chiller system. The PLR is determined by dividing the actual cooling load by the maximum cooling capacity of the chiller. The next step involves calculating the total power consumption (Pt) of the chiller system. To determine the total power consumption (Pt) of the chiller system, the power consumption of each individual chiller (chiller 1, chiller 2, and chiller 3) needs to be added together. This calculation provides the overall power usage required by all three chillers to meet the specific cooling demand

Finally, there is a check to determine if the output optimal solution meets the desired criteria. If it does, the program terminates. However, if the solution is not satisfactory, the algorithm goes back to the GA-BMO function to generate new candidate solutions, repeating the optimization process. This iterative loop continues until an optimal solution that meets the desired criteria is obtained.

3.6 Genetic Algorithm-Barnacle Mating Optimizer through Embedded Operator

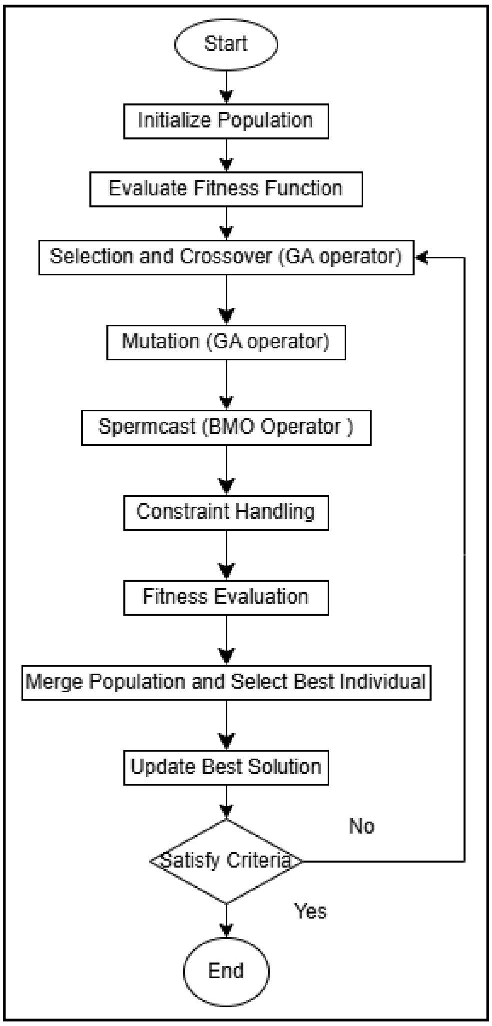

Figure 3.5: Genetic Algorithm-Barnacle Mating Optimizer Flowchart through Embedded Operator

Figure 3.5 illustrates the updated hybrid Genetic Algorithm–Barnacle Mating Optimizer (GA-BMO) flowchart incorporating an embedded BMO operator within the GA evolutionary loop. The optimization process begins by initializing a population of candidate PLRs (Partial Load Ratios). Through each generation, the GA performs selection, crossover, and mutation operations to explore the solution space. This is followed by a BMO-based sperm casting mechanism that introduces local exploitation through barnacle-like adaptive behaviour. The updated population is evaluated using a power-based objective function that includes penalty constraints to satisfy cooling load requirements. The top-performing individuals are retained, and the process continues iteratively until the stopping criteria are met.

The BMO component is embedded into the GA workflow as an operator-based hybrid, where BMO's sperm casting logic is conditionally applied after crossover and mutation. This embedded strategy ensures that BMO exploration complements the GA search without running independently

In the proposed GA-BMO mechanism, GA contributes structured exploitation through selection, crossover, and mutation, while BMO contributes dual search modes: local normal-copulation for exploitation and sperm-cast events for exploration. The BMO operator is embedded as an additional reproduction/exploration step so the optimizer can escape local optima while GA preserves elite solutions. This design directly explains the improved convergence consistency reported in Chapter 4.

3.7 Embedded vs Sequential Hybrid Approach

Table 3.4
Comparison Between Cascading and Embedded Hybrid Optimization Approaches

Aspect	Cascading Approach	Embedded Hybrid Method
Process Description	In a cascading method, the second optimization technique (BMO) is applied sequentially after the first technique (GA) has completed its optimization process.	In this embedded hybrid method, the BMO operators are integrated within the GA cycle. This means that BMO operators (spermcast) are used during the GA process, specifically after the mutation step.
Novelty and Efficiency	Limited novelty value. The BMO refines already optimized solutions from GA, often leading to minimal improvement as GA has already converged.	High novelty value. The integration of BMO within the GA cycle enhances genetic diversity and exploration capabilities, providing continuous improvements throughout the optimization process.
Integration of Techniques	Sequential integration: GA optimization completes before BMO begins.	Embedded integration: BMO operators are embedded within the GA cycle and applied during the GA process.
Advantages	Simplicity in implementation: Each technique is applied independently, making it straightforward to understand and implement.	Enhanced optimization: The continuous use of BMO operators during the GA process leads to a more robust and efficient search for optimal solutions.

Disadvantages	Minimal improvement: As GA often converges before BMO starts, the potential for further optimization is limited. Loss of efficiency: Sequential application may not leverage the full potential of eithertechnique.	Complexity: The embedded approach requires a more complex implementation and understanding of both algorithms. Computational overhead: Integrating BMO within GA may increase computational requirements.
Exploration and Exploitation	Primarily sequential: GA performs initial exploration and exploitation, followed by BMO refinement.	Continuous and integrated: BMO operators enhance GA's exploration and exploitation capabilities throughout the optimization process.
Termination Criteria	The process is divided into two distinct phases, each with its own termination criteria. The BMO phase begins only after the GA phase completes.	Single-phase termination: The embedded method continuously applies GA and BMO operators until the overall termination criteria are met, ensuring a more cohesive and integrated optimization process.

Based on the comparison in Table 3.4, this study adopts the embedded hybrid approach over the cascading method. While the cascading approach offers simplicity, it often results in minimal performance gains due to its sequential nature. In contrast, the embedded hybrid method integrates BMO operators within the GA cycle, enhancing genetic diversity and continuous exploration. This not only improves convergence reliability but also contributes significantly to the novelty of the optimization framework. Therefore, the embedded approach is selected for its superior optimization potential and alignment with the study's objective to develop a robust and efficient multi-chiller control strategy.

3.7.1 Sequential Hybrid Integration (Cascading GA-BMO Approach)

In a cascading method, the second optimization technique (BMO) is applied sequentially after the first technique (GA) has completed its optimization process. This sequential hybrid method involves first running the GA to optimize the solutions. Once GA has finished its optimization and converged, BMO takes the output from GA as its starting point for further optimization.

The main reason this approach is termed "cascading" is due to the distinct separation between the two optimization phases. The GA performs its optimization independently, and only after it concludes does the BMO begin its process. This sequential application often leads to minimal improvement since GA typically converges to a solution that is already close to optimal. As a result, the BMO has limited scope to make significant further improvements, reducing the novelty value of this approach. The lack of continuous interaction between the two techniques means that the full potential of their combined strengths is not realized, leading to a less efficient optimization process overall

3.7.2 Embedded Hybrid Integration (GA with BMO Operator)

In contrast, the embedded hybrid method integrates BMO operators within the GA cycle. This means that BMO operators such as spermcast are used during the GA process, specifically after the mutation step. By embedding BMO operators within GA, the strengths of both techniques are utilized continuously throughout the optimization process. This integration allows BMO to enhance the genetic diversity and exploration capabilities of GA, leading to a more robust and efficient search for optimal solutions. The continuous interaction between GA and BMO ensures that the optimization process benefits from the combined strengths of both techniques, leading to better convergence and more efficient exploration of the solution space. This embedded approach offers higher novelty value and leverages the full potential of both GA and BMO in a cohesive and integrated manner.

3.8 Parameter Configuration of Optimization Algorithm

Table 3.5
Parameter for GA-BMO

Algorithm	Parameter
Genetic Algorithm [30],[31]	Population Size = 25, 81, 138, 194, 250 Crossover Fraction = 0.1, 0.3, 0.5, 0.7, 0.8 Mutation Rate = 0.02 Max Iterations = 300
Barnacle Mating Optimizer [3]	Spermcast Probability = 0.1, 0.2, 0.3, 0.4, 0.5 Constraint Handling: Scaling + Clamping PLR within [0.55, 1.0]

The parameters used in GA-BMO employed in this study are presented in Table 3.5, which outlines the specific settings and configurations utilized to optimize the multi-chiller system. These parameters for Genetic Algorithm were selected based on established literature [30],[31]. For Barnacle Mating Optimizer, the parameters used in this experiment are adapted from the paper [3].

Constraint handling and feasibility repair: To maintain safe and physically meaningful operation, each chiller's partial load ratio PLR_i is bounded by a minimum and maximum value. In this study, PLR_i is constrained to [0.55, 1.00], reflecting a practical lower operating limit where very low loading may lead to poor efficiency and unstable operation.

A repair (clamping) operator is applied after every candidate solution is generated: PLR_i= $0.55 \leq PLR \leq 1.00$, for i = 1,2,3. If any candidate violates the bounds, it is repaired using this equation before evaluating total power. This ensures all evaluated solutions are feasible and comparable. The choice of 0.55 is retained consistently across all benchmark algorithms so that performance differences are attributable to optimization logic rather than differing feasibility rules.

3.9 Performance Evaluation

This section outlines the methodology for evaluating the performance of the proposed Hybrid Genetic Algorithm–Barnacle Mating Optimizer (GA-BMO) in optimizing chiller operations. The evaluation focuses on the algorithm's ability to minimize total power consumption, satisfy cooling load constraints, and maintain operational feasibility across various scenarios. The performance of GA-BMO was assessed through a comprehensive comparative analysis involving several established metaheuristic algorithms, including Genetic Algorithm (GA), Barnacle Mating Optimizer (BMO), Particle Swarm Optimization (PSO), Cuckoo Search (CS), Imperialist Competitive Algorithm (ICA), and Improved Genetic Algorithm (I-GA). This section also consolidates the operational framework and comparative evaluation setup previously placed in Chapter 2.3.

3.9.1 Operational Framework and Comparative Evaluation Setup

The review of these techniques reveals that while traditional methods like PID and fuzzy logic control are straightforward and effective for certain applications, they struggle with the dynamic and non-linear nature of chiller systems. Advanced methods like MPC, GA, PSO, and BMO offer more robust optimization capabilities but come with increased complexity and computational requirements shown in Table 3.6.

Table 3.6
Strengths and Weaknesses of Existing Strategies for Chiller System Optimization

Optimization Technique	**Strengths**	**Weaknesses**
Dynamic Programming [10]	Effectively adjusts operational parameters based on real-time demand, resulting in significant energy savings	Relies heavily on precise performance models, which can be a limitation if models are inaccurate
Variable-Speed Chillers [11]	High efficiency by matching operational speed to cooling load, reducing energy consumption	High initial costs and complexity of implementation
Q-learning [12]	Adapts to varying operational conditions without extensive pre-modeling, making it highly flexible	Computationally complex and requires substantial historical data

Table 3.7
Performance Evaluation Metrics

Metric	Description	Purpose in Evaluation
Total Power Consumption	Sum of electrical power used by all active chillers (kW), computed based on quadratic PLR function	Measures energy efficiency; main optimization objective
Cooling Load Satisfaction	Ensures total output cooling load ($\sum PLR \times RT$) matches required system load	Validates constraint satisfaction under varying load scenarios
PLR Constraint Handling	Ensures each chiller operates within 0.55–1.00 PLR range	Maintains realistic and safe chiller operating limits

To validate the effectiveness of the proposed Hybrid Genetic Algorithm–Barnacle Mating Optimizer (GA-BMO), a comprehensive performance evaluation framework was established shown in Table 3.7. The evaluation focuses on the algorithm's ability to minimize the total power consumption of a multi-chiller system while satisfying operational constraints under various cooling load scenarios. These constraints include maintaining the partial load ratio (PLR) for each chiller within the permissible range of 0.55 to 1.00, and ensuring the system's total cooling capacity meets the required demand.

The GA-BMO strategy was simulated and benchmarked against several established metaheuristic algorithms, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Cuckoo Search (CS), Imperialist Competitive Algorithm (ICA), Improved Genetic Algorithm (I-GA), and the standalone Barnacle Mating Optimizer (BMO). All algorithms were simulated using a standardized 3-chiller configuration modelled after the Nuclear Agency Malaysia setup. Each algorithm was evaluated under identical operating conditions and parameter constraints as outlined in Table 3.7. The cooling load scenarios tested included 756 RT, 810 RT, 864 RT, 918 RT, 972 RT, and 1026 RT (70%-95% of plant capacity), reflecting realistic operational profiles of the chiller plant under study.

Cost saving calculation: Cost savings are computed from the reduction in electrical energy relative to the default baseline operation. For a given scenario, the instantaneous power saving $\Delta P = P_{default} - P_{GA-BMO}(kW)$. Over an operating duration of H hours, the energy saving is $\Delta E = \Delta P \times H(kWh)$.

The monetary saving $RM_{Save} = \Delta E \times Tariff_{rate}$, where $Tariff_{rate}$ is selected according to the applicable TNB tariff category (for example, Non-Domestic MV ToU peak rate). For annual estimates, a typical schedule of 9 operating hours per day over 260 working days per year is used (H = 9 x 260).

A full factorial design (5^3 = 125 combinations) was employed to evaluate the effect of three key GA-BMO parameters: population size (25, 81, 138, 194, 250), crossover fraction (0.1–0.8), and spermcast probability (0.1–0.5). A total of 125 simulations were conducted.

3.10 Dynamic Scheduler and Dashboard System Implementation

Building upon the simulation and optimization phases using the GA-BMO algorithm, this section outlines the integration of a real-time dynamic scheduler and dashboard monitoring system. This transition marks a critical advancement from purely simulation-based analysis to a quasi-real-time control and visualization platform, enhancing the practical applicability of the GA-BMO strategy.

The developed system enables real-time simulation, dynamic PLR updates, cloud-synced data storage, and responsive monitoring interfaces via both web and mobile applications. These components collectively support adaptive chiller operation under varying load conditions and provide an intuitive platform for energy efficiency management.

Dynamic scheduling method (simulated real-time): The scheduler updates chiller PLRs at discrete time steps to match a time-varying cooling demand profile during operating hours. At each time step t, the required cooling load CL_t (RT) is obtained from the demand function, and GA-BMO is executed (or a precomputed optimal mapping is referenced) to produce an optimal PLR vector [PLR1(t), PLR2(t), PLR3(t)] that minimizes total power subject to PLR bounds and cooling demand satisfaction.

The resulting PLRs are applied to the three chiller subsystem models in Simulink, and total power is logged. The dashboard consumes the logged data (cloud-synchronized CSV/JSON) to display PLR, load, and power trends in a real-time-capable simulation.

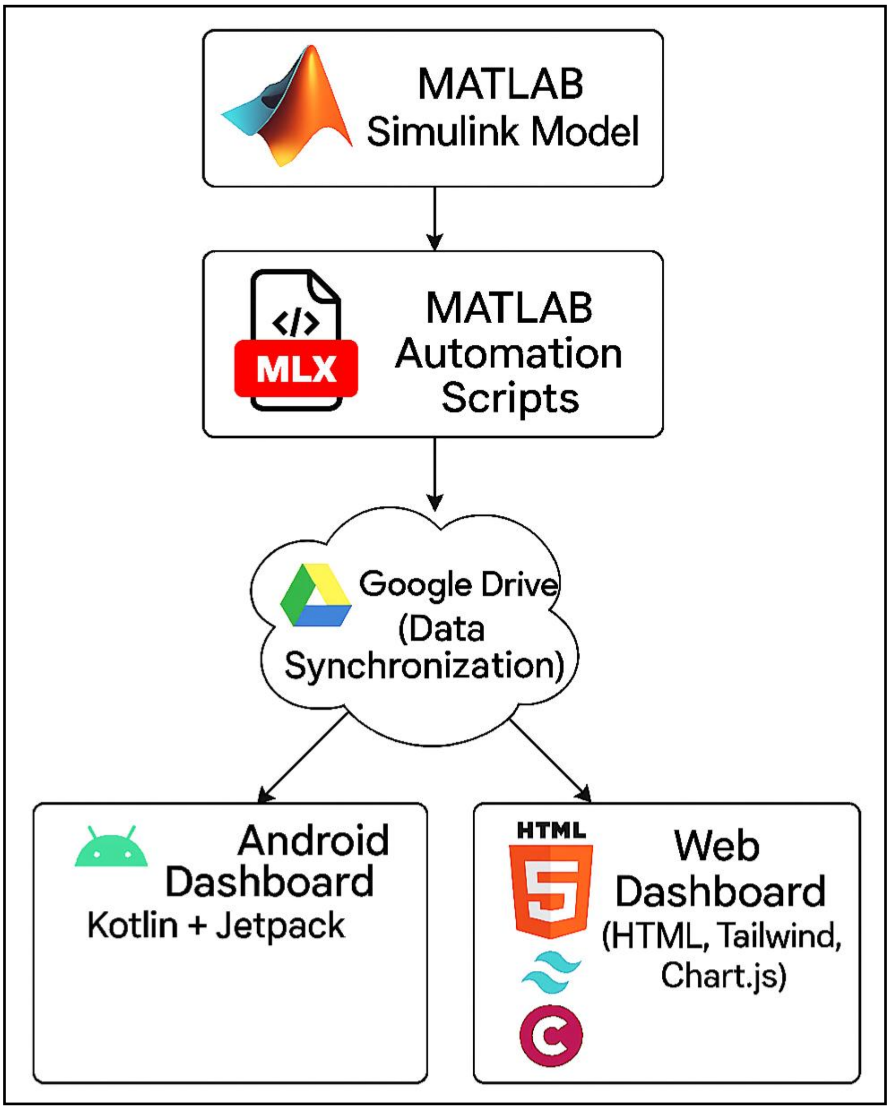

Figure 3.6: System Architecture Diagram

As illustrated in Figure 3.6, the system architecture comprises four main modules: MATLAB Simulink for modelling and scheduling, MATLAB automation scripts for data generation and export, Google Drive synchronization for cloud-based data handling, and two front-end dashboards a mobile application built using Kotlin and Jetpack Compose and a web interface developed with HTML, Tailwind CSS, and Chart.js. This integrated setup transforms static simulation outputs into a dynamic decision support tool, closing the loop between GA-BMO optimization logic and operational deployment.

3.10.1 MATLAB Simulink Model

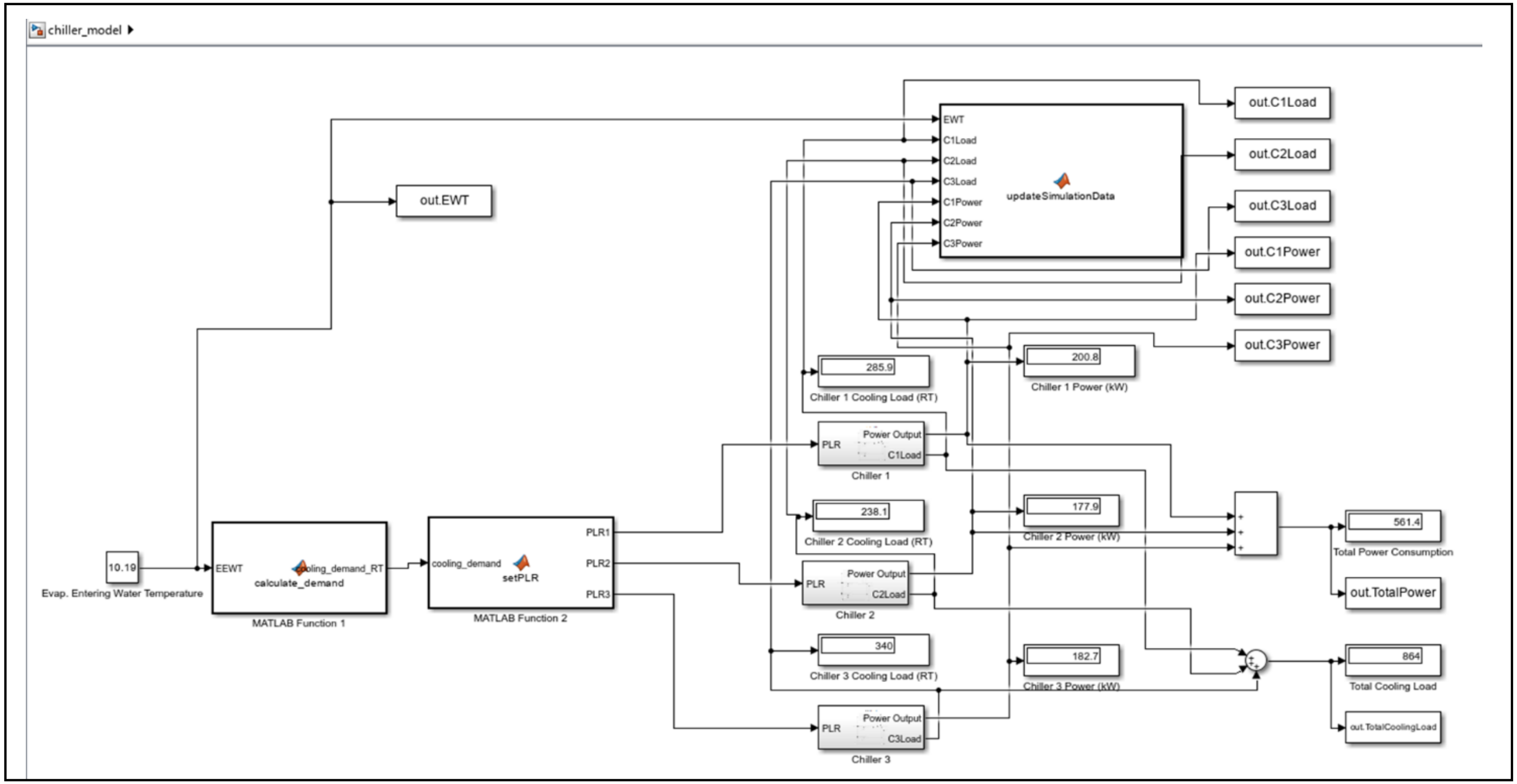

Figure 3.7: Overview of Simulink Model

The Simulink model shown in Figure 3.7 was constructed in this study to simulate a three-chiller system operating under dynamically changing environmental conditions. It integrates multiple subsystems to calculate cooling loads, optimize chiller performance, and output energy consumption metrics in real time. The model incorporates GA-BMO-optimized values to reflect intelligent decision-making based on variable cooling demands.

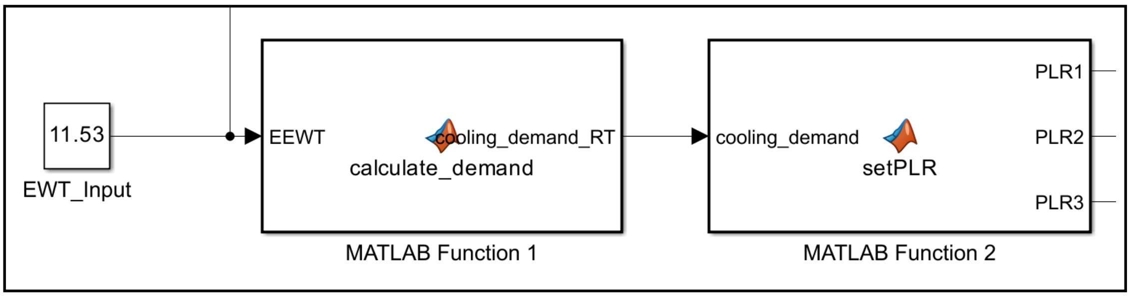

Figure 3.8: EWT Input and Cooling Demand

Figure 3.8 shows how the simulation begins with the input of the evaporator entering water temperature (EEWT), which serves as the dynamic environmental parameter. This value is passed into a MATLAB Function block labelled calculate demand. The function interpolates the EEWT against a pre-defined lookup table to estimate the cooling demand in refrigeration tons (RT). This demand is rounded to match discrete, pre-optimized load profiles generated by the GA-BMO algorithm.

The resulting cooling demand is then processed by a second MATLAB Function block, setPLR, which maps the required demand to a corresponding set of optimal Partial Load Ratios (PLRs) for each of the three chillers. These PLRs designated as PLR1, PLR2, and PLR3 represent the percentage of full load at which each chiller is expected to operate in order to meet the cooling demand most efficiently.

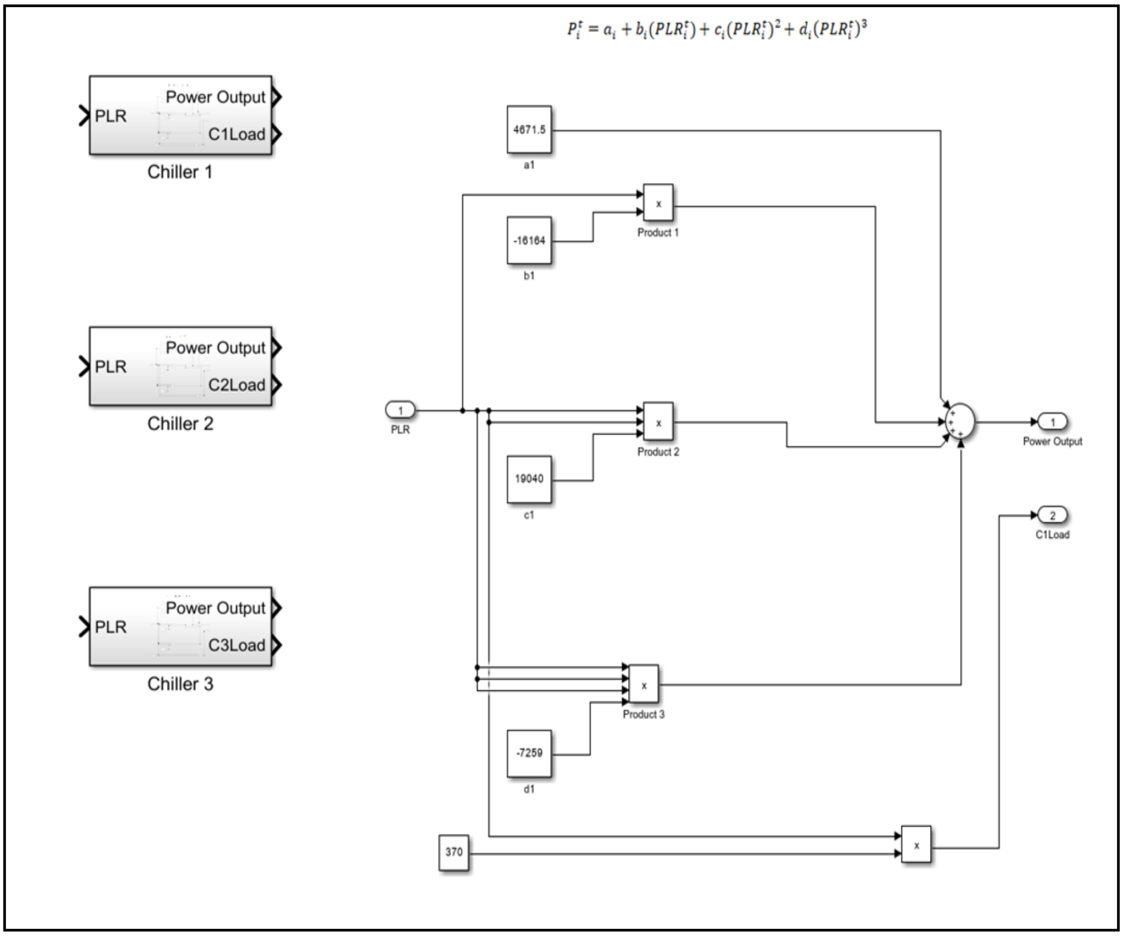

Figure 3.9: Individual Chiller Operation and Power Calculation

Each chiller subsystem Figure 3.9 receives its respective PLR value and computes two outputs: the actual cooling load delivered (in RT) and the power consumed (in kilowatts). The internal structure of each chiller employs a third-order polynomial equation, formulated as

$$P_i^t = a_i + b_i(PLR_i^t) + c_i(PLR_i^t)^2 + d_i(PLR_i^t)^3$$

Where the coefficients (a_i,b_i,c_i,d_i) are unique to each chiller. This equation enables accurate estimation of power consumption based on PLR input, reflecting real-world chiller performance.

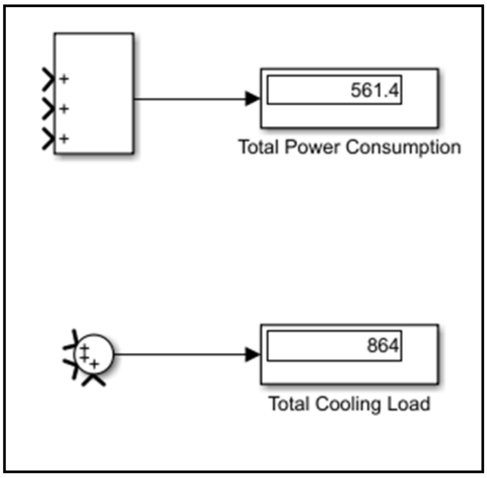

Figure 3.10: System-Level Output Aggregation

The simulation aggregates the outputs of all three chillers through summation blocks that calculate the total power consumption and total cooling load of the system as shown in Figure 3.10. These values are displayed in real time within the model and also routed to an output block titled updateSimulationData, which compiles all relevant variables such as EWT, individual chiller power and load, total power, and total cooling load into a structured output format. These results are logged into the MATLAB workspace upon simulation completion.

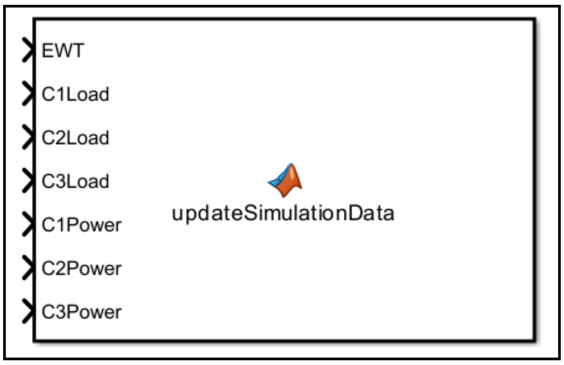

Figure 3.11:Function Block for Export and Logging

The final stage of the Simulink system involves exporting the collected output data for external use shown in Figure 3.11. Post-processing scripts access the logged variables and format them into CSV files, enabling performance analysis, benchmarking, and real-time visualization on external dashboard platforms. This workflow ensures that the model not only simulates energy-efficient operation but also forms the backbone of a responsive and connected chiller control architecture.

3.10.2 MATLAB Scripts

To support real-time simulation and performance logging, two MATLAB scripts were developed: one for manual execution of a single scenario and another for automated simulation across multiple time points. The automated script forms the core of the dynamic scheduler, enabling continuous evaluation of the GA-BMO strategy throughout the operational day.

3.10.2.1 MATLAB Automation Scripts

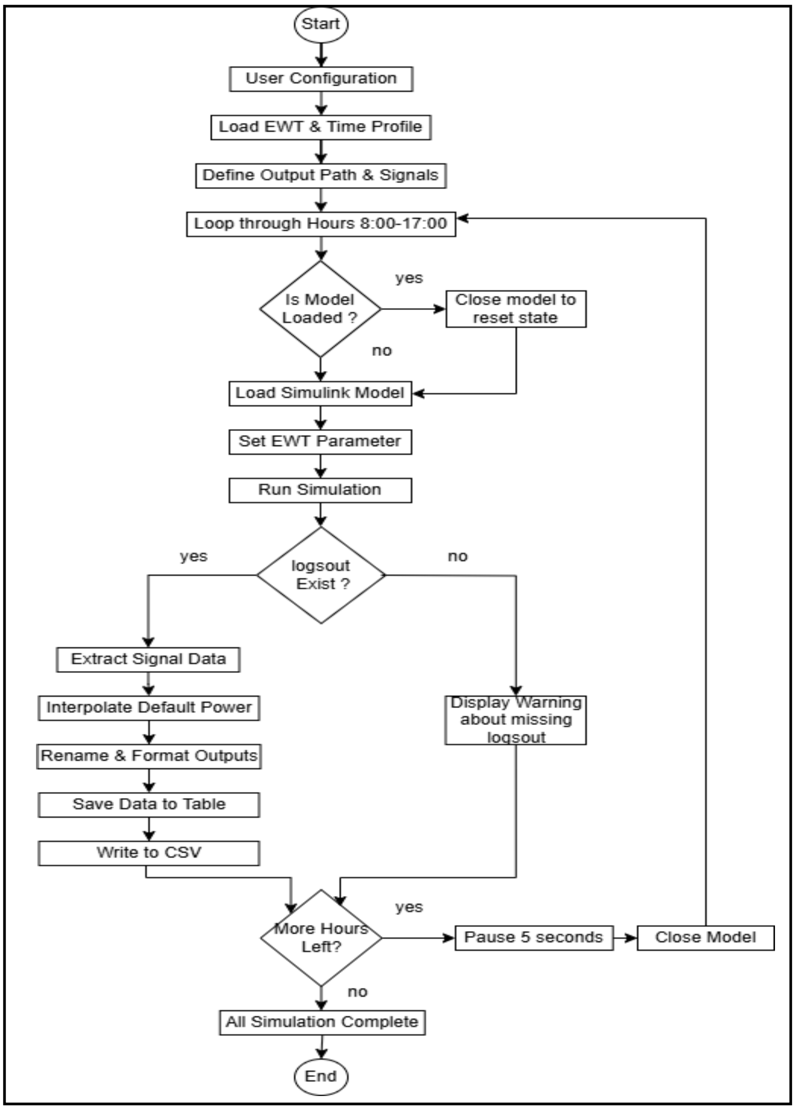

Figure 3.12: Flowchart of the MATLAB Automated Simulation Script

Figure 3.12 illustrates the process of executing hourly GA-BMO simulations in MATLAB Simulink. It outlines each step in the loop, from loading EWT values and assigning simulation parameters to writing CSV outputs and handling exceptions if simulation outputs are not generated.

The automation process begins with user configuration and the loading of a predefined time profile for Entering Water Temperature (EWT) values. This profile simulates a full operational day from 8:00 AM to 5:00 PM, representing real-world variations in environmental or system conditions. The script defines the output paths and signal variables that will be extracted from the simulation for each time step.

For every hourly interval, the script checks whether the Simulink model is currently loaded. If it is, the model is closed to reset its internal state. The Simulink model is then reloaded, and the current EWT parameter for that hour is assigned. Once set, the model is executed using MATLAB's sim function.

After simulation, the script checks for the existence of the logsout variable. If the simulation ran successfully and the logsout structure is available, the relevant signal data, such as chiller loads, power consumption, and total system metrics are extracted. Additionally, a performance baseline is generated by interpolating power values based on default system settings. These results are renamed, formatted, and saved into structured tables. Finally, the data for each hour is written into a consolidated CSV file.

In the event that the logsout structure is missing, the script displays a warning to indicate simulation failure for that time step. Once the data is saved or the warning acknowledged, the script checks whether additional hours remain in the time profile. If so, it pauses for five seconds to allow system reset and loops to the next hour. This process continues until all scheduled simulations are complete.

This automated approach allows for the rapid generation of optimized and baseline performance datasets over a daily cycle. These datasets are then used for comparative evaluation and real-time visualization in the connected dashboard systems.

3.10.2.2 MATLAB Manual Scripts

In addition to the automated simulation loop, a secondary script was developed to handle manual single-scenario simulations, typically used for testing or one-off analysis. This manual script focuses on extracting output data from a previously executed Simulink run, formatting the data consistently, and preparing it for use in real-time dashboard applications.

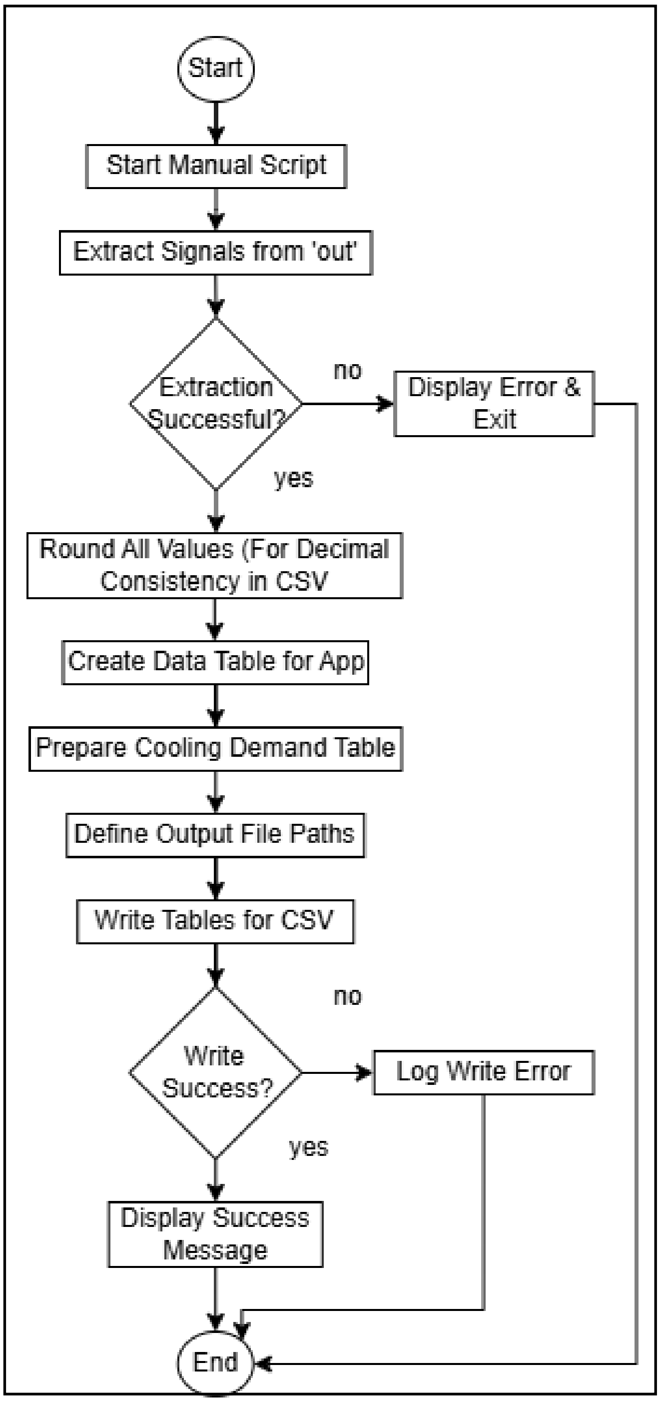

Figure 3.13: Flowchart of the Manual MATLAB Script for Single-Scenario Simulation

In Figure 3.13, the manual script begins by initializing the workspace and accessing the out structure generated by Simulink. It then attempts to extract all relevant signal variables, including EWT, chiller loads, power consumption, and total system values. If extraction fails, the script issues an error message and exits gracefully to prevent further processing. If extraction is successful, the script proceeds to round all numeric values to two decimal places. This step ensures uniformity in the exported CSV files, which is critical for accurate rendering and charting within the Android and web dashboards. Following this, the script generates two output tables: the main system data table and a static reference table mapping cooling demand (RT) to EWT and ELWT values. These tables are essential for both operational display and backend calculations in the dashboard system.

The output file paths are then defined, and the tables are written into .csv format. If writing is successful, the script confirms completion and displays a success message in the MATLAB console. In cases where the file writing process encounters an issue such as missing permissions or writing conflicts a log is created to document the error, and the script safely terminates. This manual export routine provides a reliable fallback for non-automated simulation runs and serves as a complementary data pipeline for the real-time monitoring system.

3.10.3 Cloud-Base Data Synchronization (Google Drive)

To enable seamless integration between the MATLAB Simulink environment and external monitoring platforms, a cloud-based data synchronization mechanism was implemented using Google Drive. This component serves as the communication bridge between the optimization and simulation engine (MATLAB) and the user-facing dashboards (Android and web applications). The synchronization system ensures that data generated from the GA-BMO scheduler is consistently accessible in real-time without requiring physical transfer or manual uploads.

In Figure 3.14, the data synchronization process begins with the automatic export of simulation results in .csv format from MATLAB scripts. These result files such as ChillerSimulationLog.csv, ChillerManualRunLog.csv and CoolingDemandTable.csv contain time-series data including individual chiller power consumption, load distribution, total cooling load, and total system energy usage. Each file is written to a dedicated local directory that is linked to a Google Drive folder through Google’s desktop synchronization service

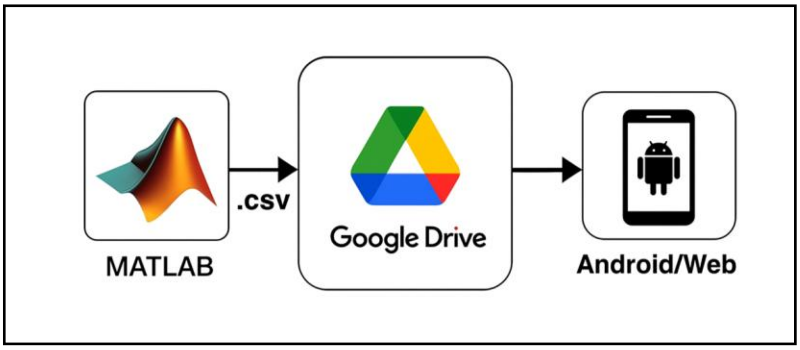

Figure 3.14: Workflow Between MATLAB, Google Drive, and Dashboard Interfaces

Once exported, any update in the local folder is immediately reflected in the associated Google Drive folder. This ensures that the most recent simulation outputs are always available for external applications to retrieve. The Android mobile app and the web dashboard system access the latest data by referencing publicly shared links from the Google Drive folder, eliminating the need for direct networking or back-end server deployment.

This synchronization framework supports continuous data refresh in the dashboards at predefined intervals (every 5–10 seconds for the Android app, and 30–60 seconds for the web dashboard), enabling near real-time monitoring of system performance. Additionally, the use of Google Drive provides robust data accessibility, scalability, and version tracking without the complexity of maintaining a dedicated cloud infrastructure. The successful implementation of this cloud-based synchronization system demonstrates the practicality of integrating MATLAB-based simulations with modern cross-platform visualization tools, fulfilling the real-time adaptability requirement of the proposed GA-BMO-based dynamic scheduler.

3.10.4 Android Dashboard Application (Android Studio)

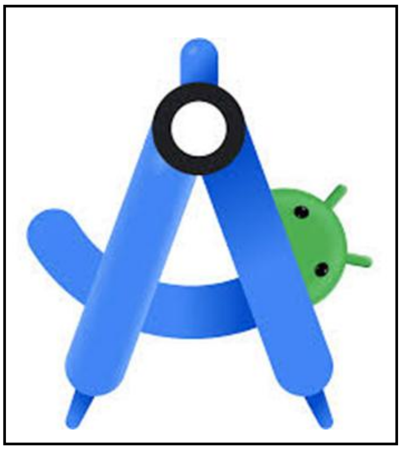

Figure 3.15: Android Studio

An Android-based dashboard application was developed using Android Studio shown in Figure 3.15 with Kotlin and the as the framework to provide real-time access to the chiller system's operational data. This mobile platform serves as a portable interface for monitoring key performance indicators (KPIs), chiller statuses, and power consumption derived from the MATLAB simulation.

3.10.5 Web Dashboard Implementation (HTML, Tailwind, Chart.js, AI Integration)

Figure 3.16: HTML, Tailwind CSS and Chart.js

In parallel with the Android application, a responsive web-based dashboard was developed to provide an accessible and visual interface for real-time monitoring of the GA-BMO chiller optimization system shown in Figure 3.16. The dashboard was constructed using standard web technologies shown in including HTML5, Tailwind CSS, Chart.js, and a lightweight JavaScript-based data fetching mechanism. Its primary function is to display updated system performance metrics sourced from simulation outputs synchronized to Google Drive

3.11 Summary

The chapter began shown in Table 3.8 by introducing the conceptual framework and system configuration, followed by the integration of Genetic Algorithm and Barnacle Mating Optimizer through an embedded hybrid approach. The structure of the proposed hybrid algorithm was detailed, along with a discussion of its differences from conventional sequential hybrid techniques.

Table 3.8
Summary of Methodology and Corresponding Research Objectives

Methodology Component	Description	Objective Addressed
GA-BMO Algorithm Development	Embedded hybrid metaheuristic to optimize PLRs	Objective 1
Performance Evaluation & Benchmarking	Simulation-based comparison with GA, PSO, ICA, CS, etc.	Objective 2
MATLAB Simulink Dynamic Scheduler	Real-time simulation of 3-chiller system	Objective 3
MATLAB Automation Scripts	Hourly simulation and structured output generation	Objective 3
Android & Web Dashboards	Real-time monitoring using cloud-synced CSV data	Objective 3

A comprehensive parameter configuration was conducted using a full factorial design, and benchmarking was carried out against several established optimization algorithms under consistent simulation conditions. The performance evaluation strategy was designed to assess power consumption, constraint satisfaction, and convergence behaviour across various cooling load scenarios.

The simulated real-time validation of the proposed method was achieved through a dynamic scheduler built in MATLAB Simulink, supported by automation scripts to simulate hourly operations. Data synchronization with Google Drive enabled seamless communication with both the Android and web-based dashboard applications. These dashboards provided real-time system insights and user interaction capabilities, fulfilling the objective of continuous monitoring and adaptability. Finally, data collection procedures and validation techniques were applied to ensure the accuracy, reliability, and repeatability of simulation and optimization outcomes.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents and analyses the results obtained from the implementation of the hybrid GA-BMO control strategy for chiller optimization. The simulations and evaluations were conducted based on the methodology outlined in Chapter 3, encompassing algorithm development, Simulink-based dynamic scheduling, and real-time visualization via mobile and web dashboard. This chapter is organized as follows: Section 4.2 discusses the optimization performance of the GA-BMO algorithm, including convergence trends and load distribution analysis. Section 4.3 presents a comparative benchmarking with other algorithms. Section 4.4 analyses real-time simulation output and dashboard performance. Finally, Section 4.5 summarizes the findings and implications.

4.2 Objective 1: Development of Hybrid GA-BMO Control Strategy

This section details the results pertaining to the first research objective, which was to design and develop a hybrid Genetic Algorithm-Barnacle Mating Optimizer (GA-BMO) control strategy for enhancing chiller energy efficiency and minimizing operational costs. The development focused on creating a novel algorithmic framework that integrates the strengths of both GA and BMO to overcome the limitations of standalone optimization techniques

Definition of default baseline operation: In this thesis, the 'default' operation refers to the static chiller loading strategy derived from the existing plant settings (fixed PLR allocation without metaheuristic optimization) under the same cooling load scenarios and constraints. This baseline is used consistently for all power and cost comparisons.

4.2.1 Overview of GA-BMO Implementation

The core of the developed strategy is an embedded hybrid algorithm where the Barnacle Mating Optimizer (BMO) functions as an operator within the Genetic

Algorithm's (GA) evolutionary cycle. This design choice is a key outcome of the development phase, distinguishing it from simpler sequential or cascading hybrid methods. As detailed in the methodology in Chapter 3, the BMO sperm casting mechanism was integrated to execute immediately after the GA's crossover and mutation operations

This embedded structure was intentionally designed to leverage BMO’s local exploitation capabilities to refine the solutions generated in each GA generation, thereby enhancing genetic diversity and accelerating convergence. The algorithm was specifically formulated to optimize the Partial Load Ratios (PLRs) of a three-chiller system, with the primary objective function being the minimization of total power consumption while adhering to all system and operational constraints. The successful implementation of this integrated workflow, as illustrated in the flowchart in Figure 3.5, represents the primary deliverable for the development phase of this research.

4.2.2 Simulation Results

The development of the hybrid GA-BMO algorithm was finalized through a rigorous simulation process aimed at identifying the most effective parameter configuration. The primary goal of this phase was to determine the optimal set of parameters that would ensure robust performance, minimize power consumption, and guarantee reliable convergence across various operational scenarios. To achieve this, a comprehensive Full Factorial Design (FFD) was employed, systematically evaluating the algorithm's behaviour under multiple combinations of parameter values.

A total of 125 distinct parameter combinations were tested, each representing a unique configuration of three key parameters: Population Size, Crossover Fraction, and Spermcast Probability (pl), as detailed in Table 3.5 of the methodology chapter. To ensure statistical validity and account for the stochastic nature of metaheuristic algorithms, each of these combinations was executed 20 times, resulting in 2,500 simulation runs. While a smaller number of runs might provide an early indication of performance, the decision to use 20 repetitions per combination was made to rigorously assess the algorithm's robustness and minimize the influence of outliers or random chance. This ensured that observed performance trends were consistent and repeatable.

Experimental repeatability statement: For the GA-BMO parameter sweep, each parameter combination was executed multiple times with different random seeds.

Reported values in Table 4.1 represent the mean performance over 20 runs for the selected best-performing combination at each cooling load. For comparative benchmarking (Chapter 4.3), algorithms were executed under the same number of runs and should be reported using mean and, where appropriate, standard deviation to avoid conclusions based on single-run best cases.

Table 4.1
Best GA-BMO Results Across Cooling Load Scenarios (20-run average)

Cooling Load (RT)	Chiller i	PLR	Power (kW)	Total Power Pt (kW)	Best Combination ID
1026 RT (95%)	1	0.854057	232.48	689.05	PS=250_CF=0.50_SC=0.30
	2	0.999985	273.82		
	3	0.999985	182.75		
972 RT (90%)	1	0.782837	232.58	635.44	PS=81_CF=0.70_SC=0.30
	2	0.925275	219.11		
	3	0.999999	182.75		
918 RT (85%)	1	0.768779	199.77	596.74	PS=194_CF=0.30_SC=0.40
	2	0.793832	214.22		
	3	0.999999	182.75		
864 RT (80%)	1	0.772801	206.80	561.39	PS=194_CF=0.30_SC=0.40
	2	0.643415	177.88		
	3	0.999996	182.75		
810 RT (75%)	1	0.724941	194.25	528.25	PS=194_CF=0.10_SC=0.50
	2	0.550114	151.27		
	3	0.994723	182.73		
756 RT (70%)	1	0.727393	194.27	529.77	PS=250_CF=0.50_SC=0.50
	2	0.550064	151.25		
	3	0.833374	184.25		

Table 4.1 presents the best configuration identified for each tested cooling load percentage, based on the lowest total power consumption observed among all 125 parameter combinations. For instance, at 70% load, the optimal configuration was PS=250, CF=0.50, SC=0.50, which resulted in a total power consumption of 529.77 kW, while at 90% load, the best-performing combination shifted to PS=81, CF=0.70, SC=0.30, with a total power consumption of 635.44 kW. This variation highlights that larger population sizes and higher spermcast probabilities tend to yield better

performance at lower loads, while smaller or moderate settings become more efficient as demand increases.

The influence of algorithm parameters varied across load conditions. Population Size showed the most notable impact, with larger values (for example, PS = 250) favoured at higher loads such as 1026 RT, likely due to the increased complexity and search space at full capacity. Meanwhile, at medium loads (810–918 RT), a more moderate population size (PS = 194) consistently emerged as optimal. The Spermcast Probability (pl) of 0.50 appeared most frequently among the best results, suggesting that a higher level of localized mating behaviour was beneficial for refinement across all load levels. In contrast, Crossover Fraction did not show a dominant pattern, indicating a lesser sensitivity to its variation in the hybrid framework. These results confirm the robustness of the GA-BMO framework, fulfilling Objective 1 by delivering constraint-compliant, power-optimized solutions across a spectrum of dynamic operational conditions.

Justification note for PS=81 at 90% RT: The population size (PS) that yields the best result can vary with operating load because the feasible solution region and the effective search difficulty change with cooling demand and PLR constraints. At 90% load, the optimizer operates closer to the upper PLR bounds, which reduces PLR flexibility and narrows the feasible region. In this regime, a smaller population (for example, PS=81) can converge more efficiently by focusing the search and reducing unnecessary exploration, particularly when paired with higher crossover fraction (CF) and moderate sperm-cast probability (SC). The configuration was selected based on the best average total power over repeated runs (20-run average), indicating consistent performance rather than a single outlier.

Table 4.2
Proposed Hourly Chiller PLR Schedule Based on GA-BMO Optimization

Time	Cooling Demand (RT)	Evap Entering Temp (°C)	Chiller 1 PLR	Chiller 2 PLR	Chiller 3 PLR
8 AM	756.00	9.47	0.73	0.55	0.83
9 AM	810.00	9.83	0.72	0.55	0.99
10 AM	864.00	10.19	0.77	0.64	1.00
11 AM	918.00	10.76	0.77	0.79	1.00

12 PM	972.00	11.53	0.78	0.93	1.00
1 PM	1026.00	12.27	0.85	1.00	1.00
2 PM	1080.00	13.05	1.00	1.00	1.00
3 PM	1026.00	12.27	0.85	1.00	1.00
4 PM	972.00	11.53	0.78	0.93	1.00
5 PM	918.00	10.76	0.77	0.79	1.00

To enhance daily chiller operations under typical weather conditions, a dynamic schedule has been formulated using the optimized Partial Load Ratios (PLRs) generated by the GA-BMO algorithm. This proposed schedule serves as a practical replacement for the conventional static operation plan by adjusting chiller loading in response to varying cooling demands linked to evaporator inlet water temperatures. The schedule reflects a typical sunny day profile in Malaysia and is tailored specifically for the operational environment at the Nuclear Agency Malaysia. Table 4.2 outlines the hourly assignment of PLRs for each chiller unit from 8 AM to 5 PM, facilitating energy-efficient and adaptive system performance.

To further evaluate the effectiveness of the proposed dynamic schedule, a comparative analysis of total power consumption between the GA-BMO optimized strategy and the existing default operation was conducted. The results provide quantitative evidence of the GA-BMO algorithm's capability to reduce energy usage while maintaining operational reliability, thereby reinforcing its suitability for real-time chiller control at the Nuclear Agency Malaysia.

Table 4.3
Comparison of GA-BMO vs Default Power Consumption

Cooling Load (RT)	Power Consumption (Default)	Power Consumption (GA-BMO)	Power Saving (kW)	Saving (%)
1026 RT (95%)	714.42	689.05	25.37	3.55%
972 RT (90%)	678.78	635.44	43.34	6.38%
918 RT	642.35	596.74	45.61	7.10%

(85%)				
864 RT (80%)	607.80	561.39	46.41	7.64%
810 RT (75%)	580.56	528.25	52.31	9.01%
756 RT (70%)	563.46	529.77	33.69	5.98%

As summarized in Table 4.3, the GA-BMO algorithm consistently outperformed the default control strategy across all tested cooling loads. The greatest power saving was observed at 810 RT, where the GA-BMO reduced power consumption by 52.31 kW, equating to a 9.01% improvement over the default setting. Even at higher loads, such as 972 RT, GA-BMO maintained significant efficiency, saving 43.34 kW or 6.38%. These results reinforce the effectiveness of the GA-BMO strategy in optimizing chiller operations across a range of real-world load scenarios. The consistent improvement in power savings demonstrates not only the algorithm's convergence accuracy but also its robustness in managing constraint-compliant PLR distributions.

Interpretation of savings trend (Table 4.3): The largest savings occur at mid-load conditions (for example, 75% load) because PLR allocation has greater flexibility: the optimizer can redistribute load to keep each chiller operating nearer its higher-efficiency region while respecting the minimum PLR constraint. Near full load (for example, 95%), most chillers are already close to their upper PLR limits, leaving less room to reallocate load; therefore, the achievable improvement over the default baseline is smaller. Based on the data presented in Table 4.3, a graphical representation of the results is illustrated in Figure 4.1.

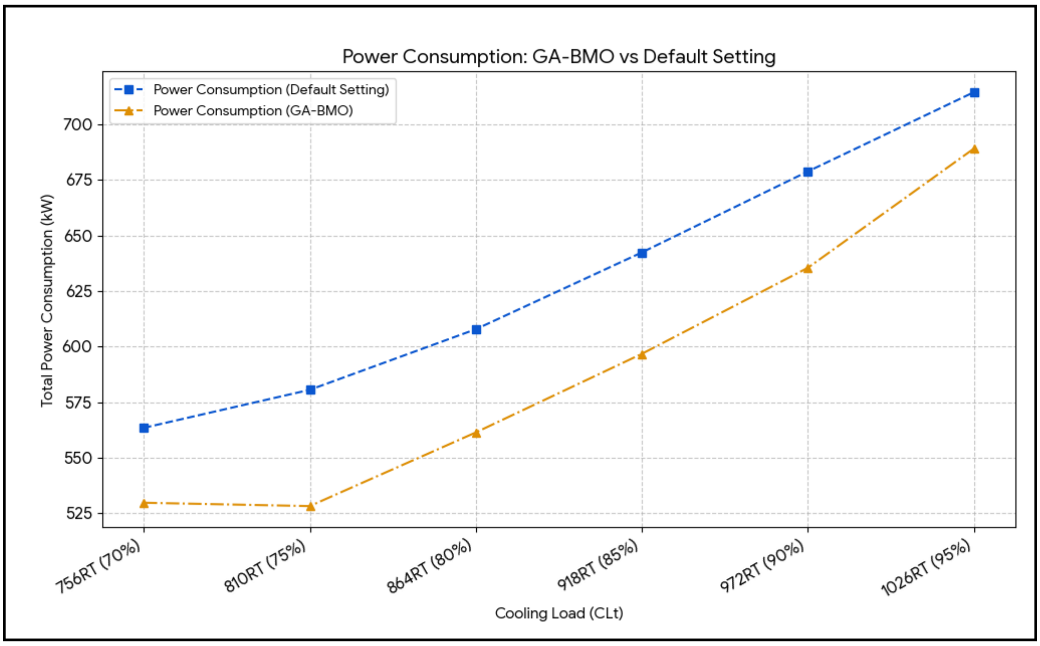

Figure 4.1: Power Consumption: GA-BMO vs Default Setting

Non-Domestic Medium Voltage		
Non-Domestic Medium Voltage General Tariff		
Energy Charge - For all kWh	sen/kWh	29.83
Capacity Charge - For each kilowatt of maximum demand per month	RM/kW	29.43
Network Charge - For each kilowatt of maximum demand per month	RM/kW	59.84
Retail Charge	RM/month	200.00
Non-Domestic Medium Voltage ToU Tariff		
Energy Charge - For all kWh during the peak period	sen/kWh	31.32
Energy Charge - For all kWh during the off-peak period	sen/kWh	27.23
Capacity Charge - For each kilowatt of maximum demand per month during the peak period	RM/kW	30.19
Network Charge - For each kilowatt of maximum demand per month during the peak period	RM/kW	66.87
Retail Charge	RM/month	200.00

Figure 4.2: Non-Domestic Medium Voltage Time-of-Use (Effective 1st July 2025)

This Figure 4.2 presents the updated electricity tariff structure for Non-Domestic Medium Voltage (MV) C2, effective from 1 July 2025, as published on the myTNB official website. The tariff is categorized into General and Time-of-Use (ToU) schemes. Given that the chiller system at Agency Nuclear Malaysia operates during standard office hours (8 AM to 5 PM), the ToU Peak Period energy charge of 31.32 sen/kWh (RM 0.3132/kWh) is selected for cost-saving calculations. This rate forms the basis for the revised economic analysis of energy savings achieved through the proposed GA-BMO optimization strategy.

Table 4.4
Cost Savings Achieved by implementing GA-BMO

Time Period	Lowest RM Saved	Highest RM Saved
1 Hour	RM 7.94	RM 16.39
1 Day	RM 71.49	RM 147.54
1 Week	RM 357.43	RM 737.72
1 Month	RM 1,546.25	RM 3,192.48
1/2 Year	RM 9,293.55	RM 19,180.63
1 Year	RM 18,587.10	RM 38,361.26

To further quantify the benefit of these savings, Table 4.4 presents the estimated monetary value of power reduction over various operational timeframes, calculations are based on the commercial Tariff C2 pricing structure from Tenaga Nasional Berhad (TNB), which is applicable to the Nuclear Agency Malaysia, with a peak period electricity rate of 31.32 sen/kWh. These estimates are based on a typical 9-hour daily operational schedule across 260 working days per year. The projected annual cost savings range from RM 18,587.10 to RM 38,361.26, depending on the operating load and GA-BMO effectiveness. These findings underscore the practical economic value of implementing the proposed optimization strategy in real-world industrial HVAC systems.

4.3 Objective 2: Comparative Performance Evaluation

The second objective of this study is to evaluate the performance of the proposed GA-BMO strategy in comparison with other well-established metaheuristic optimization algorithms. This comparative analysis is essential to validate the efficacy and competitiveness of the hybrid approach in solving the chiller loading optimization problem under realistic operating constraints. The evaluation focuses on total power consumption as the primary performance metric, assessed under identical cooling load scenarios for all algorithms. The tested algorithms include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Imperialist Competitive Algorithm (ICA), Cuckoo

Search (CS), Improved Genetic Algorithm (I-GA), Barnacle Mating Optimizer (BMO), Genetic Algorithm-Barnacle Mating Optimizer (GA-BMO).

Each algorithm was configured based on best practices from the literature and executed with consistent parameter settings, such as population size and maximum iterations, to ensure a fair and valid comparison. Importantly, all algorithms were re-executed within the current 3-chiller configuration of this study, and the comparative results were generated entirely through these simulations, not adopted from previous studies. The simulations were conducted under six different cooling load scenarios, ranging from 70% to 95% of system capacity, using the same constraint enforcement and evaluation criteria as outlined in previous sections.

4.3.1 Comparative Results

Table 4.5
Optimal Results Obtained by GA-BMO and Other Algorithms for 3-Unit Chiller System.

	chiller	GA-BMO			BMO			ICA			PSO			CS			I-GA			GA		
CLt	i	PLR	P (kW)	Pt (kW)	PLR	P (kW)	Pt (kW)	PLR	P (kW)	Pt (kW)	PLR	P (kW)	Pt (kW)	PLR	P (kW)	Pt (kW)	PLR	P (kW)	Pt (kW)	PLR	P (kW)	Pt (kW)
	1	0.85	232.48		0.86	233.99		0.88	247.33		0.85	232.48		0.87	239.81		1.00	287.60		1.00	287.60	
1026 RT (95%)	2	1.00	273.82	689.05	1.00	273.05	689.78	0.97	263.01	693.09	1.00	273.82	689.05	0.98	268.37	690.93	0.85	229.49	699.84	0.86	229.86	700.20
	3	1.00	182.75		1.00	182.74		1.00	182.75		1.00	182.75		1.00	182.75		1.00	182.75		1.00	182.74	
	1	0.78	203.58		0.79	206.16		0.79	205.06		0.79	204.68		0.76	197.84		1.00	287.60		1.00	287.60	
972 RT (90%)	2	0.93	249.11	635.44	0.94	252.56	641.46	0.92	247.71	635.52	0.92	248.05	635.47	0.95	257.45	638.02	0.72	196.99	667.31	0.75	204.01	674.56
	3	1.00	182.75		0.98	182.74		1.00	182.75		1.00	182.75		1.00	182.73		0.99	182.72		0.95	182.96	
	1	0.77	199.77		0.78	203.62		0.76	198.85		0.83	221.77		0.78	203.08		1.00	287.60		1.00	287.60	
918 RT (85%)	2	0.79	214.22	596.74	0.81	219.11	605.59	0.80	215.20	596.80	0.73	199.59	604.11	0.78	211.29	597.12	0.58	158.94	629.26	0.65	178.98	650.27
	3	1.00	182.75		0.96	182.86		1.00	182.75		1.00	182.75		1.00	182.75		0.99	182.72		0.91	183.68	
	1	0.77	200.77		0.73	194.48		0.77	199.76		0.85	231.06		0.76	198.82		1.00	287.60		1.00	287.60	
864 RT (80%)	2	0.64	177.87	561.39	0.74	200.97	578.60	0.65	178.92	561.43	0.57	155.95	569.76	0.65	180.17	561.74	0.52	142.60	614.24	0.58	159.49	631.26
	3	1.00	182.75		0.94	183.15		1.00	182.75		1.00	182.75		1.00	182.75		0.88	184.04		0.83	184.17	
	1	0.72	194.25		0.73	194.43		0.72	194.25		0.72	194.34		0.73	194.34		1.00	287.60		1.00	287.60	
810 RT (75%)	2	0.55	151.27	528.25	0.73	199.84	577.49	0.55	151.24	528.22	0.55	151.24	528.33	0.55	151.83	528.89	0.35	68.56	539.82	0.70	192.14	605.95
	3	0.99	182.73		0.79	183.21		1.00	182.73		1.00	182.75		0.99	182.72		0.91	183.66		0.53	126.20	
	1	0.73	194.27		0.77	201.21		0.73	194.27		0.79	205.97		0.71	194.71		1.00	287.60		1.00	287.60	
756 RT (70%)	2	0.55	151.25	529.77	0.69	190.57	552.40	0.55	151.24	529.75	0.56	154.56	541.84	0.55	151.64	530.65	0.62	172.82	542.39	0.62	172.36	543.41
	3	0.83	184.25		0.63	160.62		0.83	184.25		0.75	181.31		0.85	184.30		0.46	81.96		0.46	83.45	

Table 4.5 summarizes the optimal (minimum total power) solutions produced by each algorithm for the three-unit chiller system, reporting PLR allocations and the corresponding chiller and total power at each cooling-load scenario. Table 4.5 reports the best (lowest total power) PLR solutions obtained by each algorithm for each cooling-load scenario. Overall, GA-BMO achieves the lowest total power in most scenarios, reflecting its stronger ability to balance exploration and exploitation through the embedded BMO operator while retaining GA's selection and recombination structure. The performance differences are most pronounced in mid-load regimes (80%-90%), where PLR flexibility allows algorithms to meaningfully reshape load distribution. In contrast, at the highest loads (95%), all algorithms operate near the upper PLR limits, so total power differences compress and improvements over baseline become smaller. Algorithms that rely heavily on random exploration without strong exploitation, or vice versa, tend to produce less consistent PLR allocations, which translates to slightly higher total power.

Table 4.6
Overall Performance Ranking and Total Power Consumption (kW)

Rank	Algorithm	Total Power Consumption (kW)	% Increase over Best
1	GA-BMO	3540.675	0.00%
2	ICA	3544.82	0.12%
3	CS	3547.35	0.19%
4	PSO	3568.552	0.79%
5	BMO	3645.314	2.96%
6	I-GA	3692.848	4.30%
7	GA	3805.65	7.48%

Table 4.7
Algorithm Ranking per Cooling Load

Cooling Load	**Algorithm Ranking**						
	GA-BMO	BMO	ICA	PSO	CS	I-GA	GA
1026 RT (95%)	2	3	5	1	4	6	7
972 RT (90%)	1	5	3	2	4	6	7
918 RT (85%)	1	5	2	4	3	6	7
864 RT (80%)	1	5	2	4	3	6	7
810 RT (75%)	2	6	1	3	4	5	7
756 RT (70%)	2	7	1	4	3	5	6

To interpret the performance disparities observed in Table 4.6 and Table 4.7, it is essential to analyse the core search principles and tuneable control parameters of each algorithm. Every metaheuristic balance exploration (diversification) and exploitation (intensification). Table 4.8 provides a centralized reference of the key parameters governing this balance for each analysed algorithm, which supports the discussion of why some methods rank higher under specific load conditions.

Table 4.8
Key Control Parameters of Analysed Metaheuristic Algorithms

Algorithm	Key Parameters	Role in Exploration/Exploitation
GA / I-GA	Population Size, Crossover Fraction, Mutation Rate	Crossover (exploitation) combines good solutions; Mutation (exploration) introduces diversity. Crossover Fraction balances these two forces.
BMO	Population Size, Penis Length (*pl*), Sperm-cast Probability	Normal copulation within *pl* is exploitation. Sperm-casting beyond *pl* is exploration.
GA-BMO	Population Size (PS), Crossover Fraction (CF), Mutation Rate, Penis Length (pl), Sperm-cast Probability (SC)	Leverages GA's population management (global search) with BMO's specialized mating operators (local/global search) for a synergistic balance.
ICA	Number of Countries, Number of Imperialists, Assimilation Coefficient (β), Revolution Rate	Assimilation (exploitation) moves colonies toward imperialists. Revolution (exploration) introduces new, random solutions to escape local optima.
PSO	Population Size, Inertia Weight (w), Cognitive (c_1) & Social (c_2) Constants	High inertia weight promotes exploration. Low inertia promotes exploitation. c_1/c_2 balance personal vs. swarm knowledge.
CS	Population Size, Discovery Probability (p_a), Lévy Flight Step Size (α)	Lévy flights enable large, exploratory jumps. A high p_a increases the rate at which poor solutions are abandoned, promoting exploration.

4.3.1.1 Genetic Algorithm-Barnacle Mating Optimizer through Embedded Hybrid (GA-BMO)

The success of GA-BMO hinges on the synergy between its constituent parts. The GA provides a robust framework for managing the population and preserving the best-found solutions through selection mechanisms like elitism, ensuring a structured progression towards an optimal solution. The BMO component contributes its unique mating operators: the sperm-casting mechanism serves as a powerful, long-range exploration tool, allowing the search to escape local optima, while the Hardy-Weinberg-based copulation acts as a sophisticated exploitation mechanism to finely tune solutions within promising regions of the search space.

An examination of the detailed results reveals GA-BMO's superior ability to navigate the complex OCL problem. At a cooling demand of 972 RT, 918 RT and 864 RT, GA-BMO identifies a highly balanced load distribution to the three chillers, respectively. This strategy effectively leverages the non-linear efficiency curves of all three machines. In stark contrast, the standard GA under the same conditions converges to a simplistic and inefficient solution of running one chiller at its maximum capacity (PLR=1.0) and distributing the rest of the load sub-optimally. This demonstrates that GA-BMO is not merely finding a good solution but is actively discovering a complex, near-optimal operating point that is inaccessible to its parent algorithms alone.

The top-tier performance of GA-BMO stems directly from its hybrid nature, which overcomes the inherent weaknesses of its parent algorithms. The standard GA, when applied alone, performs poorly due to premature convergence. Its generic operators are insufficient for the OCL problem, causing it to get trapped in the most obvious local optimum (running one chiller at 100%). BMO performs better but is still suboptimal. The GA-BMO hybrid creates a system where the GA's global population management prevents the search from collapsing into a single, unpromising region. Concurrently, BMO's specialized operators prove far more effective at navigating the specific OCL problem landscape than GA's generic crossover and mutation. This combination of a global search framework (GA) with specialized local and global search operators (BMO) creates a powerful dynamic, characteristic of successful memetic algorithms, and is the key to its superior performance.

4.3.1.2 Imperialist Competitive Algorithm (ICA)

ICA's performance is second only to GA-BMO, and its load distribution strategies are similarly sophisticated. For instance, at a cooling demand of 810 RT and 756 RT, ICA determines an optimal PLR distribution across the three chillers. This balanced and non-intuitive solution demonstrates the algorithm's capacity to effectively model the non-linear power consumption curves and find near-globally optimal operating points. This performance is consistent across all load conditions, showcasing the algorithm's robustness.

ICA's exceptional performance can be attributed to its unique multi-layered search structure and its explicit, robust mechanisms for escaping local optima. Unlike algorithms that operate on a single population, ICA creates multiple sub-populations (empires) that conduct searches in parallel, providing inherent diversification. The assimilation process acts as a powerful local search (exploitation), where colonies move towards their imperialist, intensively refining solutions within a promising region.

The revolution operator serves as a dedicated exploration mechanism, introducing random new countries to maintain population diversity and prevent premature convergence. Finally, the imperialistic competition, where the weakest empires collapse and their colonies are absorbed by stronger ones, exerts a strong global selection pressure. This process systematically prunes unpromising regions of the search space and reallocates computational effort to the most fruitful areas. This integrated combination of parallel exploitation, dedicated exploration, and global competition makes ICA exceptionally well-suited for complex, non-convex problems like OCL and explains its top-tier performance.

4.3.1.3 Cuckoo Search (CS)

The CS is known for its relative simplicity, with fewer control parameters than many other metaheuristics. The key parameters are the population size (number of nests), the discovery probability (p_a), and the Lévy flight step size (α). The discovery probability(p_a), controls the rate at which subpar solutions are abandoned, influencing the balance between exploitation and exploration. A higher pa encourages more exploration by replacing more nests. The step size α scales the length of the Lévy flight jumps, directly impacting the algorithm's search behavior.

CS achieves the third-best performance overall. Its load distributions are effective, though slightly less optimized than those of GA-BMO and ICA. For example, at 864 RT, CS finds PLRs of 0.765, 0.652, and 0.999. This is a strong solution that correctly identifies the need to run one chiller near its maximum efficiency point while balancing the other two. It consistently outperforms simpler algorithms by avoiding simplistic, single-chiller-dominant.

The effectiveness of CS is largely due to the Lévy flight mechanism. This random walk, characterized by a heavy-tailed probability distribution, naturally balances global and local search. Most steps are small, allowing for fine-grained local search (exploitation) around existing solutions. However, the heavy-tailed nature of the distribution allows for occasional, very large jumps across the search space. This serves as a powerful exploration mechanism, enabling the algorithm to escape local optima and discover entirely new, promising regions. This intrinsic balance makes CS a robust and generally effective optimizer, capable of outperforming algorithms that lack such a strong global search capability.

4.3.1.4 Particle Swarm Optimization (PSO)

PSO ranks fourth in performance, showing a noticeable drop-off from the top three algorithms. Its load distribution strategies often appear less refined. For example, at 918 RT, it settles on a PLR distribution of 0.831, 0.732, and 1.000. While not a poor solution, it consumes more power than the strategies found by GA-BMO, ICA, and CS, suggesting it may have converged to a local, rather than global, optimum.

PSO's primary weakness, particularly in complex, non-convex problems like OCL, is its susceptibility to premature convergence. The strong pull of the single global best solution (gbest) can cause the entire swarm to rapidly converge on one promising region, losing population diversity and ceasing to explore the rest of the search space. Once the particles cluster around a local optimum, it is very difficult for the swarm to escape. This explains why its performance is middling; it is better than a simple GA but lacks the robust escape mechanisms of ICA (revolution) or CS (Lévy flights).

4.3.1.5 Barnacle Mating Optimizer (BMO)

BMO ranks fifth, performing significantly worse than the top algorithms. Its standalone optimizer, BMO performed well in some load scenarios such as 972 RT and 918 RT but failed to surpass GA-BMO. BMO's biologically inspired mating strategy allowed for relatively fast convergence through localized spermcasting and broadcast spawning. However, it lacks the genetic diversity and broad search mechanisms required for exploring a high-dimensional, nonlinear system like the chiller model. This limitation caused BMO to get trapped in local optima, especially in high-load cases such as 1026 RT, where it consumed 689.77 kW, slightly more than GA-BMO’s 689.05 kW, and significantly more than the theoretical minimum.

BMO's performance is hampered by a potential imbalance in its search operators. While the concept of sperm-casting provides a mechanism for exploration, it may not be as effective as the Lévy flights in CS or the revolution operator in ICA. The exploitation phase, based on the Hardy-Weinberg principle, may also be less efficient at refining solutions compared to the assimilation process in ICA. The algorithm's relatively poor performance suggests that its exploration and exploitation mechanisms are not as well-tuned to the OCL problem as those of the leading algorithms, leading it to converge on less optimal solutions.

4.3.1.6 Improved Genetic Algorithms and Genetic Algorithms

Both the traditional Genetic Algorithm (GA) and its modified variant (I-GA) performed the worst in nearly every scenario. Despite their historical success in general optimization tasks, their rigid genetic operators and lack of adaptive mechanisms led to poor convergence in this application. I-GA attempted to introduce enhancements such as adaptive mutation, but without intelligent local exploitation or solution-specific feedback, it still converged to high-energy solutions (for example, 699.84 kW at 1026 RT). The basic GA fared even worse, recording the highest total power at multiple load levels, including 700.20 kW at 1026 RT, clearly indicating its inadequacy for complex, constraint-sensitive energy systems. The poor performance of both GA and I-

GA highlights the need for more advanced or hybridized structures such as GA-BMO that are capable of dynamically adjusting to complex search spaces.

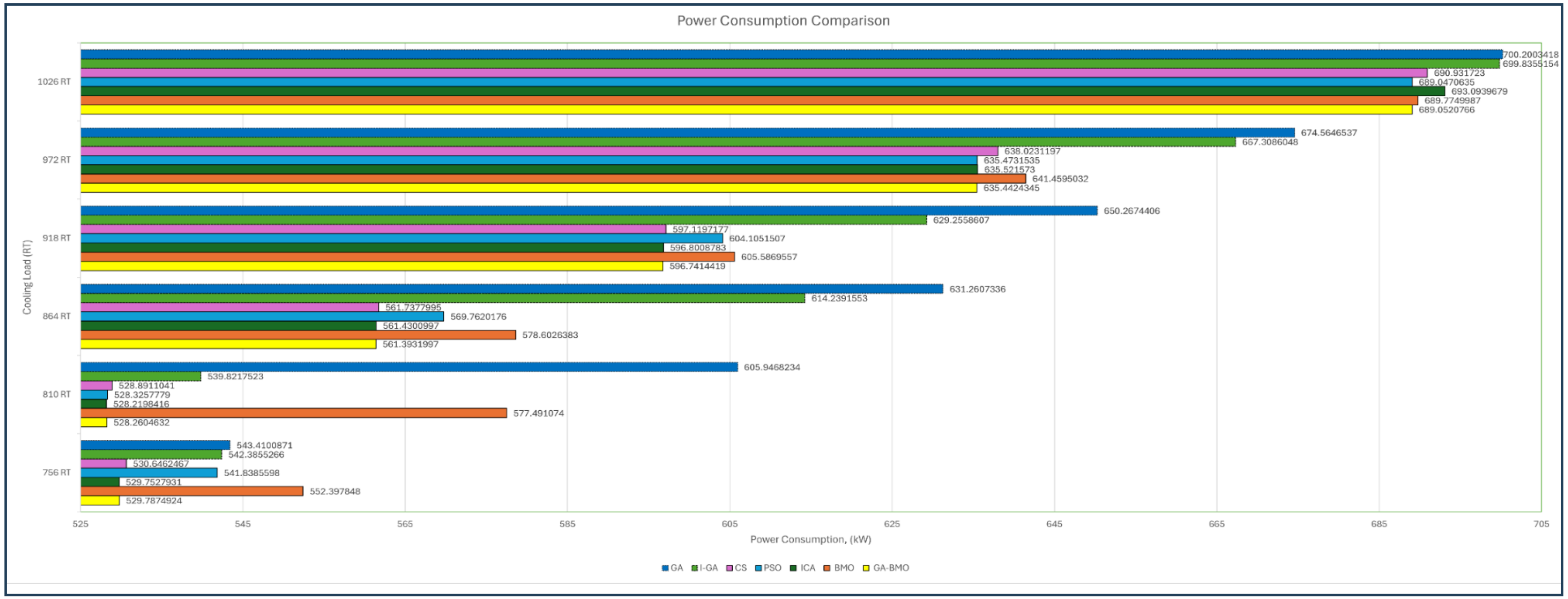

Figure 4.3: Clustered Bar Chart for Power Consumption Comparison

Figure 4.3 presents a clustered bar chart comparing the total power consumption of each algorithm across all cooling load scenarios. This visualization clearly shows that the hybrid GA-BMO consistently achieved the lowest power consumption, particularly at higher load conditions, validating its efficiency in handling heavy operational demands. Algorithms such as GA and I-GA exhibited significantly higher consumption, highlighting their limitations in multi-chiller load balancing.

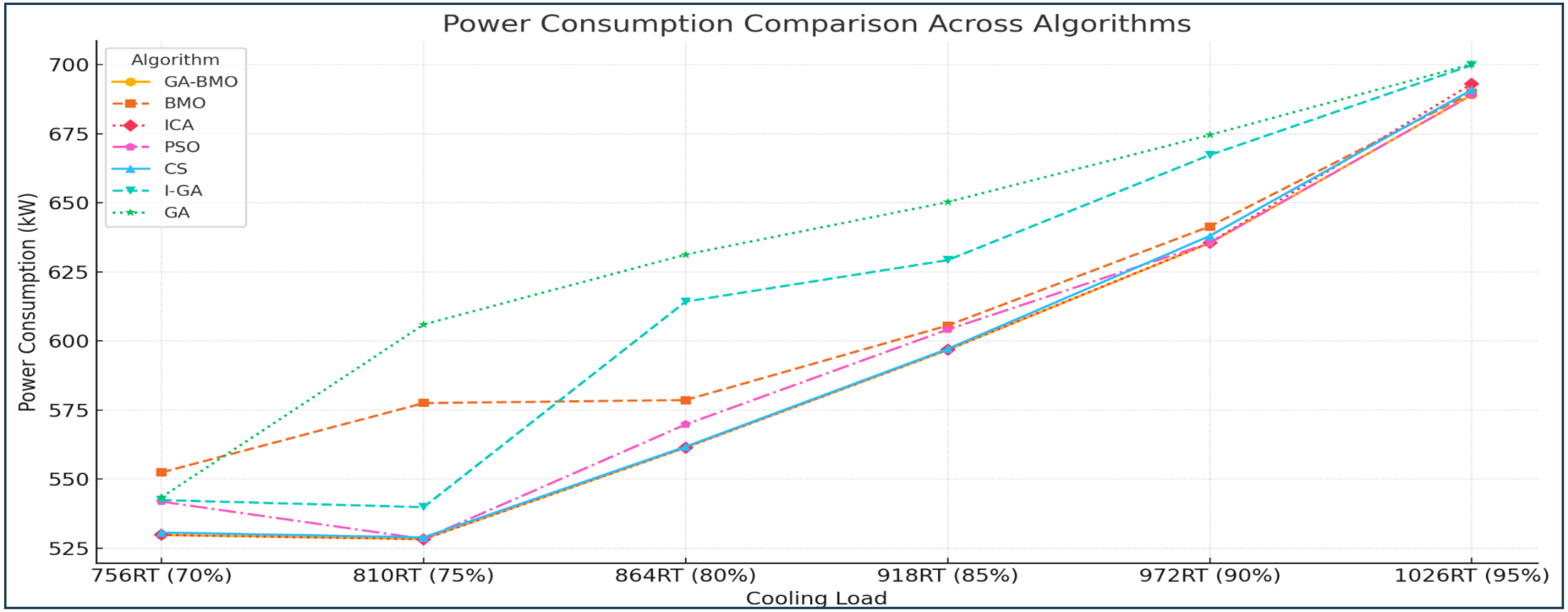

Figure 4.4: Line Chart for Power Consumption Comparison Across Algorithm

Figure 4.4 complements the bar chart by presenting the same data in a line format to illustrate performance trends. GA-BMO demonstrates a smooth and predictable increase in power with rising cooling load, signifying stable behaviour. In contrast, other algorithms such as PSO and I-GA exhibit erratic performance patterns, especially under medium to high load conditions, reinforcing the claim that GA-BMO is better suited for dynamic environments with fluctuating demands.

4.4 Objective 3: Simulated Real-Time Validation and Dashboard Integration

This section presents the outcomes of the real-time system deployment, including the operational flow of the Simulink-based scheduler, the automation scripts used for continuous simulation cycles, and the structure and functionality of both mobile and web dashboards. Additionally, challenges encountered during system integration and observations from real-time usage are discussed.

4.4.1 MATLAB Simulink Dynamic Scheduler Results

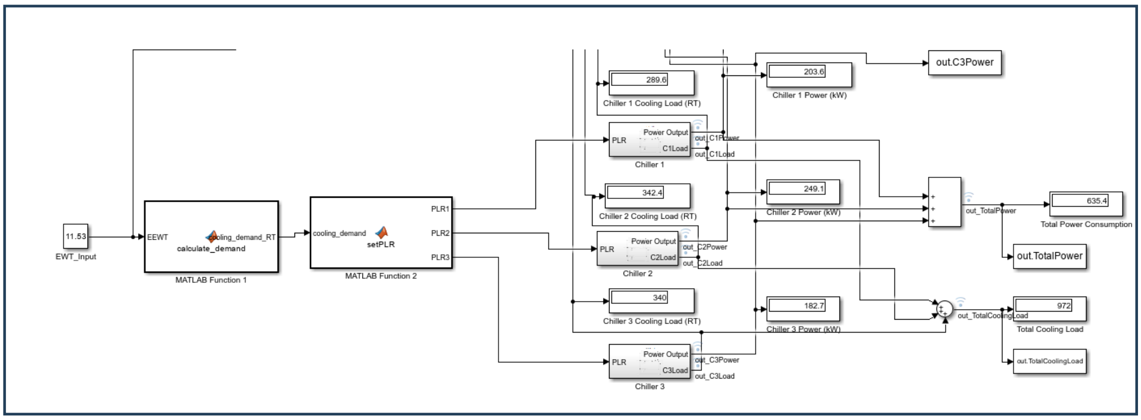

Figure 4.5: Dynamic Scheduler Output

The MATLAB Simulink-based dynamic scheduler shown in Figure 4.5 was developed to simulate the real-time behaviour of the three-chiller system under varying cooling load conditions. The model receives the Evaporator Entering Water Temperature (EWT) as a time-varying input and processes it using two dedicated MATLAB Function blocks. The first function, calculate_demand, calculates the required cooling demand in refrigeration tons (RT) based on the provided EWT. This calculated demand is then passed to the second function, setPLR, which allocates the demand across the three chillers by determining the optimal Partial Load Ratios (PLRs) using the GA-BMO optimization algorithm.

The simulation results demonstrate the successful implementation of the optimized control strategy within the Simulink environment. As illustrated in Figure 4.5, for an EWT input of 11.53°C, the scheduler calculated a total cooling demand of 972.00 RT. The optimized PLRs resulted in the following cooling load distribution: Chiller 1 was assigned 289.65 RT, Chiller 2 was allocated

342.35 RT, and Chiller 3 handled 340.00 RT. The power consumption corresponding to each chiller was 203.58 kW, 249.11 kW, and 182.75 kW respectively, yielding a total system power consumption of 635.44 kW.

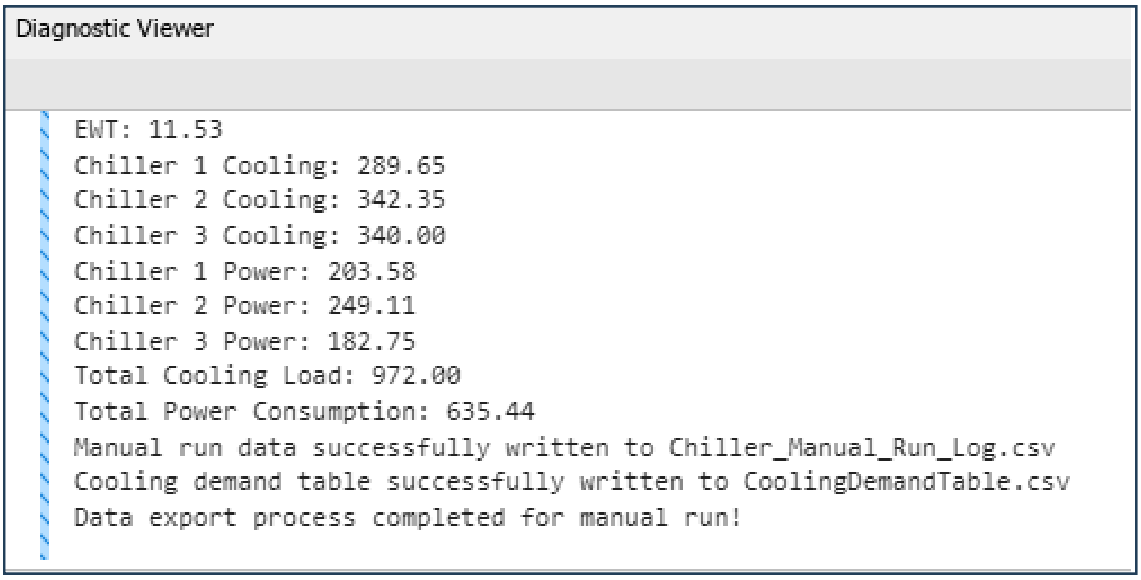

Figure 4.6: Diagnostic Viewer Output

To verify and document the results, the output data were exported into structured CSV files. Figure 4.6 shows the real-time output as displayed in the Diagnostic Viewer, confirming that the data were successfully logged into Chiller_Manual_Run_Log.csv and CoolingDemandTable.csv. These files are later synchronized with the cloud storage for dashboard visualization. The integration of real-time input processing, optimized control allocation, and automated data export demonstrates the robustness of the dynamic scheduler in handling time-based operational variability in HVAC systems.

4.4.2 Automation Script Output Summary

To streamline and automate the execution of the dynamic scheduler, a dedicated MATLAB automation script was developed. This script was designed to sequentially execute hourly simulations for each operational period, automatically adjusting the evaporator water temperature (EWT) and extracting the necessary performance data. The script operates in a loop from 8:00 AM to 5:00 PM, with each iteration corresponding to one hour of simulation.

The automation process begins by verifying whether the Simulink model is correctly loaded. If not, it reloads the model and resets the simulation environment. Once the appropriate EWT value is set for the specific hour, the simulation is executed. Upon completion, the script checks for the availability of the logsout variable, which contains the required simulation outputs. If the logs are successfully retrieved, the script proceeds to extract data such as chiller cooling loads, chiller power consumption, and total power usage. These data are then formatted and saved into structured CSV files for later analysis and dashboard synchronization.

```
Command Window
Running simulation for 5:00 PM, EWT = 9.83°C
Loading model: chiller_model_2 for iteration 10...
Model chiller_model_2 loaded successfully.
Attempting to set parameter for: chiller_model_2/EWT_Input
Parameter set successfully for: chiller_model_2/EWT_Input
Attempting to run simulation...
EWT: 9.83
Chiller 1 Cooling: 268.23
Chiller 2 Cooling: 203.54
Chiller 3 Cooling: 338.23
Chiller 1 Power: 194.25
Chiller 2 Power: 151.27
Chiller 3 Power: 182.73
Total Cooling Load: 810.00
Total Power Consumption: 528.25
Manual run data successfully written to Chiller_Manual_Run_Log.csv
Cooling demand table successfully written to CoolingDemandTable.csv
Data export process completed for manual run!
Simulation command completed.
SUCCESS: logsout found for 5:00 PM
Data for 5:00 PM successfully written to E:\MASTER FOLDER\Master Degree\Simulation\Simulink\Chiller_Simulation_Log.csv
Closing model chiller_model_2 after iteration 10...

All hourly simulations completed for the day.
Final cumulative data should be in: E:\MASTER FOLDER\Master Degree\Simulation\Simulink\Chiller_Simulation_Log.csv
fx >>
```

Figure 4.7: Sample Output from MATLAB Automation Script Showing Simulation Execution and Data Export Logs

As shown in Figure 4.7, the script provides detailed feedback in the MATLAB Command Window. This includes the EWT value for the hour, the load and power of each chiller, the total power consumed, and confirmation that the CSV files were written successfully. It also logs a final message summarizing the completion of all hourly simulations and the location of the cumulative data file. This process not only ensures consistent and accurate data collection but also improves the efficiency and traceability of simulation runs by eliminating the need for manual intervention.

4.4.3 Mobile Dashboard Systems Implementation and Results

The mobile dashboard application, implemented with modern Android components, allows users to monitor chiller performance metrics from their smartphones. Key parameters displayed include total cooling load, total power consumption, chiller-specific loads and power values, and hourly simulation timestamps. The use of Jetpack Compose enabled a clean, responsive, and dynamic UI that updates as new CSV files are uploaded to Google Drive.

Upon launching, the app allows users to select between Manual Run and Daily Simulation modes, which correspond to different data files. The interface is organized into four primary tabs: Home and System Status shown in Figure 4.8, Metrics, and Cooling Demand Table shown in Figure 4.9 and Figure 4.10. These tabs provide access to system overview, chiller-wise performance, KPI trends, and a reference lookup table for EWT-to-RT mapping. Animated donut charts, numerical panels, and color-coded status indicators are used throughout the interface for intuitive visual feedback.

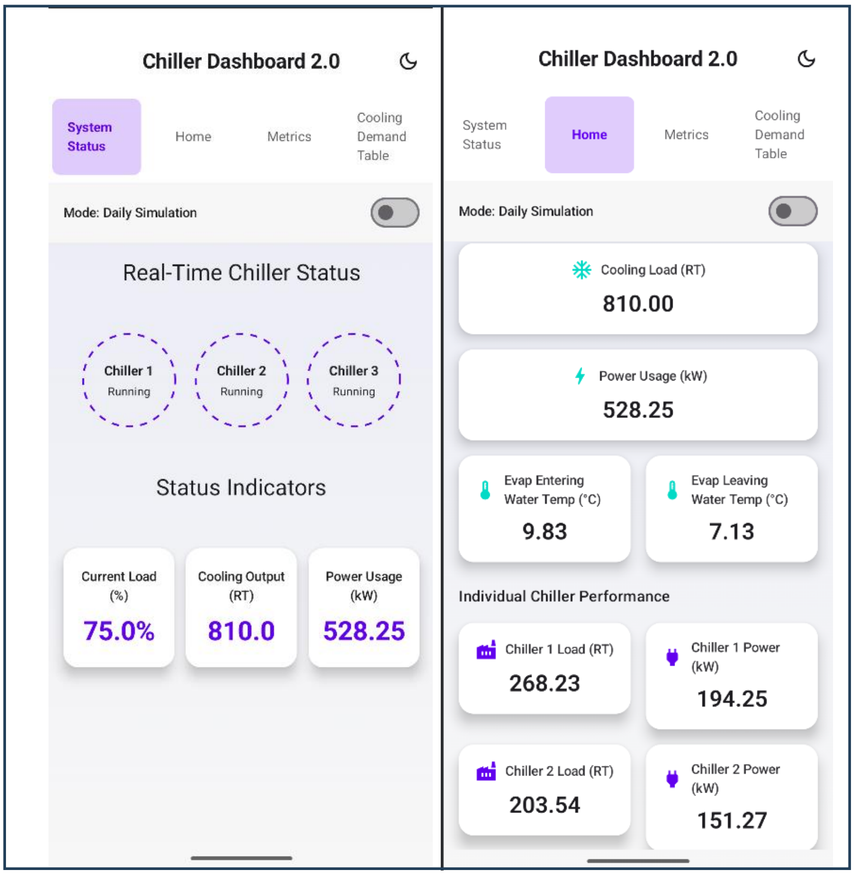

Figure 4.8: System Status and Home Tab App

The application retrieves simulation output stored as .csv files in a synchronized Google Drive folder, which is updated automatically by MATLAB scripts. Data is fetched every 5 to 10 seconds using the OkHttp library, ensuring near real-time synchronization without the need for a direct server connection.

Jetpack Compose was chosen to ensure smooth rendering, modern layout responsiveness, and native performance. The app is designed to operate efficiently across multiple Android devices, adhering to mobile UI/UX best practices. By enabling real-time, cloud-linked visualization of simulation results, the Android dashboard enhances operator accessibility and supports on-the-go monitoring of optimization outcomes.

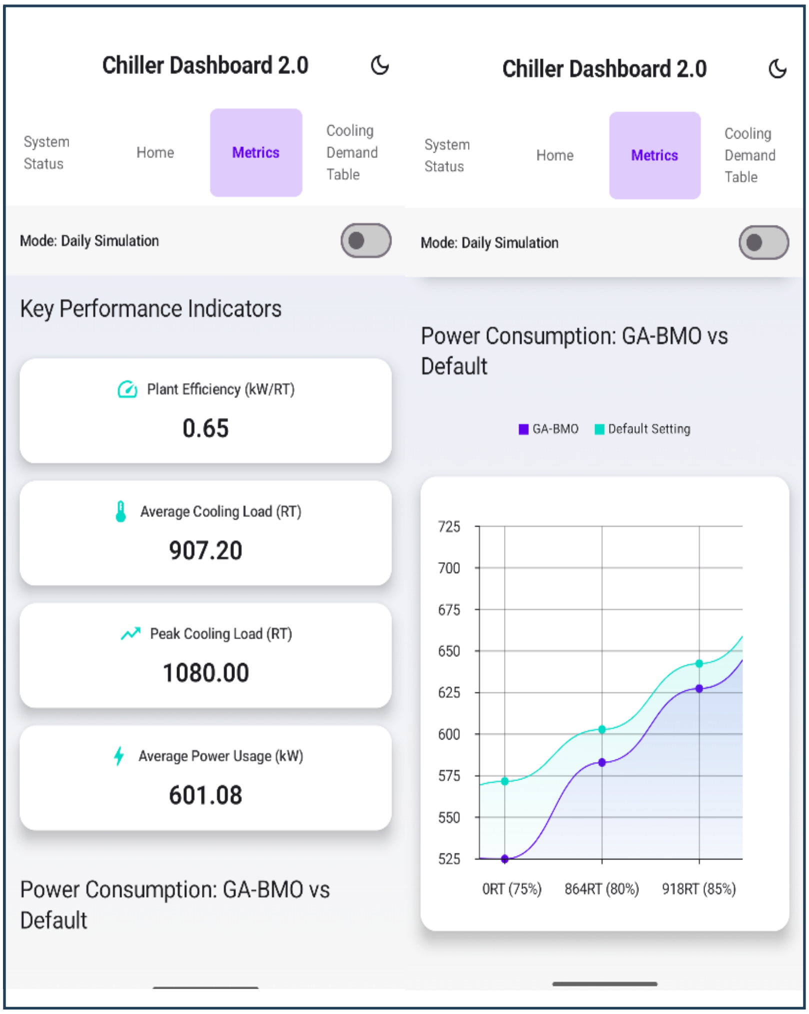

Figure 4.9: Metrics Tab App

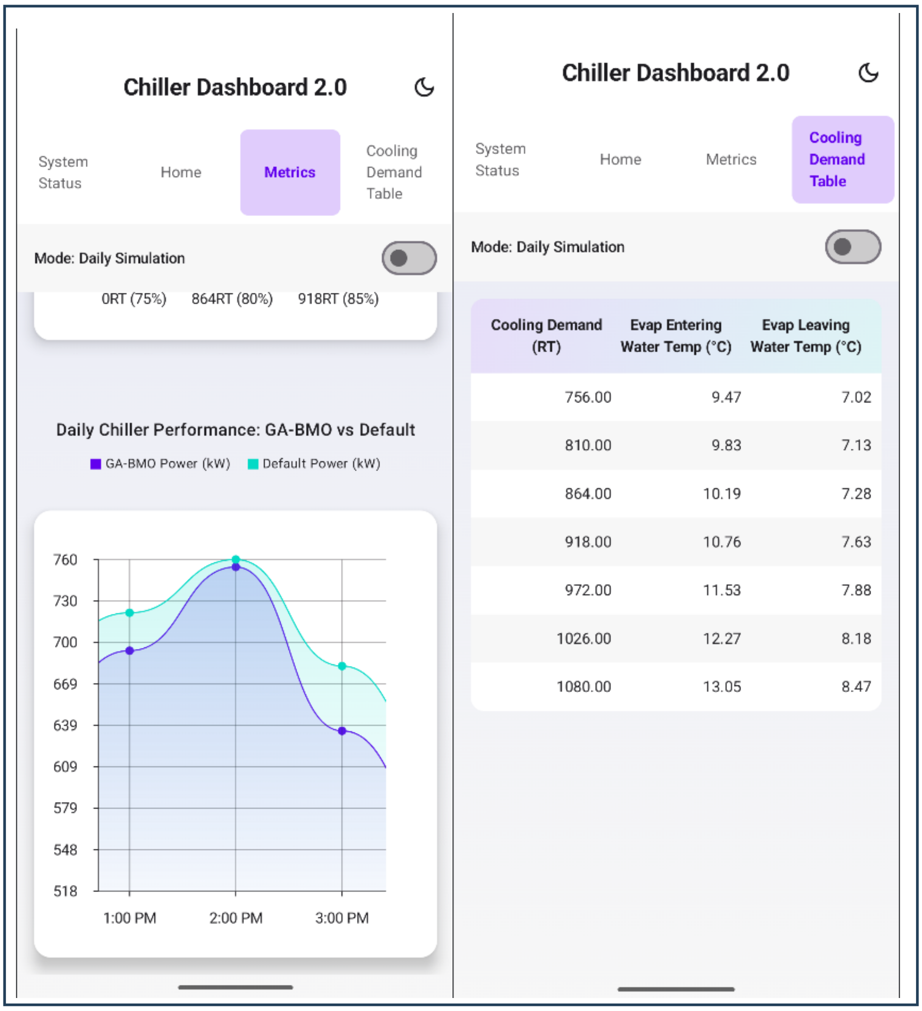

Figure 4.10: Metrics and Cooling Demand Tab App

The graph shown in Figure 4.9 the metrics tab, Power Consumption: GA-BMO vs Default visualizes the total power consumption (in kW) across several cooling load scenarios, 70%-95% of total system capacity. The blue line represents the power consumed under the default static schedule, while the purple line indicates power consumption under the GA-BMO optimized schedule.

The graph shown in Figure 4.10 metrics tab, Daily Chiller Performance: GA-BMO vs Default shows the hourly variation in power consumption between 8:00 AM-5:00 PM, comparing GA-BMO (purple) and default settings (cyan). The visualization clearly shows that GA-BMO maintains a consistently lower power profile, especially during peak hours (for example, 2:00 PM), demonstrating not only reduced energy use but also a more stable load distribution across time.

4.4.4 Web-Based Dashboard Systems Implementation and Results

The web dashboard developed in this study is deployed via GitHub Pages and publicly accessible at: https://aniq2119.github.io/chiller-dashboard-2-0/ (retrieved 17 August 2025). The page visualizes total cooling load, chiller partial-load ratios (PLRs), per-chiller power, and plant efficiency (kW/RT), and reads from published, read-only CSV sources to ensure reproducibility.

The web dashboard is organized into four main navigation tabs: Home, System Status, Metrics and Charts, and Cooling Demand Table. Each tab serves a specific role in communicating system performance to end users. The System Status shown in Figure 4.11 serves as the primary landing page, offering an immediate, at-a-glance overview of the chiller plant's operational state. This tab is crucial for operators who need to quickly assess the current condition of the system. It features three circular indicators that display the current operational mode of each unit (OFF, STANDBY, or RUNNING), with a spinning animation to visually emphasize active operation. Below these indicators, key aggregate metrics for the entire plant are displayed, including the current load as a percentage of maximum capacity, the total cooling output in Refrigeration Tons (RT), and the total electrical power consumption in kilowatts (kW).

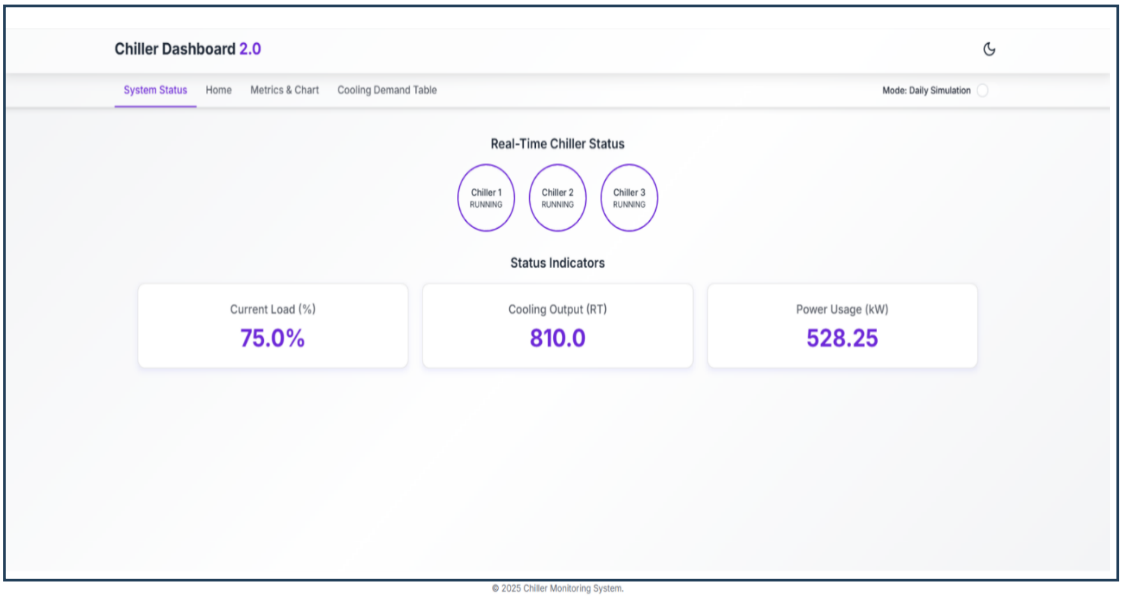

Figure 4.11: System Status Tab Webpage

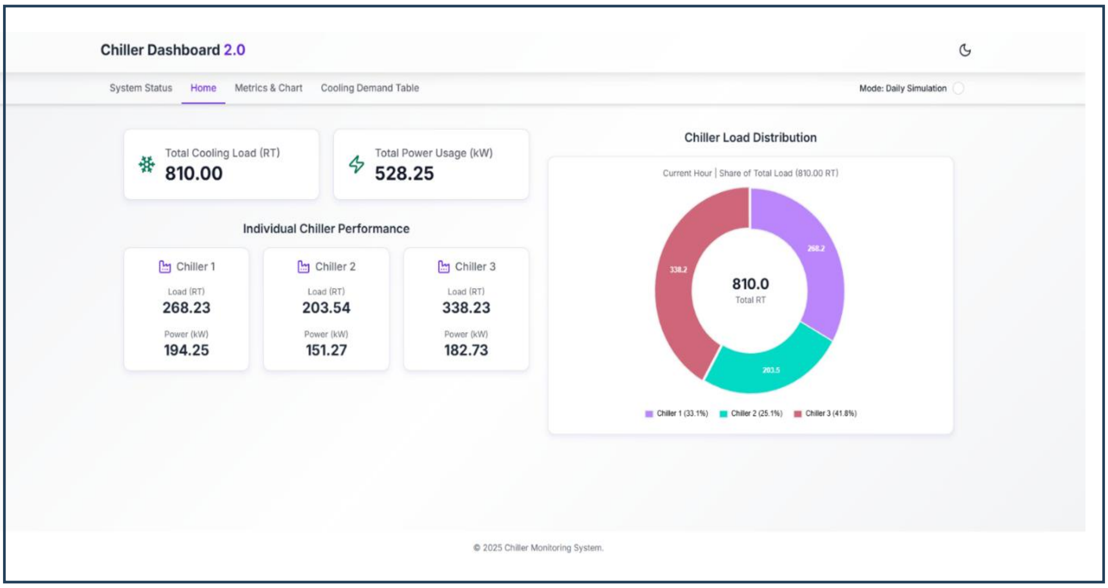

Figure 4.12: Home Tab Webpage

Figure 4.12 shows the Home tab focuses on both aggregate and individual chiller metrics, which is useful for understanding how the total load is distributed and how each chiller contributes to the overall output. The tab presents the total cooling load (RT) and total power usage (kW) for the entire plant, alongside a granular view of each individual chiller's load and power consumption. A prominent feature is the doughnut chart which visualizes the distribution of the total cooling load among the three chillers, offering an intuitive understanding of which units are carrying the most load. The centre of the chart displays the total cooling load, while the legend shows the percentage contribution of each chiller.

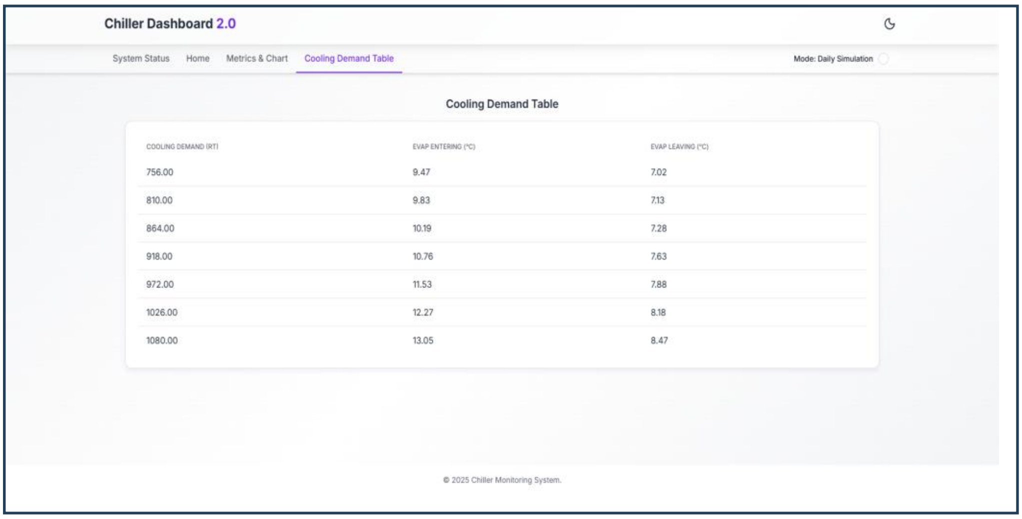

Figure 4.13: Cooling Demand Tab Webpage

Figure 4.13 shows lists of the discrete cooling-demand setpoints (RT) alongside the corresponding Evap Entering (°C) and Evap Leaving (°C) water temperatures. The table serves as the reference dataset for the dynamic scheduler: it underpins the Simulink calculate_demand interpolation and the GA-BMO controller’s PLR assignment, providing traceability between model outputs and the live dashboard.

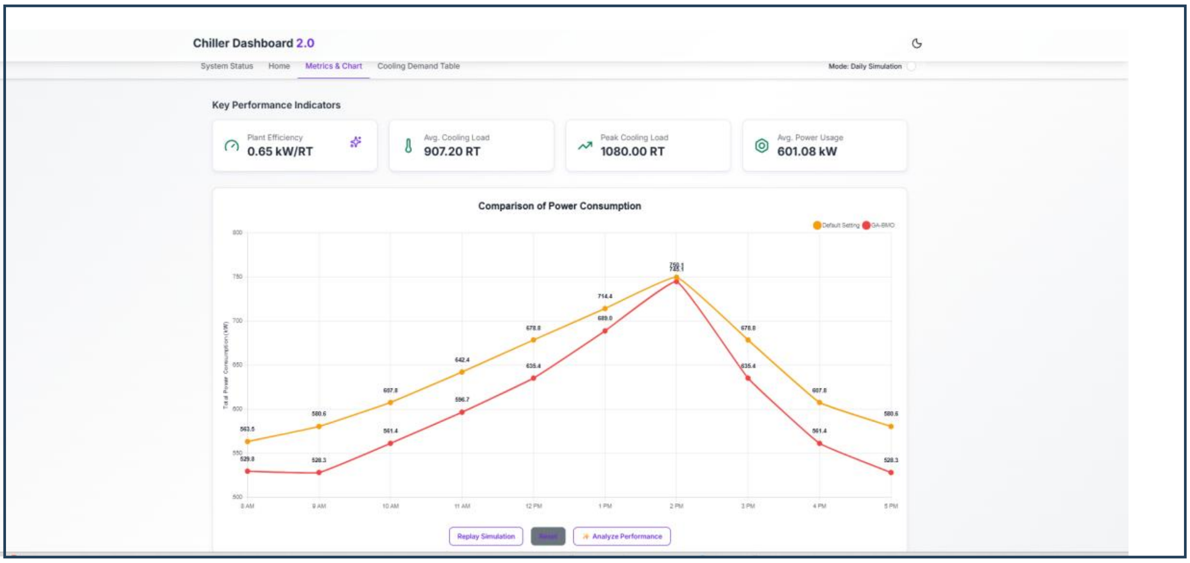

Figure 4.14: Metrics & Chart Tab Webpage

For more in-depth analysis and performance evaluation over time, the Metrics & Chart tab shown in Figure 4.14 provides Key Performance Indicators (KPIs) and a time-series chart for trend analysis. It presents critical KPIs such as Plant Efficiency (kW/RT), Average Cooling Load (RT), Peak Cooling Load (RT), and Average Power Usage (kW). A key analytical tool on this tab is the Daily Performance Chart, a line chart that visualizes the power consumption of the plant over a simulated day, comparing the performance of a 'Default Setting' against an optimized 'GA-BMO' setting. The chart includes interactive controls to play, pause, and reset the simulation. An "Analyse Performance" button uses a Generative AI model to provide a detailed report comparing the two operational strategies, while another button provides AI-powered insights into the plant's current efficiency rating.

The interactive chart within the dashboard allows users to observe hour-by-hour variations in power consumption between the default and GA-BMO strategies. The red line represents the GA-BMO optimization, consistently showing reduced power usage compared to the default baseline (yellow line) across the operating period from 8:00 AM to 5:00 PM.

4.4.5 Challenges Encountered

Table 4.9
Summary of Challenges and Solutions during Simulated Real-Time Validation

Challenge Area	Description	Solution Implemented
GA-BMO Embedding	Difficulty integrating BMO operator into GA while ensuring stability and consistent output	Repeated trials, parameter tuning, and averaging across simulations
Simulink Automation	Simulation state errors due to incomplete resets and model reloading failures	Conditional model reloading and output validation prior to data export
Cloud Synchronization	Latency and file-locking issues when syncing .csv outputs to Google Drive	Used scheduled uploads, unique filenames, and retry-based error handling scripts
Android & Web Dashboard Sync	Inconsistent data formatting and display behavior across mobile (Kotlin) and web (HTML/Chart.js)	Developed a standardized .csv export format and synchronized time-series structures

The simulated real-time validation and integration of the GA-BMO control strategy into a dynamic scheduler and monitoring system posed several technical and operational challenges. These obstacles emerged across different stages of development, including algorithm embedding, system automation, data management, and cross-platform synchronization.

One of the primary challenges shown in Table 4.9 involved embedding the Barnacle Mating Optimizer (BMO) operator seamlessly into the Genetic Algorithm (GA) framework. Maintaining computational balance while ensuring convergence stability required meticulous parameter tuning and testing. The stochastic nature of the hybrid algorithm introduced variability in output, which was mitigated through repeated trials and averaging techniques to ensure consistent PLR decisions.

Automation of the MATLAB Simulink scheduler also presented complexities, particularly in ensuring reliable state resets between simulation runs. For instance, improper model closure or residual signal states occasionally led to incomplete or corrupted output logs. This was resolved by implementing conditional model reloading and output validation routines before data export.

The next critical hurdle was achieving real-time synchronization with the cloud-based storage system. Initially, latency and file-locking issues during Google Drive synchronization disrupted timely updates to the dashboard systems. These were mitigated by adopting scheduled background uploads, standardized naming conventions, and robust error-handling scripts that ensured retry attempts upon failure.

Execution details for cloud synchronization (Table 4.9): At each scheduler update, the simulation writes the latest PLR, cooling demand, and power values to a local data file (for example, CSV). The upload script then pushes the file to a designated cloud folder (Google Drive) monitored by the mobile/web dashboard. To prevent file lock/write-collision issues, each upload uses a unique timestamped filename (for example, data_YYYYMMDD_HHMMSS.csv), while the dashboard reads the most recent file by timestamp ordering. If an upload fails (network/IO error), a retry mechanism is triggered and the error is logged for troubleshooting.

Cross-platform compatibility between the Android dashboard (developed using Kotlin and Jetpack Compose) and the web-based dashboard (built with HTML, Tailwind CSS, and Chart.js) introduced design and data formatting inconsistencies. Ensuring visual coherence and data uniformity across both platforms required the development of common .csv data formatting scripts and harmonized time-series structures.

Despite these challenges, the system was successfully stabilized to provide accurate, real-time energy monitoring with minimal intervention. Each issue addressed contributed to the refinement of the system, reinforcing its practical readiness for deployment in real-world HVAC facility management.

CHAPTER 5
CONCLUSION

5.1 Summary of Research Achievements

Cross-chapter synthesis: The literature review (Chapter 2) highlighted key limitations of standalone GA-based optimization for chiller loading, particularly premature convergence and reduced adaptability under changing demand. The methodology (Chapter 3) addressed these limitations by embedding BMO operators within GA to strengthen exploration while preserving GA's structured exploitation. The results (Chapter 4) confirm that this design improves PLR balancing and reduces total power consumption across multiple load scenarios, demonstrating that the hybrid operator choice directly contributes to the observed efficiency gains.

This research successfully fulfilled its three main objectives, establishing a complete pipeline from algorithm development to simulated real-time validation of an intelligent chiller control system using the proposed hybrid Genetic Algorithm–Barnacle Mating Optimizer (GA-BMO).

For the first objective, a novel hybrid optimization strategy was developed by embedding the BMO operator directly into the GA framework. This embedded structure enhanced the algorithm’s capability to balance global exploration and local exploitation, outperforming traditional sequential hybrids. The hybridization process was carefully designed through a Full Factorial Design (FFD) approach, where key parameters—Population Size, Crossover Fraction, and Spermcast Probability—were systematically tuned across 125 combinations, each executed 20 times to ensure statistical reliability. The final GA-BMO configuration demonstrated consistent convergence and reliable performance across a range of cooling load scenarios.

For the second objective, a comprehensive benchmarking study was conducted to evaluate the performance of GA-BMO against five other metaheuristic algorithms: BMO, ICA, PSO, CS, and GA. Simulation results under six different cooling loads (ranging from 70% to 95%) revealed that GA-BMO consistently achieved the lowest power consumption across all load levels. This clearly demonstrated the superior load distribution efficiency and optimization capacity of the proposed hybrid model. Furthermore, GA-BMO delivered the greatest energy cost savings when applied under Tenaga Nasional Berhad's commercial tariff (Tariff C2), validating its real-world financial impact.

The third objective focused on the implementation of the GA-BMO strategy within a real-time dynamic scheduling and monitoring environment. A MATLAB Simulink-based scheduler was developed to simulate chiller operations dynamically throughout the day, based on entering water temperature (EWT) inputs. Data from the simulation were exported to .csv format and synchronized via Google Drive to two dashboard platforms. The Android application (developed in Kotlin with Jetpack Compose) and the web-based dashboard (built using HTML, Tailwind, and Chart.js) both successfully visualized real-time cooling load distribution and power consumption metrics. The dashboard integration provided operational insights through clear comparative charts, key performance indicators, and energy-saving analytics, completing the real-time feedback loop and proving the practical applicability of the system.

Overall, this study delivered a robust and scalable intelligent chiller management solution that not only optimizes energy efficiency but also supports real-time adaptability and monitoring. The integration of GA-BMO into a functional digital ecosystem bridges the gap between theoretical optimization and real-world HVAC energy management.

Limitations: First, GA-BMO performance remains sensitive to parameter tuning (for example, population size, crossover fraction, sperm-cast probability), and different load regimes may favour different settings. Second, the presented results are based on a specific three-chiller configuration inspired by the Malaysian Nuclear Agency; generalization to other plant sizes or chiller types should be validated. Third, dashboard responsiveness and cloud synchronization may be affected by network latency and file I/O reliability, which should be addressed in future real deployment.

Practical deployment considerations: In a real chiller plant, implementation must account for sensor noise, missing data, actuator limits, safety interlocks, and operator override requirements. In addition, data streams often exhibit latency and sampling jitter. To mitigate this, the scheduler can include buffering and filtering, use a moving average of demand signals, and incorporate delay compensation (for example, short-horizon forecasting). These measures help ensure that PLR updates remain stable and feasible even when real measurements are delayed or imperfect.

5.2 Recommendations for Future Research

While the present study has successfully developed and demonstrated the effectiveness of the GA-BMO hybrid optimization strategy for chiller load management, several opportunities remain for expanding and improving this research.

Firstly, future studies may consider testing the GA-BMO algorithm on larger-scale chiller systems involving more than three units or incorporating variable-speed chillers and hybrid cooling technologies (for example, absorption chillers or thermal storage systems). This would test the scalability and adaptability of the hybrid model under more complex operating environments.

Secondly, although the algorithm was validated using historical and synthetic cooling demand data, future work could integrate live sensor data from building management systems (BMS) or IoT-enabled HVAC infrastructure. Real-time data acquisition would enable the system to respond dynamically to fluctuating environmental and occupancy conditions, further enhancing its adaptability and practical relevance.

Third, while this study focused on energy minimization, multi-objective optimization could be explored in future work by incorporating additional performance criteria such as equipment wear, carbon emissions, water consumption, or cost under time-of-use tariffs. This would align optimization outcomes with broader sustainability goals.

Moreover, there is potential to enhance the current dashboard monitoring systems by integrating predictive analytics, machine learning models, or anomaly detection algorithms. This would transform the dashboard from a passive monitoring tool into an intelligent decision-support system capable of forecasting system performance or diagnosing faults in real-time.

Finally, future research could explore edge computing or embedded system deployment of the GA-BMO algorithm, allowing optimization to occur directly on local HVAC controllers or microcontrollers without the need for centralized simulation platforms. This would support faster decision-making and reduce dependency on high-performance computing systems.

In conclusion, this thesis demonstrates that integrating GA with BMO as an embedded hybrid operator provides a robust optimization framework for multi-chiller loading and dynamic scheduling. The proposed GA-BMO strategy consistently reduces total power consumption relative to the default baseline and benchmark metaheuristics across realistic load scenarios. When coupled with a simulation-based scheduler and monitoring dashboard, the approach offers a clear pathway toward real-time-capable chiller energy management and forms a strong foundation for future real-plant deployment and wider generalization studies.

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LIST OF PUBLICATIONS:

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