Energy Characteristics of Multi-chiller Load Distribution Algorithms in a Large Office Building

Jiwon Park[a, 1], Jae Hwan Cha[a, 1], Yeobeom Yoon[b], Kwang Ho Lee[a, *]

[a] Department of Architecture, College of Engineering, Korea University, Seoul, Republic of Korea

[b] Buildings and Transportation Science Division, Oak Ridge National Laboratory, Oak Ridge, TN, USA

Abstract

This study evaluates the energy efficiency of multi-chiller systems in large office buildings, focusing on their optimization across various climate zones as defined by ASHRAE. Using EnergyPlus for simulations, the research examines five different load distribution algorithms in multi-chiller systems that range from one to ten chillers, aiming to understand their effectiveness in 15 distinct climate zones. The primary objectives of the study include identifying the energy efficiency of multi-chiller systems in each climate zone, determining the appropriate number of chillers for each zone, and evaluating the performance of the load distribution algorithms. Based on the U.S. Department of Energy's commercial building model, the results suggest that multi-chiller systems can significantly reduce cooling energy consumption in various climates. Among the algorithms evaluated, the Sequential Uniform Part Load Ratio (SUPLR) algorithm demonstrates notable efficiency, especially in the 4A climate zone (Baltimore), where it achieves substantial energy savings. Applying the SUPLR algorithm in a multi-chiller setup with four chillers in this zone leads to an estimated 24.5% reduction in energy usage, equivalent to 183MW annually. The research indicates that a range of 3 to 5 chillers is typically optimal for most climate zones. In-depth analysis in the 4A climate zone highlights the importance of minimizing operation hours at low Part Load Ratios (PLR) to ensure that chillers operate at a high Coefficient of Performance (COP). This strategy underscores the potential of well-designed multi-chiller systems to reduce cooling energy demand, particularly in climates with transitional seasons. This study provides an overview of the energy-saving potential of multi-chiller systems, applicable across a variety of climatic scenarios.

Keywords: Multi-chiller System, Part Load Ratio, Chiller Staging, Load Distribution Algorithm

1. Introduction

The challenge of mitigating global climate change is intimately linked to the reduction of greenhouse gas emissions. A predominant source of these emissions, contributing to around 76%, is energy consumption [1]. In this context, the building sector plays a significant role, accounting for about 30% of total annual global energy consumption [2]. This substantial proportion underscores the building sector's potential for significant energy savings, particularly through the optimization of Heating, Ventilating, and Air Conditioning (HVAC) systems. In buildings, HVAC systems are a major energy consumer, accounting for approximately 39% of energy usage [3]. Consequently, there is significant potential for energy savings in buildings through the implementation of efficient HVAC design and control measures, thereby minimizing HVAC energy consumption [4,5].

The variability in HVAC sizing plays a crucial role in determining HVAC system energy efficiency. Research indicates that variations in HVAC sizing methods can lead to up to a 20% difference in HVAC equipment capacity for identical buildings, thus significantly impacting HVAC energy efficiency and overall building energy consumption [6–8]. The problem of building energy efficiency reduction due to overestimation of HVAC capacity is frequently observed in practice [9]. Errors in HVAC capacity estimation, whether an underestimation or an overestimation, can lead to various operational challenges, including load-capacity imbalances, difficulties in maintaining desired temperatures, and premature equipment wear, as well as elevated initial costs and expanded installation space requirements [10]. Therefore, proper HVAC sizing is not only crucial for optimizing energy efficiency but also plays a key role in operational and maintenance aspects.

The challenge of HVAC sizing is further complicated by the unique features of individual buildings. Despite typically following guidelines set by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) [7], the process can still result in system capacity underestimation or overestimation due to varying interpretations among different experts, especially concerning extreme temperature conditions [9].

Focusing on chillers, which account for approximately 27% of an HVAC system's energy consumption [3], their efficiency significantly impacts overall building energy usage. The efficiency of these chillers varies with the Part Load Ratio (PLR) [11], highlighting the importance of capacity design. Ensuring the efficiency of chillers from the beginning is vital for long-term energy savings, given their typical lifespan of approximately 22 years [12]. Furthermore, given the effects of climate change and the evolving cooling requirements, particularly evident in the forecasts for Seoul, a region classified under ASHRAE Climate Zone 4A [13,14], it is imperative to consistently introduce additional chiller units and employ advanced control strategies. This ensures the effective distribution of the cooling load among both existing and newly installed chillers. In response to these changing demands, multi-chiller systems, comprising two or more chillers operating in parallel or series, have gained widespread adoption. Multi-chiller systems offer numerous advantages, such as operational flexibility, stability during maintenance, and reduced power consumption under varied PLR conditions [3,15,16]. Hence, there is a growing focus on advancing research and development efforts aimed at optimizing multi-chiller systems. Studies on the system configuration and control strategies of multi-chiller systems have been actively conducted to date.

Firstly, research for improving the configuration of multi-chiller systems includes Park's study on life cycle cost analysis in office buildings, which underscored the economic benefits of multi-equipment systems using different types of heat source equipment. The research demonstrated that regardless of the heat source, multi-equipment systems are cost-effective for large office buildings [17]. This discovery underscores the effectiveness of a multi-chiller system in optimizing building maintenance costs. Lee extended this line of inquiry with a comprehensive analysis based on literature reviews and case studies. Lee's research on oversized heat source equipment in office buildings showed that optimal energy savings were achieved with a strategic division of chiller capacity and a 7:3 allocation ratio for boilers in a dual-boiler and dual-chiller system.

In addition, Lee's findings indicate that in a system equipped with two boilers and two chillers, employing two of each appliance proves to be more energy-efficient compared to using only one of each. Furthermore, optimal energy savings were achieved by equally dividing the capacity of chillers and differentiating the capacity of boilers at a ratio of 7:3 [18]. This study demonstrated the energy-saving effects of multi chiller systems and proposed paths for further advancement.

Next, studies that evaluate and improve various load distribution control logics for distributing cooling loads are as follows. Firstly, Seo's research on the PLR characteristics and energy consumption patterns of compression chillers in commercial buildings underscored the significance of operating chillers efficiently under low cooling load conditions. The study proposed that a sequential load distribution algorithm was the most energy-efficient on an annual basis, as it effectively operates during transitional seasons, whereas a uniform load distribution method was preferable during peak summer periods [19]. This study underscores the importance of a comprehensive understanding for optimizing chiller operation across various seasons.

Jia introduced a method aimed at optimizing the distribution of cooling loads among chillers, coupled with simultaneous adjustments to the cooling coil exhaust air setpoint temperature. Implemented in a semiconductor factory located in Tianjin, China, this approach resulted in a notable 16.4% decrease in cooling energy consumption [20]. This research showcases the potential of employing advanced control strategies in multi-chiller systems to achieve substantial energy savings for buildings.

Additional contributions to the field are evident in Gunay's exploration of sequential load distribution within multi-chiller systems. This study achieved approximately a 25% decrease in cooling energy usage in a facility equipped with five chillers of varying capacities in Ottawa, Canada [21]. Gunay's research provides valuable insights into the benefits of sequential load distribution, especially in buildings with large-scale chiller systems. This is particularly crucial as larger chillers must efficiently manage a wide range of cooling loads, making sequential load distribution an optimal strategy for enhancing energy efficiency and operational effectiveness.

Arahal highlighted the substantial research focus on achieving optimal load distribution among chillers in multi-chiller systems [22]. This research area has seen extensive exploration, including investigations into diverse optimization algorithms such as evolutionary strategies, genetic algorithms, particle swarm algorithms, and invasive weed optimization algorithms [23–26]. Each of these studies contributes to a deeper understanding of how different algorithmic approaches can enhance the energy efficiency of chiller systems.

Stewart utilized the Shuffled Complex Evolution algorithm in two commercial buildings in Melbourne, resulting in energy savings of up to 16.6% [27]. Homod proposed a Deep Clustering of Cooperative Multi-agent Reinforcement Learning approach, achieving approximately 44.5% energy savings [28].

Lastly, Jun utilized an adaptive genetic algorithm to optimize load distribution in a dual-chiller system [29]. Junwei applied a genetic algorithm to optimize multi-chiller system control, achieving significant energy savings on a typical summer day [30]. Beghi effectively optimized load distribution for multi-chiller systems using the Particle Swarm Optimization (PSO) algorithm, surpassing sequential and symmetric strategies [31].

These studies collectively offer valuable insights into the intricate challenges of optimizing

HVAC systems, especially in the context of multi-chiller systems. However, despite these advancements, a significant gap remains in determining the optimal number of chillers to achieve maximum efficiency, further complicated by the computational intricacies of various control algorithms. This review underscores the need for additional research, not only focusing on effective control strategies but also addressing practical implementation challenges, especially across diverse climatic and building conditions.

Our study addresses this gap by evaluating the effectiveness of five adaptable, computationally efficient algorithms within EnergyPlus for practical applications. The research aims to provide a foundational guide for advanced control strategy analysis in multi-chiller systems. Specifically, it examines the cooling energy efficiency across a range of multi-chiller configurations, from one to ten chillers, using different load distribution algorithms in large office buildings across 15 ASHRAE climate zones. The main aspects of this investigation encompass:

- To identify climate zones where multi-chiller systems offer the most significant efficiency advantages.
- To ascertain the optimal number of chillers for each climate zone, striking a balance between efficiency and practical operational considerations.
- To evaluate and compare the effectiveness of different load distribution algorithms in terms of their impact on cooling energy savings.
- To analyze the factors influencing the superior performance of these algorithms, aiming to provide insights that can guide future HVAC system design and control.

2. Methodology

2.1 Selection of Simulation Programs and Modeling Methods

In this study, building performance simulations were conducted using EnergyPlus, developed by the U.S. Department of Energy (DOE), which employs various thermodynamic theories for simulation [32]. Additionally, the study utilized the commercial reference building model developed by the U.S. DOE [33]. These models aim to represent approximately 70% of the U.S. building stock, encompassing various building types with different programs. Furthermore, these buildings are categorized into three construction-year categories (pre-1980, post-1980, new construction) for each ASHRAE climate zone [33]. The study centered on the newly constructed large office building model compliant with the ANSI/ASHRAE/IESNA Standard 90.1-2004, given the prevalent use of chillers in large-scale office environments.

The large office building model comprises 12 floors, with each floor divided into 4 perimeter zones, 1 core zone, and 1 IT closet zone. Covering a total floor area of 46,321.5 square meters, the building features a window-to-wall ratio of 40%. Heating is provided by gas boilers, while cooling is primarily handled by chillers in most areas, excluding the IT closet zone [33]. This study examined large office building models across 15 distinct climatic zones to determine the optimal number of chillers for each climate, identify climates where implementing multi-chiller systems provides the greatest energy-saving benefits, and discover the most effective algorithm for cooling load distribution. In the names of the climatic zones, the numerical values denote temperature characteristics, with higher numbers indicating colder climates, ranging from 1 to 8. The letters in the climatic zone names represent humidity characteristics, where A signifies humid climates, B signifies dry climates, and C signifies marine climates. Furthermore, the climatic regions are grouped from 1A to 3B based solely on Cooling Degree Days (CDD), from 3C to 4B based on both CDD and Heating Degree Days (HDD), and from 4C to 8A based solely on HDD.

Table 1 presents an overview of the 15 climatic zones analyzed in this study, providing details on their respective characteristics and the specific regions chosen for simulation and analysis [34]. In the names of the climatic zones, the numerical values denote temperature characteristics, with higher numbers indicating colder climates, ranging from 1 to 8. The letters in the climatic zone names represent humidity characteristics, where A signifies humid climates, B signifies dry climates, and C signifies marine climates. Furthermore, the climatic regions are grouped from 1A to 3B based solely on Cooling Degree Days (CDD), from 3C to 4B based on both CDD and Heating Degree Days (HDD), and from 4C to 8A based solely on HDD.

Table 1. Overview of the 15 climatic zones

Climate Zone	Characteristic	Annual Climate	Example Region
1A	Very hot/Humid	5000 < CDD 10ºC	Miami
2A	Hot/Humid	3500 < CDD 10ºC ≤ 5000	Houston
2B	Hot/Dry	3500 < CDD 10ºC ≤ 5000	Phoenix
3A	Warm/Humid	2500 < CDD 10ºC < 3500	Atlanta
3B	Warm/Dry	2500 < CDD 10ºC < 3500	Las Vegas
3C	Warm/Marine	CDD 10ºC ≤ 2500 and HDD 18ºC ≤ 2000	San Francisco
4A	Mixed/Humid	CDD 10ºC ≤ 2500 and HDD 18ºC ≤ 3000	Baltimore
4B	Mixed/Dry	CDD 10ºC ≤ 2500 and HDD 18ºC ≤ 3000	Albuquerque
4C	Mixed/Marine	2000 < HDD 18ºC ≤ 3000	Seattle
5A	Cool/Humid	3000 < HDD 18ºC ≤ 4000	Chicago
5B	Cool/Dry	3000 < HDD 18ºC ≤ 4000	Boulder
6A	Cold/Humid	4000 < HDD 18ºC ≤ 5000	Minneapolis
6B	Cold/Dry	4000 < HDD 18ºC ≤ 5000	Helena
7A	Very cold	5000 < HDD 18ºC ≤ 7000	Duluth
8A	Subarctic	7000 < HDD 18ºC	Fairbanks

To accurately capture the building conditions of each region, the model for each climate integrated specific U-values for the envelope and Solar Heat Gain Coefficients (SHGC) for windows. Ensuring consistency across different climates, this study adopted values provided by the DOE model. Recognizing the potential variability in climate scenarios used in simulations, the study employed Typical Meteorological Year (TMY) climate scenarios from the DOE. This approach facilitated a comprehensive assessment spanning the entire year from January 1st to December 31st, accommodating the diverse cooling seasons observed across different regions.

While utilizing the equipment auto-sizing feature in EnergyPlus, relying on the design day for chiller sizing, it became apparent that the capacity of chillers was occasionally overestimated in certain regions. Following the ASHRAE standard, which mandates that annual setpoint not met hours should not exceed 300 hours [34], the calculation of cooling setpoint not met hours was based on the ratio of hours requiring cooling to those requiring heating. Through an iterative process of trial and error, adjustments were made to the chiller sizing to ensure that the overall cooling setpoint not met hours remained within this specified threshold.

The overall research methodology is illustrated in Figure 1. Given the complexity of modeling multi-chiller systems with three or more chillers in the EnergyPlus software, the simulation models for each climate were streamlined to include a single chiller. To replicate multi-chiller configurations, load distribution and electricity consumption calculations were conducted using data derived from simulations. This encompassed crucial parameters such as cooling demand rate, total chiller capacity, and chilled water inlet and outlet temperatures. These calculations were executed alongside the embedded load distribution algorithm and electricity consumption formulas within EnergyPlus. The computations were performed using Google Colab, leveraging the Python programming language.

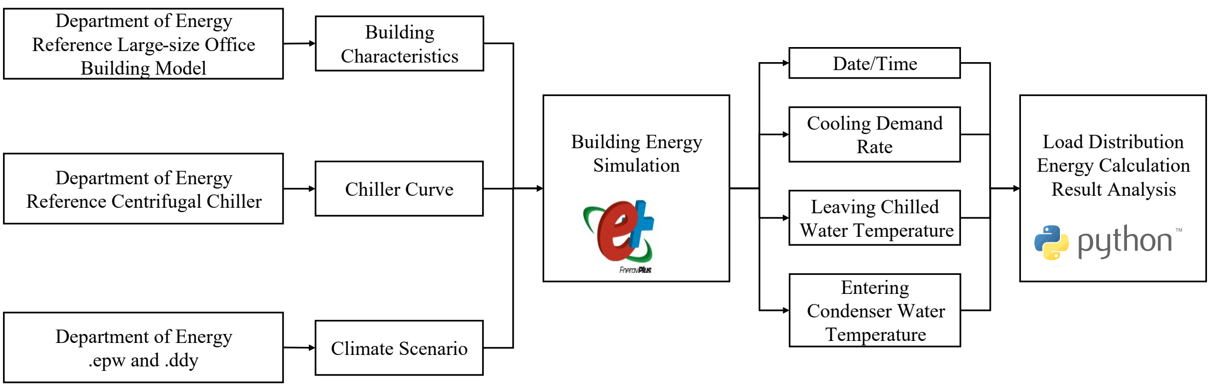

Figure 1. Research Methodology

2.2. Load Distribution Algorithms

EnergyPlus provides users with a choice of five load distribution algorithms, offering a diverse range of options [35]. These algorithms operate within an open-loop control system, adhering to pre-defined logic that is relatively straightforward. This approach reduces computation time by eliminating the need for complex algorithms or calculations. However, relying solely on pre-defined logic may limit adaptability to unforeseen circumstances and may not guarantee optimal outcomes.

The five distribution algorithms available in EnergyPlus are Uniform Load (UL), Sequential Load (SL), Uniform Part Load Ratio (UPLR), Sequential Uniform Part Load Ratio (SUPLR), and Optimal Part Load Ratio (OPLR). Each algorithm has a distinct activation strategy for chillers within a system. For instance, some algorithms, like the UL, require that all chillers be activated simultaneously, regardless of the total load, ensuring uniform wear but potentially leading to inefficiencies under partial load conditions. Conversely, algorithms like the SL activate chillers sequentially based on the size of the load, potentially saving energy by running only the necessary chillers at any given time. While the fundamental characteristics of multi-chiller systems have been previously examined, this section focuses on summarizing the attributes of these five algorithms when applied to multi-chiller systems with chillers of equal capacity. In scenarios with four identical chillers, each algorithm distributes the total cooling load across the chillers differently, and these distribution methods are illustrated schematically in Figure 2. Detailed descriptions of each algorithm can be found from Sections 2.2.1 to 2.2.5.

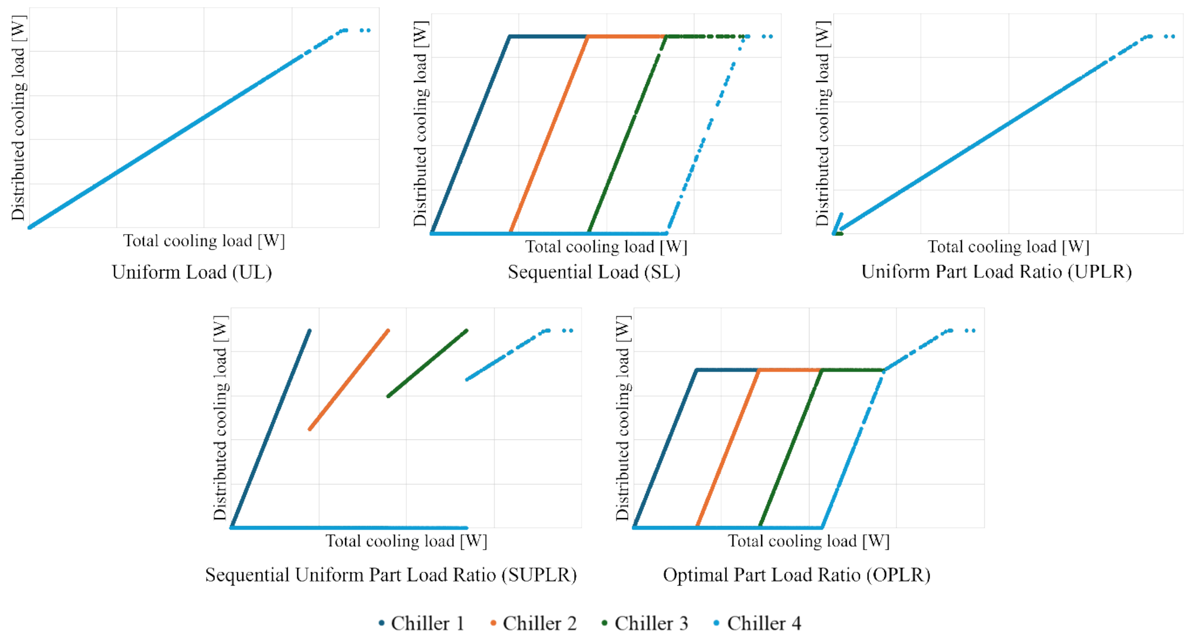

Figure 2. distributed cooling load trend of each chiller in different load distribution algorithm

2.2.1. Uniform Load (UL) Distribution algorithm

The Uniform Load (UL) algorithm equitably distributes the cooling load among all chillers in the system, ensuring that each operates at a consistent load. This uniform distribution, as depicted in Figure 3, enhances system durability by promoting even energy consumption and wear, thereby reducing the likelihood of premature chiller maintenance or failure.

The UL approach prioritizes operational simplicity and reliability. By treating each chiller equally, it avoids the complexities and potential biases inherent in more dynamic loading strategies. This not only simplifies management for facility managers but also ensures consistent operating conditions, beneficial for maintenance scheduling and lifespan prediction of equipment.

However, it is important to acknowledge that while this method promotes equitable chiller usage, it may not always be the most energy-efficient, particularly under partial load conditions. In such cases, operating fewer chillers at higher efficiency—allowing some units to rest or operate minimally—could conserve more energy. Compared to other algorithms that dynamically adjust according to actual load, the UL method offers less flexibility in responding to fluctuating demands.

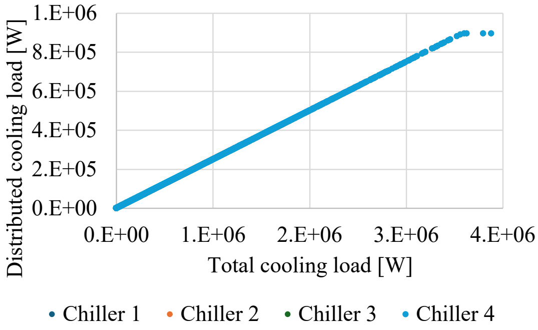

Figure 3. Load distribution characteristic for each chiller of UL distribution algorithm

2.2.2. Sequential Load (SL) Distribution Algorithm

The Sequential Load (SL) distribution algorithm allocates the cooling load among the chillers in a predetermined sequential order, as illustrated in Figure 4. This method activates chillers one at a time, based on the incremental cooling load requirements. This sequential activation allows the system to maintain a higher Part Load Ratio (PLR) during periods of low cooling demand, optimizing energy efficiency.

As each chiller is activated, it initially operates at a lower PLR because the previously activated chillers have already absorbed a significant portion of the cooling demand. Therefore, subsequent chillers handle progressively smaller loads, which can lead to reduced operational efficiency for these later units. The SL algorithm effectively manages the load distribution to ensure that each chiller contributes to meeting the total cooling requirement, yet the initial chillers in the sequence may bear a larger operational burden compared to those activated later.

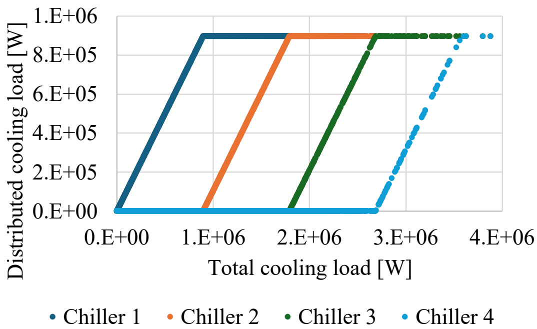

Figure 4. Load distribution characteristic for each chiller of SL distribution algorithm

2.2.3. Uniform Part Load Ratio (UPLR) Distribution Algorithm

The Uniform Part Load Ratio (UPLR) distribution algorithm is specifically engineered to efficiently allocate the cooling load among all operational chillers, ensuring each maintains a consistent Part Load Ratio (PLR). This contrasts with the Uniform Load (UL) algorithm, which evenly distributes the total cooling load among all chillers, irrespective of their individual efficiency at different PLRs. Figure 5 illustrates the distribution of cooling load in UPLR, where each chiller is adjusted to operate at the same

PLR, optimizing the system's performance under varying load conditions.

When the total cooling load drops below the minimum PLR that the largest chiller can handle efficiently, UPLR adapts by operating only the first chiller. This strategic operation is in sharp contrast to UL, which would continue to distribute the load evenly across all chillers, potentially leading to inefficiencies when chillers operate below their minimum PLR. By focusing on minimizing PLR variations, UPLR avoids the inefficiencies associated with the UL method under low-load conditions.

In this study, which assumes uniform capacities for all chillers, the first chiller under UPLR manages the cooling alone during minimal load situations, optimizing wear distribution and enhancing system reliability.

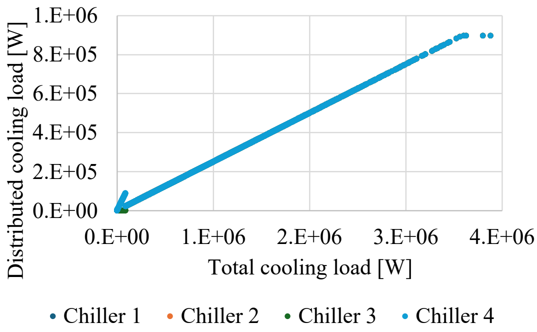

Figure 5. Load distribution characteristic for each chiller of UPLR distribution algorithm

2.2.4. Sequential Uniform Part Load Ratio (SUPLR) Distribution Algorithm

The Sequential Uniform Part Load Ratio (SUPLR) distribution algorithm activates chillers based on the cooling load and a predefined sequence, ensuring that each activated chiller maintains an identical Part Load Ratio (PLR), as illustrated in Figure 6. Unlike methods that distribute equal cooling loads among all chillers, SUPLR adjusts the actual load each chiller handles to achieve the same PLR across different chillers. This is crucial in systems where chillers may have varying capacities; although each chiller operates at the same PLR, the actual cooling load they manage can differ depending on their capacity. While SUPLR might initially appear similar to the Sequential Load (SL) algorithm in terms of sequential activation, the key difference lies in how SUPLR not only sequences chillers but also balances the load among them to maintain uniform PLR, enhancing efficiency and system adaptability.

This approach contrasts with the SL algorithm, which activates chillers sequentially based on the load but does not adjust the loads to standardize PLR among the activated chillers. By ensuring a uniform PLR, SUPLR optimizes the operational efficiency of each chiller, regardless of its size or capacity. This method prevents scenarios where larger capacity chillers operate at lower efficiencies due to inadequate load distribution.

In this study, with the assumption of uniform chiller capacities, SUPLR ensures that once a chiller is activated, it contributes equally to the cooling demand in terms of PLR. This not only promotes more stable and predictable chiller performance but also enhances overall energy efficiency and system reliability by avoiding the inefficiencies associated with disparate operating conditions.

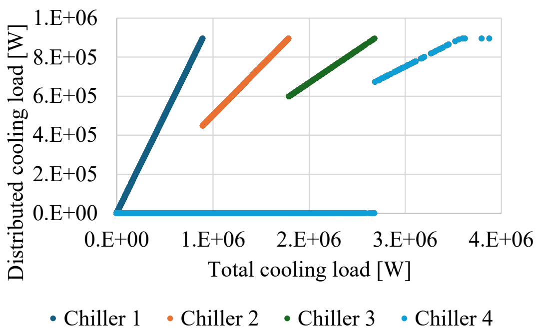

Figure 6. Load distribution characteristic for each chiller of SUPLR distribution algorithm

2.2.5. Optimum Part Load Ratio (OPLR) Distribution Algorithm

The Optimal Part Load Ratio (OPLR) algorithm activates chillers based on the cooling load, similarly to the SL and SUPLR algorithms, but with a strategic emphasis on optimizing operational efficiency. As depicted in Figure 7, OPLR distributes the cooling load among chillers to achieve an optimal Part Load Ratio (PLR) for each unit. The process entails sequentially activating chillers until each reaches a predefined optimal PLR, typically set at 0.8 for this study, a PLR value identified for achieving a high Coefficient of Performance (COP) [36]. Once a chiller reaches this optimal point, the next chiller in the sequence is activated. After all chillers have reached their optimal PLR, any remaining cooling load is evenly distributed among them.

This method is particularly beneficial in systems composed of multiple chillers as it aims to operate as many units as possible at their optimal PLR. By strategically balancing the load to maximize the overall efficiency of the plant, OPLR may occasionally operate certain chillers at less than their individual optimal conditions. This approach enhances the collective performance of the cooling installation, prioritizing the efficiency of the entire system over the peak efficiency of any single chiller.

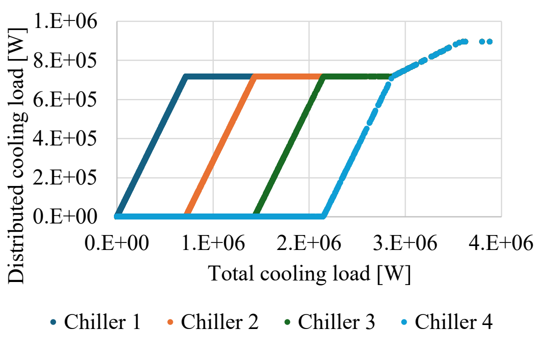

Figure 7. Load distribution characteristic for each chiller of OPLR distribution algorithm

2.3. Energy Consumption Calculation Formulas

This study examines various chiller sequencing methods. The control strategy for chiller sequencing is implemented via an open-loop system based on predefined rules. These rules are described in detail in Section 2.2. Unlike some systems that use optimized control with specific objective functions and constraints, this method does not incorporate an optimization model. Instead, operational constraints are applied based on practical scenarios. For instance, if the cooling load is less than the minimum part load ratio (minimum PLR), the chillers are controlled to operate at the chiller cycling ratio. Conversely, if the cooling load exceeds the total capacity of the chillers, they are assumed to operate at their maximum capacity for the purposes of our calculation. The calculation of chiller energy consumption was conducted using the formula employed by EnergyPlus [35]. Hourly chiller electricity consumption was determined using the equation provided below.

$$P_{chiller} = \dot{Q}_{ref} * CAPFT * \frac{1}{COP_{ref}} * EIRFT * EIRFPLR * CylingRatio$$

The model utilizes performance data under reference conditions and employs three curve fits for cooling capacity and efficiency to predict chiller operation under off-reference conditions. In this study, the chiller was assumed to be a standard water-cooled centrifugal chiller according to DOE-2.1E [37], and the chiller performance curves were based on the DOE-2.1E HERM-CENT curves. $\dot{Q}_{ref}$ represents the rated capacity of the chiller, COP_{ref} denotes the rated Coefficient of Performance (COP), and the *CyclingRatio* indicates the extent to which the chiller operates in an on-off cycle when the PLR is lower than the minimum PLR. It can be calculated as follows [35].

$$CyclingRatio = \min\left(\frac{PLR}{PLR_{min}}, 1.0\right)$$

CAPFT and EIRFT represent the ratios that modify capacity and energy consumption fluctuations based on alterations in leaving chilled water temperature and entering condenser fluid temperature, respectively. In contrast, EIRFPLR adjusts energy consumption fluctuations based on changes in PLR. These ratios are derived from relationships that employ coefficients derived from regression analysis using actual chiller data.

1) Cooling Capacity Function of Temperature Curve

$$CAPFT = -0.00021708x^2 + 0.0389016x - 0.00094284y^2 - 0.0468684\,y - 0.00034344\,xy + 0.257896$$

$$\because 5 \le x = Leaving\,chilled\,water\,temperature \le 10, \quad 24 \le y = Entering\,condenser\,fluid\,temperature \le 35$$

2) Energy Input to Cooling Output Ratio Function of Temperature Curve

$$EIRFT = -0.00450036x^2 + 0.058212x - 0.000486y^2 - 0.00243\,y - 0.001215\,xy + 0.933884$$

$$\because 5 \le x = Leaving\,chilled\,water\,temperature \le 10, \quad 24 \le y = Entering\,condenser\,fluid\,temperature \le 35$$

3) Energy Input to Cooling Output Ratio Function of PLR Curve

$$EIRFPLR = 0.46371x^2 + 0.313387x + 0.222903 \qquad \because 0 \le x = PLR \le 1.15$$

2.4 Selection of Simulation Scenarios: Refinement and Rationalization

In this study, a comparative analysis of cooling energy consumption was conducted between single-chiller systems and multi-chiller systems comprising 2 to 10 chillers. The analysis was performed on systems where the chillers in the multi-chiller configuration had identical capacities. Additionally, to check whether variables other than PLR, such as chiller capacity, had an additional impact on performance, an analysis of the datasets provided by EnergyPlus, which included the performance data of 160 different chillers, revealed no significant correlation between chiller capacity and COP (Figure 8). The linear regression analysis showed a slope of 0.00008, indicating that capacity variation has a much smaller impact on performance than PLR changes. Therefore, the study assumed uniform performance across all different capacities of chillers.

The analysis also utilized large office reference building models from 15 different regions (1A – 8A). Each system was assessed under five distinct load distribution algorithms: UL, SL, SUPLR, UPLR, and OPLR.

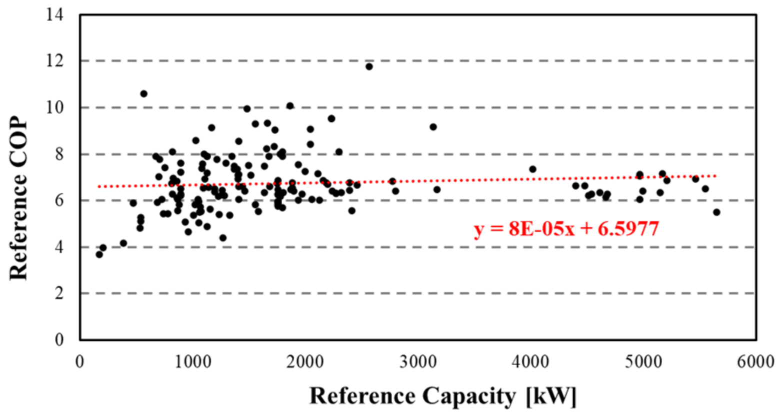

Figure 8. Scatter Plot of COP of Chillers over Capacity of Chillers from the EnergyPlus Chiller Dataset

3. Results and Analysis

3.1. Analysis of Cooling Energy Savings by Climate Zone

In this study, the effectiveness of multi-chiller systems at the reference large-size office building was validated by comparing their annual cooling energy savings with systems equipped with a single chiller. Across all 15 climate zones considered, multi-chiller systems demonstrated a beneficial effect in saving cooling energy. Among all simulation cases for each climate zone, the SUPLR distribution algorithm consistently yielded the most significant energy savings. The most substantial cooling energy savings varied from a minimum of 8.34% to a maximum of 55.10%, corresponding to absolute values ranging from 74.09MW to 189.60MW.

8A, 3C, and 7A climate zones demonstrated the highest annual cooling energy savings in percentage terms. However, their absolute megawatt values of cooling energy savings are relatively small. In contrast, climate zones like 4A, 2A, and 3A stood out for achieving the greatest annual cooling energy savings in absolute megawatt values. This distinction can be attributed to their overall cooling energy consumption, which resulted in a decrease in the percentage of savings for climate zones with higher overall cooling energy consumption annually. Table 2 presents the annual maximum cooling energy savings for each climate zone.

Table 2. Maximum cooling energy saving of each climate zone

ASHRAE Climate zone	Maximum cooling energy saving (%)	Maximum cooling energy saving (MW)
1A	8.34	133.90
2A	14.36	**178.42**
2B	12.43	150.25
3A	19.33	**153.30**
3B	17.30	124.14
3C	**46.88**	142.17
4A	25.44	**189.60**
4B	23.05	120.20
4C	36.82	90.21
5A	23.26	120.91
5B	32.82	135.98
6A	28.26	139.89
6B	27.52	74.09
7A	**39.82**	121.88
8A	**55.10**	100.81

As more chillers are added to a multi-chiller system, managing multiple chillers becomes more complex and costly, potentially leading to increased failure rates and maintenance challenges. In this study, we set the threshold at which the energy savings effect increases by less than 0.9554% when installing additional chillers through regression analysis. This was based on the regression coefficient of -0.9554 and the 95% confidence interval ranging from -1.0861 to -0.8247. It was determined that below these figures, the practical energy savings from installing additional chillers would be difficult to expect. Therefore, for the optimization of maintenance efficiency and maximization of energy savings, an energy savings increase rate of 0.9554% was established as the standard for the installation of additional chillers. The energy savings and threshold for each region are detailed in Table 3.

Given the diverse cooling energy consumption patterns across climate zones, distinct energy-saving patterns were observed for each. The optimal number of chillers tended to increase as regions transitioned from drier climate zones to cooler climate zones. Although slight variations were observed across regions, except for extreme climates like 1A and 8A, the optimal number of chillers typically ranged between 3 and 5. Across all climates, the SUPLR algorithm consistently delivered the highest energy savings when employing the optimal number of chillers. For a detailed breakdown of the cooling energy savings achieved by each load distribution algorithm, segmented by the number of chillers and across different climate zones, refer to Appendix A: 'Cooling Energy Saving Effectiveness of Load Distribution Algorithms by Number of Chillers. The optimal energy savings for each climate zone are as follows: 1A-122MW, 2A-171MW, 2B-143MW, 3A-143MW, 3B-115MW, 3C-136MW, 4A-183MW, 4B-115MW, 4C-87MW, 5A-115MW, 5B-131MW, 6A-132MW, 6B-69MW, 7A-116MW, 8A-98MW.

Table 3. Maximum cooling energy saving of each climate zone and number of chiller combination

Climate Zone \ No. of Chillers	2	3	4	5	6	7	8	9	10
1A	**7.59%**	8.31%	8.34%	8.23%	8.15%	7.98%	7.88%	7.78%	7.65%
2A	11.85%	**13.74%**	14.19%	14.34%	14.36%	14.31%	14.23%	14.18%	14.06%
2B	10.07%	**11.80%**	12.24%	12.42%	12.43%	12.41%	12.33%	12.28%	12.18%
3A	15.25%	**18.06%**	18.83%	19.14%	19.33%	19.29%	19.24%	19.18%	19.13%
3B	13.51%	**16.06%**	16.90%	17.22%	17.26%	17.30%	17.30%	17.25%	17.19%
3C	31.80%	39.87%	43.10%	**44.73%**	45.61%	46.17%	46.51%	46.73%	46.88%
4A	19.32%	23.29%	**24.50%**	24.99%	25.24%	25.44%	25.42%	25.37%	25.33%
4B	17.50%	20.92%	**22.15%**	22.62%	22.89%	22.95%	23.05%	23.01%	23.00%
4C	25.70%	31.79%	34.22%	**35.41%**	36.01%	36.40%	36.60%	36.73%	36.82%
5A	17.23%	20.97%	**22.16%**	22.74%	23.04%	23.19%	23.23%	23.26%	23.24%
5B	23.76%	28.76%	30.63%	**31.64%**	32.15%	32.41%	32.62%	32.71%	32.82%
6A	20.43%	25.03%	**26.65%**	27.41%	27.83%	28.05%	28.18%	28.20%	28.26%
6B	19.51%	23.91%	**25.73%**	26.56%	26.93%	27.22%	27.37%	27.44%	27.52%
7A	26.90%	33.81%	36.65%	**37.99%**	38.73%	39.16%	39.44%	39.68%	39.82%
8A	36.42%	46.29%	50.27%	52.27%	**53.38%**	54.08%	54.54%	54.87%	55.10%

In the subsequent section, an evaluation of chiller efficiency was conducted based on the PLR, a crucial factor known to influence the COP of chillers Additionally, an analysis of annual energy consumption was performed to assess the efficacy of multi-chiller systems across all regions. For the purposes of this analysis, it is assumed that all chillers follow the same performance curve, as depicted in Figure 9, where the COP curve is based on PLR for a single-chiller system. This assumption is applied consistently across all chillers in the study. Figure 9 illustrates the distribution of PLR and COP for a single-chiller system. As depicted, chillers exhibit notably low COPs at low PLRs. Consequently, operating chillers at low COPs for cooling loads below 20% of their capacity results in increased energy consumption. Therefore, by increasing the number of chillers, the capacity of individual units decreases, thereby narrowing the range of cooling loads associated with low PLRs for each chiller. Consequently, operating multiple chillers at higher PLRs for the same cooling load is expected to yield higher COPs compared to a single chiller system, thus reducing cooling energy consumption.

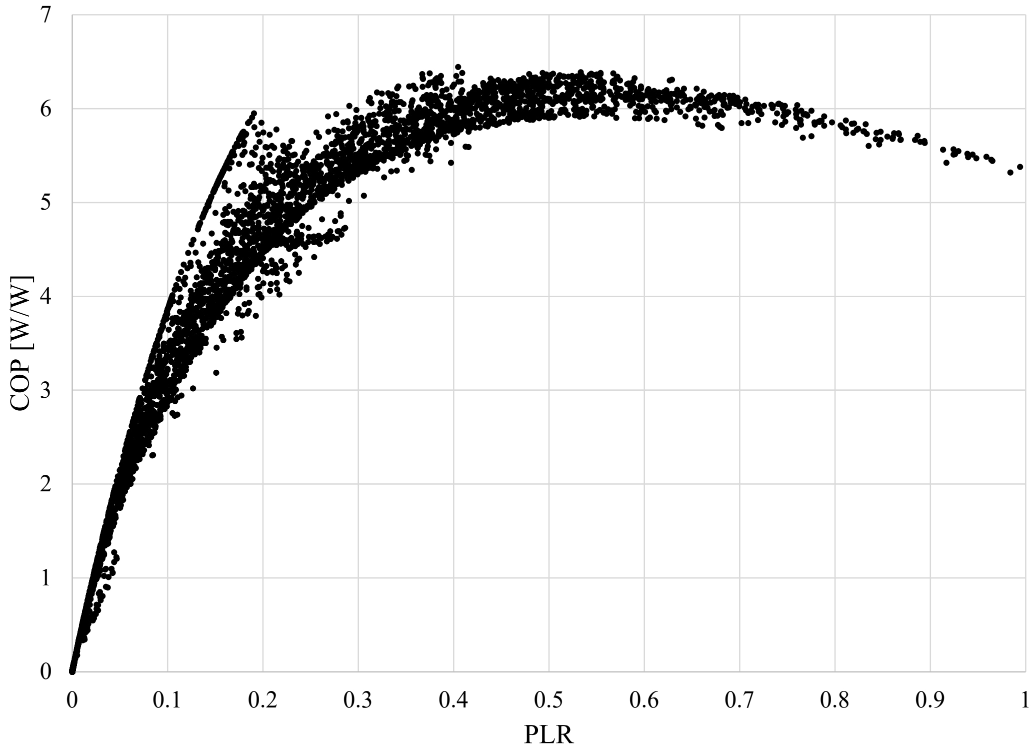

Figure 9. COP by PLR of chiller

Across the 15 climate zones, variations are observed in both the percentage and absolute amount of cooling energy savings. Notably, certain climate zones like 1A, 2B, and 2A show relatively lower reduction percentages compared to others. Conversely, climate zones such as 3C, 7A, and 8A exhibit higher reduction percentages, indicating a greater potential for cooling energy savings through multi-chiller systems. These trends highlight the diverse impacts of climatic characteristics on energy-saving potential across different climate zones.

To further explore this analysis, the annual PLR frequency distribution of selected climate zones was examined and illustrated in Figure 10. The distribution was divided into 10 categories to evaluate the frequency distribution of PLR in zones with both the lowest (1A, 2B, and 2A) and highest (3C, 7A, and 8A) cooling energy reduction percentages.

Climate zones with lower cooling energy reduction percentages exhibited an annual PLR distribution resembling a normal distribution. In contrast, those with higher cooling energy reduction percentages displayed a concentration of PLRs below 0.2. This low PLR range indicates operation at very low COPs, as previously noted and illustrated in Figure 9, emphasizing the significance of minimizing the duration of low PLR operation to achieve energy savings.

Multi-chiller systems offer greater energy-saving advantages in climate zones characterized by frequent low PLR operation. By reducing the occurrence of chillers operating at low PLRs through effective load distribution, these systems demonstrate their efficacy in achieving energy savings. Thus, assessing the effectiveness of multi-chiller systems can be streamlined by analyzing the PLR frequency profile in regions designated for multi-chiller system implementation.

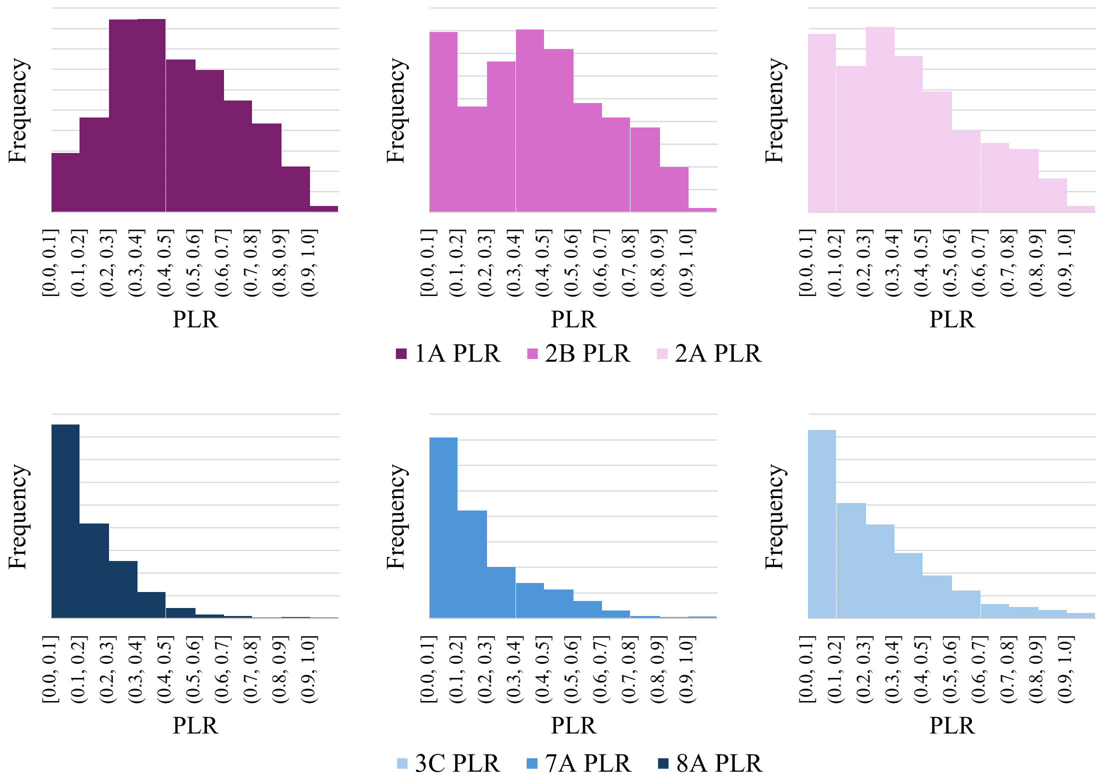

Figure 10. Annual PLR distribution of chillers. above three climates have low cooling energy saving (%) and below three regions have great cooling energy saving (%)

In ASHRAE Climate zones 2A, 3A, and 4A, multi-chiller systems displayed significant annual cooling energy savings in absolute terms (MW). Despite the lower percentage of cooling energy savings observed in climate zone 2A, it exhibited superior absolute annual cooling energy reduction. This can be attributed to the high annual cooling energy demand in climate zone 2A, where substantial reductions in cooling energy result in lower percentage values relative to the absolute amount saved. Therefore, evaluating the effectiveness of multi-chiller systems requires considering both the reduction percentage and the actual amount of cooling energy saved. It's important to note that the interaction between cooling load occurrence frequency profiles and annual cooling energy demand influences both the absolute and percentage of annual cooling energy savings.

In contrast, within climate zones categorized based on cooling degree days, such as zones 1, 2, 3, and 4, the more humid A climate zones outperformed the drier B climate zones in terms of cooling energy savings. Zones 2A and 4A, in particular, displayed noteworthy cooling energy savings. Consequently, regions with higher humidity levels are anticipated to benefit more from multi-chiller systems in reducing cooling energy consumption.

3.2. Analysis of Cooling Energy Savings Effects Based on Load Distribution Algorithms

Upon conducting a comprehensive comparative analysis of annual cooling energy savings across all regions with 2 to 10 chillers, it was noted that, with the exception of the 9-chiller case in 1A and the 10-chiller cases in 2A, 3A, and 3B, the SUPLR algorithm consistently yielded the most substantial cooling energy savings effects. This section delves deeper into the examination, focusing on the region demonstrating the highest annual cooling energy savings (MW), specifically the 4A (mixed/humid) climate zone.

3.2.1 Annual Cooling Energy Savings in the 4A (Mixed/Humid) Climate Zone

Figure 11 illustrates the annual temperature distribution in the Baltimore (4A) region. It is evident that Baltimore (4A) experiences a wide range of temperatures, with maximum and minimum temperatures reaching 35.6°C and -16.7°C, respectively, indicative of distinct summer, winter, and transitional seasons.

Chiller capacity is typically designed to handle higher load conditions, especially during the summer season. However, this can lead to oversized capacity for smaller load conditions. As a result, during transitional seasons when only light loads are present, chillers may operate for extended periods at low PLRs. Given the close relationship between chiller COP and PLR, reducing the duration of low PLR operation is expected to result in significant annual cooling energy savings.

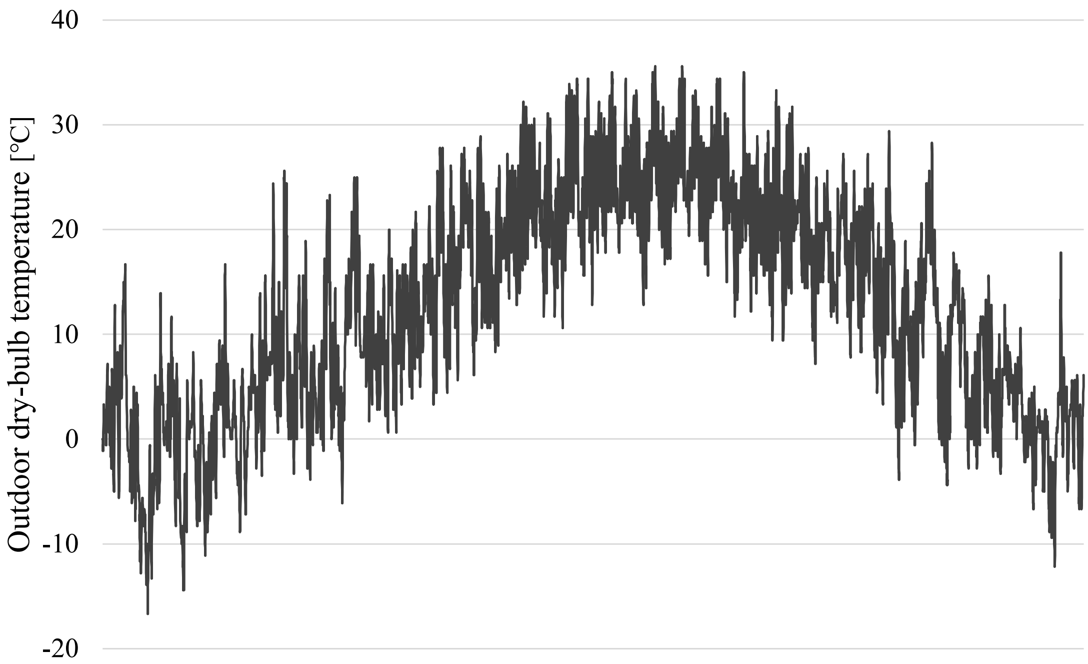

Figure 11. Annual outdoor dry-bulb temperature distribution of Baltimore (4A) climate

When applying a multi-chiller system with different load distribution algorithms and varying numbers of chillers in Baltimore, the annual cooling energy savings (%) for each combination are depicted in Figure 12.

The UL algorithm evenly distributes the load across all chillers, resulting in each chiller operating at the same PLR as in a single chiller system. Consequently, increasing the number of chillers does not lead to energy savings.

The UPLR algorithm distributes the cooling load across all chillers to maintain the same PLR. However, if the distributed load falls below the minimum PLR of a single chiller, the respective chiller remains inactive, while the remaining chillers handle the load. This results in some energy savings in segments where the cooling load is below the minimum PLR of a single chiller.

SL distributes the load up to the maximum capacity of the activated chiller before activating the next one. Consequently, SL operates with a small number of chillers if the load is small. However, when an additional chiller is activated, its PLR decreases since other chillers already handle the majority of the cooling load, resulting in low PLR and low COP.

In contrast, the SUPLR algorithm activates chillers similarly to SL but ensures that all activated chillers operate at the same PLR. Consequently, this algorithm minimizes the occurrence of chillers operating at low PLR and low COP, effectively reducing the range of overall cooling load operated at low COP.

On the other hand, OPLR distributes the load up to the set optimum PLR before activating the next chiller, with subtle differences. However, SL, SUPLR, and OPLR algorithms all sequentially activate chillers and distribute the load accordingly.

Recognizing the escalating maintenance challenges linked to a greater number of chillers, our primary goal was to identify the ideal number of chillers for operational efficiency. This study aimed to determine a threshold where the variation in annual cooling energy savings remained negligible, staying below 1% as the number of chillers increased. In the Baltimore (4A) region, it was determined that four chillers represented the optimal number, with the SUPLR algorithm providing the most effective load distribution. This implementation yielded a significant 24.5% annual cooling energy savings.

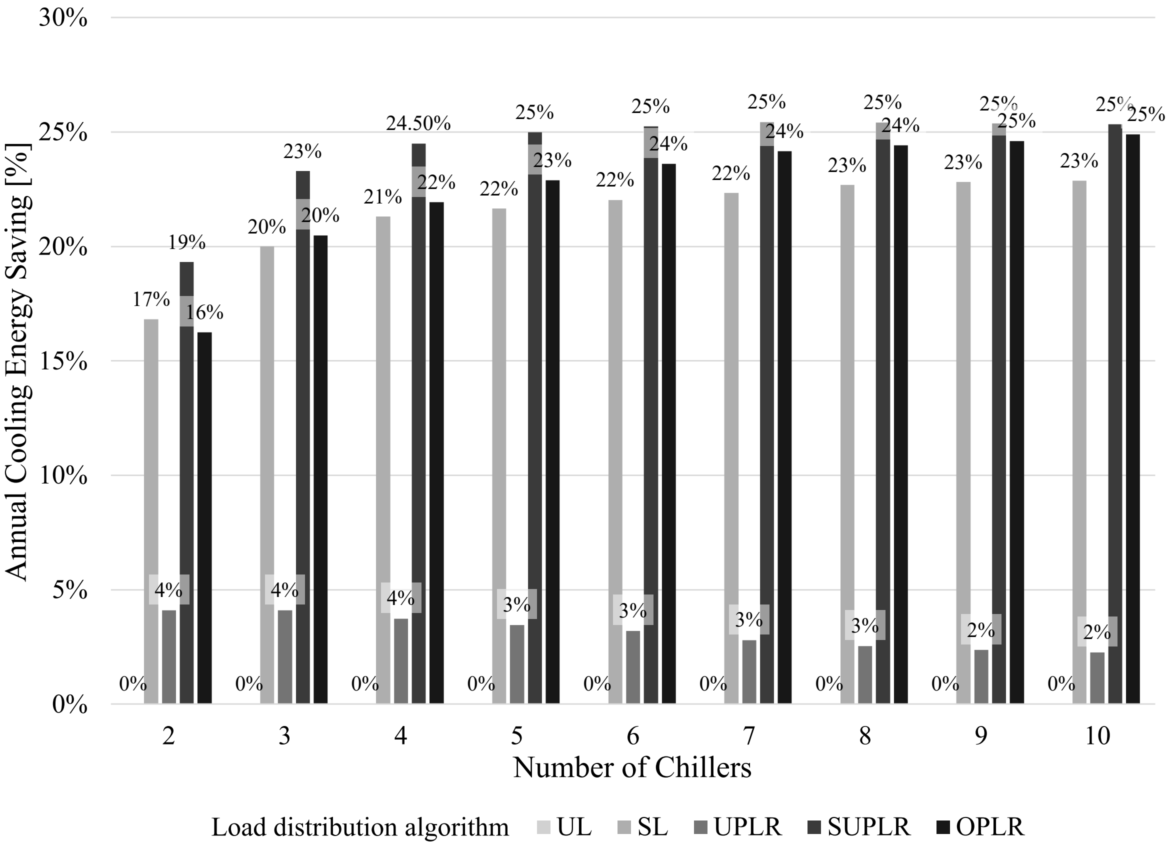

Figure 12. Cooling energy saving (%) of Baltimore (4A) by number of chillers and load distribution algorithms

3.2.2 Detailed Analysis of Chiller Performance Across PLR Ranges

To comprehend the enhanced cooling energy savings achieved by the multi-chiller system, an analysis was conducted on the behavior of a system utilizing an optimal count of four chillers for each algorithm. Figure 13 illustrates the cumulative cooling energy consumption within each PLR range for each algorithm. The baseline depicts a single chiller, while all other scenarios, excluding the baseline, comprise four chillers. To facilitate comparison, the energy consumption for scenarios excluding the baseline was aggregated by summing up the energy usage of the four chillers.

As illustrated, the load distribution algorithms—SL, SUPLR, and OPLR—that resulted in superior cooling energy savings notably decreased energy consumption during low PLR operation compared to the baseline. Conversely, energy consumption increased in the higher PLR range for the SL, SUPLR, and OPLR algorithms. The SUPLR algorithm, by extending operational hours in high PLR ranges and thus minimizing the occurrence of low-efficiency chiller operation, exhibited the most significant cooling energy savings.

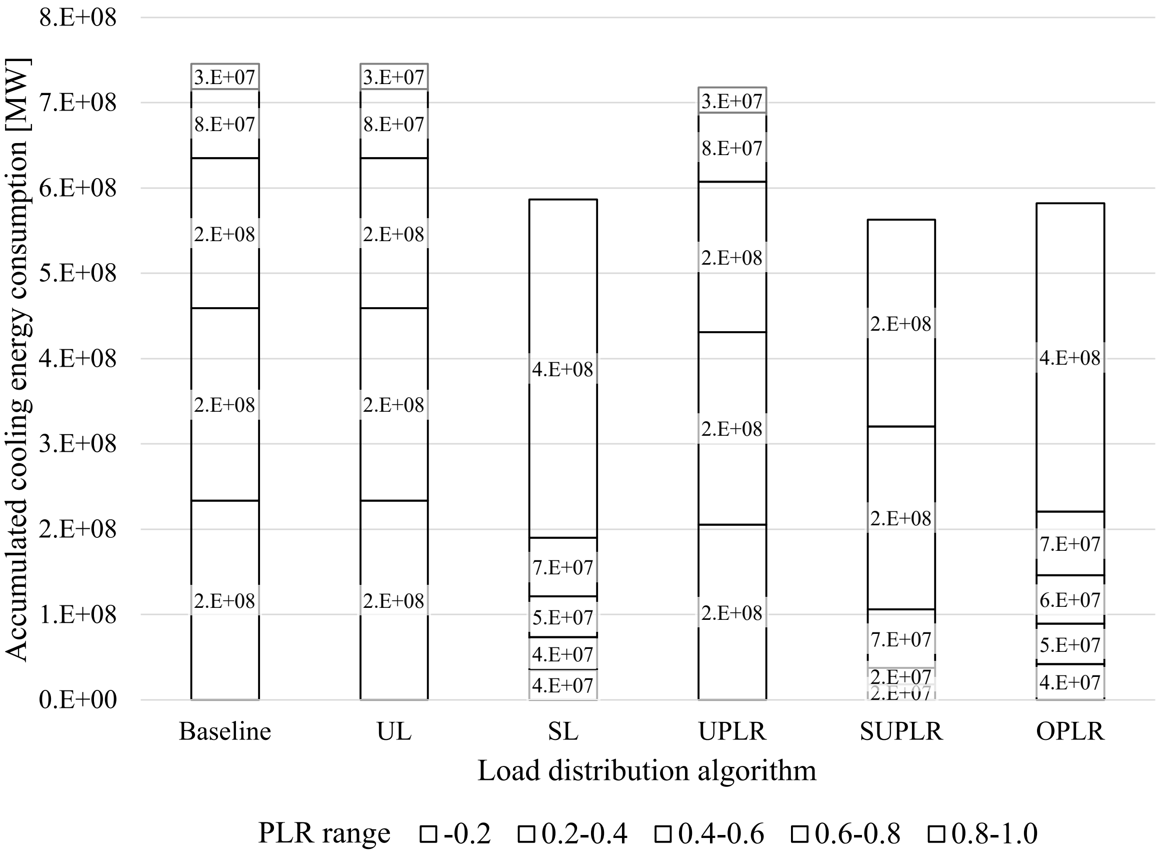

Figure 13. Accumulated annual cooling energy consumption by each load distribution algorithm

3.2.3 Operating Hours and Efficiency Across PLR Ranges

Figure 14 illustrates the cumulative operating hours for each chiller in a multi-chiller system with four chillers, based on five load distribution algorithms. It's evident that the baseline and algorithms resulting in only marginal energy savings, such as UL and UPLR, have a significant portion of operating hours in the low PLR range (below 0.2). For instance, in the baseline case, roughly 51% of the total operating hours occur in the low PLR range, indicating substantial inefficiency.

In contrast, load distribution algorithms that demonstrate superior cooling energy savings, such as SL, SUPLR, and OPLR, show a noticeable decrease in operating hours in the low PLR range, accompanied by a corresponding increase in operating hours in the high PLR range. Specifically, the SUPLR algorithm, which delivers the most significant energy savings, reduces the operating hours of chiller 1 in the low PLR range to as low as 0.2 by approximately 65% compared to the baseline. Moreover, chillers 2, 3, and 4 show no operating time in this PLR range, indicating their complete avoidance of low PLR operation.

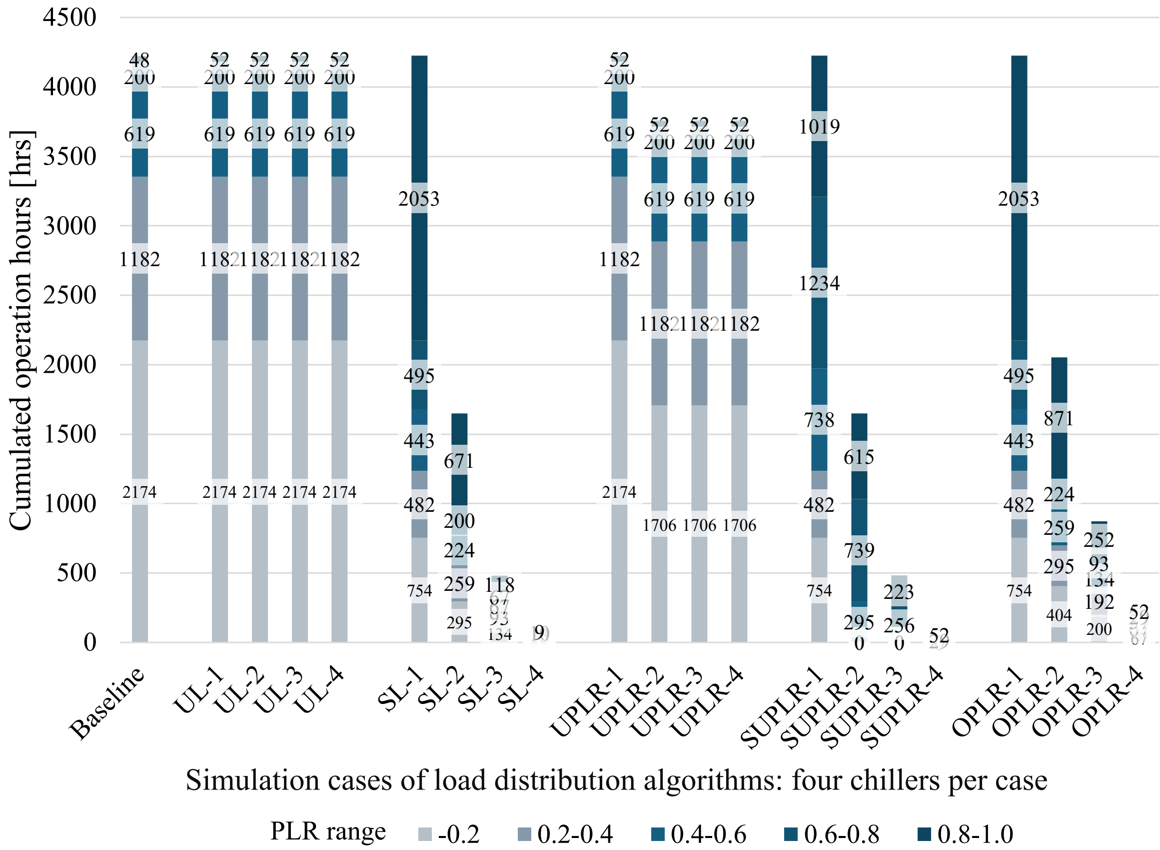

Figure 14. Cumulated operation hours of each PLR range of chillers by load distribution algorithm

3.2.4 Seasonal Variation in Chiller Coefficient of Performance

The seasonal average chiller COP, calculated based on the total electricity consumption for each season over the specified period, for both the Baseline with one chiller and the multi-chiller system comprising four chillers with each load distribution algorithm combination, is presented in Figure 15. Baltimore (4A) experiences four distinct seasons: winter from December to February, spring from March to May, summer from June to August, and autumn from September to November [38].

Upon reviewing the seasonal average COP for the Baseline, it's apparent that during spring and autumn, the seasonal average chiller COP is lower. This contrasts with the hot summer season, which boasts a average COP of 5.53, highlighting that reduced cooling demands during these transitional periods make the average COP lower. Specifically, the seasonal average COP values are 3.56 and 4.14, respectively, indicating operation at reduced average COP levels.

However, upon implementing the SL, SUPLR, and OPLR distribution algorithms in the system with four chillers, a significant enhancement in the seasonal average COP is observed during spring and autumn. This improvement ensures that even during transitional seasons with lower cooling demands, the chillers operate at nearly the same COP as during summer. Notably, the seasonal average COP during summer is also elevated. Thus, it's evident that the multi-chiller system effectively contributes to reducing cooling energy consumption, especially during transitional seasons.

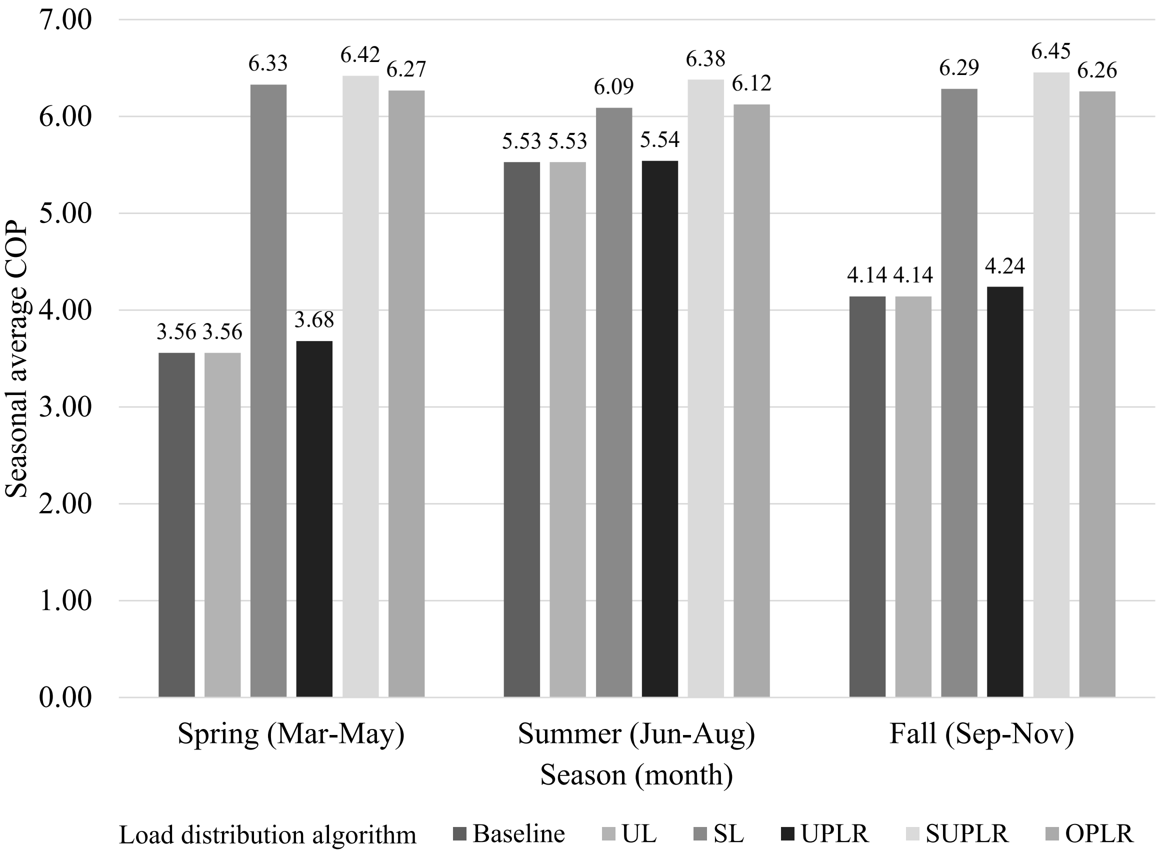

Figure 15. Seasonal COP of multi-chiller system by each load distribution algorithm

3.2.5 Hourly PLR Characteristics on a Typical Day

An analysis was conducted on hourly PLR characteristics for both the baseline system with a single chiller and the system equipped with four chillers employing the SUPLR distribution algorithm. This analysis focused on a typical day (May 31st), to explore the operational dynamics of the SUPLR distribution algorithm, recognized for its remarkable cooling energy reduction capabilities. The findings are presented in Figure 16.

On May 31st, a transitional period in the Baltimore (4A) region [38], the baseline case exhibits cooling loads ranging from PLR 0.22 to 0.64 throughout the day. Since May 31st does not experience notably high loads like peak summer days, the multi-chiller system indicates that all four chillers do not operate simultaneously. Instead, depending on the load size, one to three chillers are active.

At 7 AM, coinciding with the lowest load, the Baseline operates at approximately 0.22 PLR. However, with SUPLR, only one chiller runs at a higher PLR of around 0.87. During moderate load conditions at noon, the baseline operates at approximately 0.40 PLR, while Chillers 1 and 2 in the SUPLR case operate at roughly 0.81 PLR. By 4 PM, during the peak load of the day, the baseline operates at approximately 0.64 PLR, while Chillers 1, 2, and 3 in the SUPLR case operate at about 0.86 PLR.

As a result, SUPLR effectively adjusts the number of chillers and distributes the total cooling load accordingly during transitional periods with PLRs ranging from 0.22 to 0.64. It ensures that each chiller operates at a high PLR exceeding 0.52, even under light loads, enabling efficient operation.

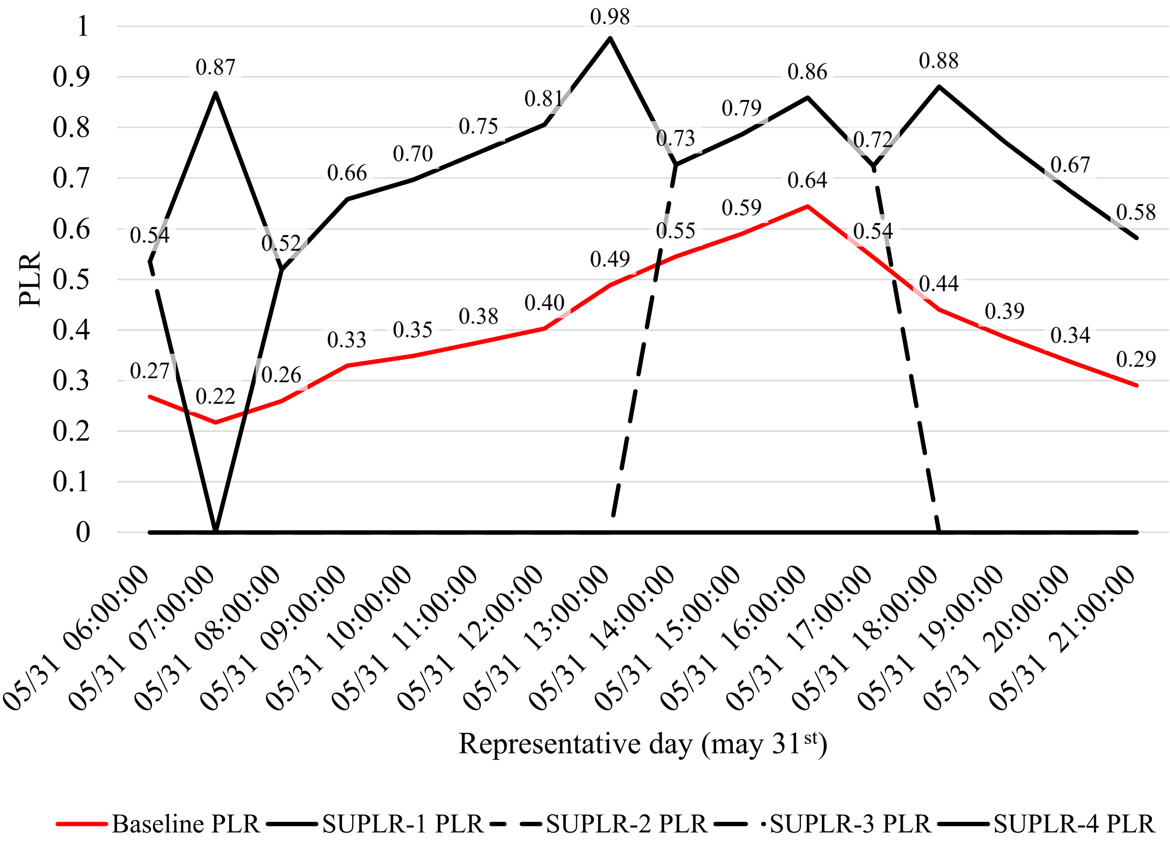

Figure 16. PLR characteristic of chillers of baseline system and optimum system on representative day

3.3. Limitations and Future Directions

This study aimed to identify the most effective climatic zones for multi-chiller systems, understand the characteristics of such systems, and determine the optimal number of chillers and load distribution algorithms for each climatic zone through simulation methodology. However, the utilization of the Typical Meteorological Year provided by the DOE as the climate scenario, and the adoption of the DOE's commercial reference large office model as the building performance simulation model, introduced several uncertainties into the research findings.

In this study, we have assumed that all chillers in the multi-chiller system have identical capacities. This simplification helps to streamline the analysis and focus on the impact of different sequencing algorithms. However, it is acknowledged that such an assumption may not accurately represent real-world scenarios where chillers of different capacities are likely to yield variations in energy-saving effects. Recognizing this as a limitation of the current study, we highlight the need for future research to explore multi-chiller systems with diverse chiller capacities. This forthcoming area of research aims to determine the optimal capacity allocation and understand the implications of various chiller capacities on energy performance. In light of this, additional work specifically investigating the optimization of chiller capacity combinations is already underway and is currently under review, promising to provide a more comprehensive understanding of the dynamics in multi-chiller systems.

This study focused solely on the energy consumption of chillers. Notably, the energy consumption associated with pumps, although significant, was not included in our analysis. This decision was made to maintain the study's manageability and to focus on isolating the effects of different number of chiller and load distribution algorithms across various climate zones. Future research could benefit from incorporating pump energy consumption to provide a more comprehensive assessment of total system energy efficiency. This would help in understanding the complete impact of load distribution strategies on the overall energy consumption in cooling systems.

Additionally, for practical real-world applications, a comparison and analysis of five fundamental rule-based control methods adopted into the EnergyPlus software was conducted. Despite their simplicity, these algorithms were found to lead to significant energy savings in cooling operations. However, leveraging various machine learning algorithms, which are rapidly evolving, could potentially yield even greater energy savings. Hence, future research should focus on utilizing algorithms that offer low computational costs while delivering excellent cooling energy savings performance.

4. Conclusion

In this study, the energy-saving potential of multi-chiller systems was examined across 15 climatic zones spanning from 1A to 8A for a large-sized reference building. Exploring configurations ranging from 1 to 10 chillers and employing five load distribution algorithms, optimal cooling energy savings were identified with 3 to 5 chillers across most zones, excluding the extreme climates of 1A (hot) and 8A (cold). Notably, the SUPLR algorithm consistently demonstrated the most efficient cooling energy savings across all zones.

Among these zones, the 4A climate zone (Baltimore) stood out for its highest annual cooling energy savings. Implementing a multi-chiller system comprising 4 chillers with load distribution by the SUPLR algorithm resulted in a substantial annual cooling energy saving of approximately 24.5% or 183MW. Further analysis focused on the 4A climate zone (Baltimore) revealed the significant role of the SUPLR load distribution algorithm in achieving the highest energy savings rate. By effectively minimizing operation in the low PLR range (below 0.2), this algorithm ensured that chillers maintained optimal COP levels.

Notably, the SUPLR algorithm substantially enhanced chiller average COP during transitional seasons such as spring and winter, contributing to overall system efficiency improvements. Thus, the adoption of well-designed multi-chiller systems holds tremendous promise for significantly reducing cooling energy consumption in climatic zones experiencing transitional seasons.

Acknowledgement

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (No. 2022R1A2C2006469). This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government(MSIT, MOE) and (No. 2019M3E7A1113095). ※ MSIT : Ministry of Science and ICT, MOE : Ministry of Education

Appendix A. Cooling Energy Saving Effectiveness of Load Distribution Algorithms by Number of Chillers

Table A. 1. Cooling Energy Savings Achieved by the Uniform Load (UL) Algorithm

No. of Chillers / Climate Zone	2	3	4	5	6	7	8	9	10
1A	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2A	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2B	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3A	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3B	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3C	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4A	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4B	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4C	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5A	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5B	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6A	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6B	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7A	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8A	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table A. 2. Cooling Energy Savings Achieved by the Sequential Load (SL) Algorithm

No. of Chillers / Climate Zone	2	3	4	5	6	7	8	9	10
1A	2.7%	3.2%	3.8%	4.3%	4.8%	4.9%	5.1%	5.2%	5.3%
2A	8.3%	9.2%	10.2%	10.7%	11.1%	11.3%	11.5%	11.6%	11.8%
2B	6.1%	6.8%	8.2%	8.8%	9.2%	9.4%	9.6%	9.7%	9.9%
3A	12.1%	14.2%	15.2%	15.5%	15.9%	16.3%	16.5%	16.6%	16.6%
3B	9.8%	12.0%	12.8%	13.6%	14.1%	14.2%	14.5%	14.6%	14.8%
3C	31.2%	38.5%	40.9%	42.4%	43.4%	43.9%	44.3%	44.6%	44.7%
4A	16.8%	20.0%	21.3%	21.6%	22.0%	22.3%	22.7%	22.8%	22.9%
4B	14.3%	17.1%	18.0%	19.0%	19.5%	19.8%	20.0%	20.3%	20.4%
4C	24.3%	29.4%	31.5%	32.7%	33.4%	33.9%	34.1%	34.4%	34.6%
5A	14.1%	17.2%	18.6%	19.5%	20.0%	20.3%	20.6%	20.7%	20.9%
5B	22.8%	25.1%	27.4%	28.1%	29.0%	29.5%	29.8%	30.1%	30.2%
6A	17.7%	22.0%	23.4%	24.1%	24.8%	25.3%	25.5%	25.9%	25.9%
6B	16.9%	20.8%	22.3%	23.5%	24.2%	24.5%	24.8%	25.0%	25.2%
7A	25.1%	31.5%	34.3%	35.5%	36.3%	36.8%	37.2%	37.3%	37.6%
8A	36.3%	45.4%	48.9%	50.5%	51.6%	52.0%	52.5%	52.8%	53.2%

Table A. 3. Cooling Energy Savings Achieved by the Uniform Part Load Ratio (UPLR) Algorithm

No. of Chillers / Climate Zone	2	3	4	5	6	7	8	9	10
1A	0.9%	0.9%	0.5%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%
2A	1.8%	1.8%	1.5%	1.2%	1.1%	1.0%	0.9%	0.9%	0.8%
2B	2.5%	2.6%	1.8%	1.7%	1.6%	1.5%	1.3%	1.3%	1.3%
3A	2.7%	2.6%	2.4%	2.0%	1.7%	1.5%	1.4%	1.2%	1.2%
3B	3.5%	3.8%	3.4%	2.7%	2.4%	2.3%	2.1%	1.8%	1.6%
3C	10.9%	11.1%	9.5%	9.5%	9.4%	9.1%	7.4%	6.2%	6.0%
4A	4.1%	4.1%	3.7%	3.5%	3.2%	2.8%	2.5%	2.4%	2.3%
4B	5.1%	6.0%	5.9%	5.9%	5.8%	5.6%	5.2%	5.2%	5.2%
4C	7.8%	8.5%	7.4%	7.6%	7.7%	7.6%	6.8%	5.6%	5.4%
5A	4.4%	4.9%	4.8%	4.6%	4.2%	4.1%	4.1%	4.1%	4.0%
5B	8.2%	9.8%	10.4%	10.4%	10.5%	10.4%	10.2%	10.0%	10.0%
6A	5.6%	6.2%	6.1%	6.2%	5.7%	5.4%	5.3%	5.2%	5.2%
6B	7.4%	9.0%	9.1%	9.3%	9.3%	9.0%	8.9%	8.9%	8.9%
7A	9.8%	11.5%	12.1%	11.9%	11.6%	11.6%	11.5%	11.3%	11.3%
8A	12.8%	13.2%	12.1%	11.9%	11.4%	10.7%	10.5%	10.5%	10.6%

Table A. 4. Cooling Energy Savings Achieved by the Sequential Unifrom Part Load Ratio (SUPLR) Algorithm

No. of Chillers / Climate Zone	2	3	4	5	6	7	8	9	10
1A	7.6%	8.3%	8.3%	8.2%	8.1%	8.0%	7.9%	7.8%	7.7%
2A	11.9%	13.7%	14.2%	14.3%	14.4%	14.3%	14.2%	14.2%	14.1%
2B	10.1%	11.8%	12.2%	12.4%	12.4%	12.4%	12.3%	12.3%	12.2%
3A	15.3%	18.1%	18.8%	19.1%	19.3%	19.3%	19.2%	19.2%	19.1%
3B	13.5%	16.1%	16.9%	17.2%	17.3%	17.3%	17.3%	17.3%	17.2%
3C	31.8%	39.9%	43.1%	44.7%	45.6%	46.2%	46.5%	46.7%	46.9%
4A	19.3%	23.3%	24.5%	25.0%	25.2%	25.4%	25.4%	25.4%	25.3%
4B	17.5%	20.9%	22.1%	22.6%	22.9%	22.9%	23.1%	23.0%	23.0%
4C	25.7%	31.8%	34.2%	35.4%	36.0%	36.4%	36.6%	36.7%	36.8%
5A	17.2%	21.0%	22.2%	22.7%	23.0%	23.2%	23.2%	23.3%	23.2%
5B	23.8%	28.8%	30.6%	31.6%	32.2%	32.4%	32.6%	32.7%	32.8%
6A	20.4%	25.0%	26.6%	27.4%	27.8%	28.1%	28.2%	28.2%	28.3%
6B	19.5%	23.9%	25.7%	26.6%	26.9%	27.2%	27.4%	27.4%	27.5%
7A	26.9%	33.8%	36.6%	38.0%	38.7%	39.2%	39.4%	39.7%	39.8%
8A	36.4%	46.3%	50.3%	52.3%	53.4%	54.1%	54.5%	54.9%	55.1%

Table A. 5. Cooling Energy Savings Achieved by the Optimum Part Load Ratio (OPLR) Algorithm

No. of Chillers / Climate Zone	2	3	4	5	6	7	8	9	10
1A	3.7%	5.0%	6.0%	6.9%	7.1%	7.5%	7.8%	7.9%	8.1%
2A	8.6%	10.7%	12.0%	12.8%	13.2%	13.5%	13.8%	13.9%	14.1%
2B	6.6%	8.9%	10.2%	10.9%	11.4%	11.8%	12.1%	12.3%	12.4%

3A	12.1%	15.2%	16.3%	17.2%	17.8%	18.2%	18.5%	18.7%	18.9%
3B	10.2%	12.9%	14.6%	15.5%	16.0%	16.5%	16.8%	17.0%	17.2%
3C	30.8%	37.9%	41.1%	42.9%	44.0%	44.7%	45.2%	45.6%	45.8%
4A	16.3%	20.5%	21.9%	22.9%	23.6%	24.2%	24.4%	24.6%	24.9%
4B	13.4%	17.3%	19.5%	20.6%	21.2%	21.8%	22.1%	22.4%	22.7%
4C	24.1%	29.5%	32.2%	33.6%	34.5%	35.1%	35.5%	35.9%	36.1%
5A	13.5%	18.0%	19.7%	20.8%	21.5%	22.0%	22.4%	22.6%	22.9%
5B	20.3%	25.8%	27.8%	29.4%	30.3%	31.0%	31.4%	31.9%	32.2%
6A	17.1%	22.2%	24.0%	25.4%	26.2%	26.8%	27.1%	27.4%	27.7%
6B	17.4%	21.3%	23.8%	25.0%	25.7%	26.4%	26.7%	27.1%	27.4%
7A	24.5%	31.7%	34.7%	36.2%	37.2%	37.7%	38.3%	38.7%	39.0%
8A	35.8%	45.0%	48.6%	50.6%	51.7%	52.4%	53.1%	53.6%	54.0%

References

[1] A. Soleymani, P. van den Brom, S. Ahmed, M. Konings, E. Sjoer, L. Itard, W. Zeiler, M. De Laat, M. Specht, Learnings Networks and Professional Development in Building Energy Management Systems Industry, Educ. Sci. 13 (2023) 215. https://doi.org/10.3390/educsci13020215.

[2] Buildings – Analysis, Int. Energy Agency (n.d.). https://www.iea.org/reports/buildings (accessed May 25, 2023).

[3] R.V. Rao, Optimization of Multiple Chiller Systems Using TLBO Algorithm, in: R.V. Rao (Ed.), Teach. Learn. Based Optim. Algorithm Its Eng. Appl., Springer International Publishing, Cham, 2016: pp. 115–128. https://doi.org/10.1007/978-3-319-22732-0_8.

[4] F. Wang, H. Lin, W. Tu, Y. Wang, Y. Huang, Energy Modeling and Chillers Sizing of HVAC System for a Hotel Building, Procedia Eng. 121 (2015) 1812–1818. https://doi.org/10.1016/j.proeng.2015.09.161.

[5] N.S. Raman, B. Chen, P. Barooah, On Energy-Efficient HVAC Operation with Model Predictive Control: A Multiple Climate Zone Study, Appl. Energy 324 (2022) 119752. https://doi.org/10.1016/j.apenergy.2022.119752.

[6] Y. Kang, G. Augenbroe, Q. Li, Q. Wang, Effects of Scenario Uncertainty on Chiller Sizing Method, Appl. Therm. Eng. 123 (2017) 187–195. https://doi.org/10.1016/j.applthermaleng.2017.05.041.

[7] Y. Sun, L. Gu, C.F.J. Wu, G. Augenbroe, Exploring HVAC System Sizing Under Uncertainty, Energy Build. 81 (2014) 243–252. https://doi.org/10.1016/j.enbuild.2014.06.026.

[8] F.W.H. Yik, W. Lee, J. Burnett, P. Jones, Chiller Plant Sizing by Cooling Load Simulation as a Means to Avoid Oversized Plant, HKIE Trans. Hong Kong Inst. Eng. 6 (1999) 19–25. https://doi.org/10.1080/1023697X.1999.10667801.

[9] E. Djunaedy, K. van den Wymelenberg, B. Acker, H. Thimmana, Oversizing of HVAC System: Signatures and Penalties, Energy Build. 43 (2011) 468–475. https://doi.org/10.1016/j.enbuild.2010.10.011.

[10] K.-C. Yoon, D.-Y. Park, G. Yun, Y.-M. Kim, Y.-S. Kim, K.-S. Kim, The Heating Energy Saving Effect by Operating Number Control of Boilers in Office Building, J. Korean Inst. Archit. Sustain. Environ. Build. Syst. 7 (2013) 120–125.

[11] B.M. Seo, K.H. Lee, Detailed Analysis on Part Load Ratio Characteristics and Cooling Energy Saving of Chiller Staging in an Office Building, Energy Build. 119 (2016) 309–322. https://doi.org/10.1016/j.enbuild.2016.03.067.

[12] American Society of Heating, Refrigerating and Air-Conditioning Engineers, Equipment life expectancy chart, ASHRAE (n.d.). http://weblegacy.ashrae.org/publicdatabase/system_service_life.asp?selected_system_type=2 (accessed September 1, 2023).

[13] J. Park, K.H. Lee, S.H. Lee, T. Hong, Benefits Assessment of Cool Skin and Ventilated Cavity Skin: Saving Energy and Mitigating Heat and Grid Stress, Build. Environ. 247 (2024) 111027. https://doi.org/10.1016/j.buildenv.2023.111027.

[14] Framework to Assess Climate Change Impact on Heating and Cooling Energy Demands in Building Stock: A Case Study of Belgium in 2050 and 2100, Energy Build. 298 (2023) 113547. https://doi.org/10.1016/j.enbuild.2023.113547.
[15] A.J. Ardakani, F.F. Ardakani, S.H. Hosseinian, A Novel Approach for Optimal Chiller Loading Using Particle Swarm Optimization, Energy Build. 40 (2008) 2177–2187. https://doi.org/10.1016/j.enbuild.2008.06.010.
[16] Z. Li, J. Gao, J. Guo, Y. Xie, X. Yang, M.-J. Li, Optimal Loading Distribution of Chillers Based on an Improved Beluga Whale Optimization for Reducing Energy Consumption, Energy Build. 307 (2024) 113942. https://doi.org/10.1016/j.enbuild.2024.113942.
[17] P. Lyool, S. Jung, Life Cycle Costing through Operating Number Control of Air Conditioning Systems in Office Buildings, Korea J. Air-Cond. Refrig. Eng. 14 (2002) 14–988.
[18] W.-J. Lee, E.-C. Kang, E.-J. Lee, O. Byung-Chil, S. U-Cheul, A Study on the Operation Performance of Central Plant Equipment According to Part Load Characteristics, Korean J. Air-Cond. Refrig. Eng. 25 (2013) 392–397.
[19] B.-M. Seo, B.-H. Yu, K.-H. Lee, A Detailed Analysis of the Part Load Ratio and Cooling Energy Characteristics of Chiller Operation in an Office Building, Korean J. Air-Cond. Refrig. Eng. 27 (2015) 567–573. https://doi.org/10.6110/KJACR.2015.27.11.567.
[20] L. Jia, J. Liu, S. Wei, Optimal Chiller Loading in Dual-Temperature Chilled Water Plants for Energy Saving, Energy Build. 252 (2021) 111425. https://doi.org/10.1016/j.enbuild.2021.111425.
[21] H.B. Gunay, A. Ashouri, W. Shen, Load Forecasting and Equipment Sequencing in a Central Heating and Cooling Plant: A Case Study, ASHRAE Trans. 125 (2019) 513–523.
[22] M.R. Arahal, M.G. Satué, M.G. Ortega, Optimal Chiller Loading Including Transients, Energy Build. 253 (2021) 111527. https://doi.org/10.1016/j.enbuild.2021.111527.
[23] Y.-C. Chang, Optimal Chiller Loading by Evolution Strategy for Saving Energy, Energy Build. 39 (2007) 437–444. https://doi.org/10.1016/j.enbuild.2005.12.009.
[24] Y.-C. Chang, J.-K. Lin, M.-H. Chuang, Optimal Chiller Loading by Genetic Algorithm for Reducing Energy Consumption, Energy Build. 37 (2005) 147–155. https://doi.org/10.1016/j.enbuild.2004.06.002.
[25] Z. Zheng, J. Li, P. Duan, Optimal Chiller Loading by Improved Artificial Fish Swarm Algorithm for Energy Saving, Math. Comput. Simul. 155 (2019) 227–243. https://doi.org/10.1016/j.matcom.2018.04.013.
[26] Z. Zheng, J. Li, Optimal Chiller Loading by Improved Invasive Weed Optimization Algorithm for Reducing Energy Consumption, Energy Build. 161 (2018) 80–88. https://doi.org/10.1016/j.enbuild.2017.12.020.
[27] I. Stewart, L. Aye, tim peterson, Global Optimisation of Chiller Sequencing and Load Balancing Using Shuffled Complex Evolution, in: International Building Performance Simulation Association & AIRAH, Melbourne, 2017: pp. 1–9.
[28] R.Z. Homod, Z.M. Yaseen, A.K. Hussein, A. Almusaed, O.A. Alawi, M.W. Falah, A.H. Abdelrazek, W. Ahmed, M. Eltaweel, Deep Clustering of Cooperative Multi-Agent Reinforcement Learning to Optimize Multi Chiller HVAC Systems for Smart Buildings Energy Management, J. Build. Eng. 65 (2023) 105689. https://doi.org/10.1016/j.jobe.2022.105689.
[29] Z. Jun, Z. Kan-yu, Optimal Load Distribution Strategy for Multiple Chiller Water Units Based on Adaptive Genetic Algorithms, in: 2010 Second WRI Glob. Congr. Intell. Syst., 2010: pp. 5–8. https://doi.org/10.1109/GCIS.2010.64.
[30] Y. Junwei, C. Cheng, P. Dongmei, Z. Xuan, A Numerical Study on the Optimization Method to Optimize the Cooling Load Sharing for a Multi-Chiller System in a Shopping Mall, Energy Procedia 142 (2017) 1977–1984. https://doi.org/10.1016/j.egypro.2017.12.398.
[31] A. Beghi, L. Cecchinato, G. Cosi, M. Rampazzo, A PSO-Based Algorithm for Optimal Multiple Chiller Systems Operation, Appl. Therm. Eng. 32 (2012) 31–40. https://doi.org/10.1016/j.applthermaleng.2011.08.008.
[32] U.S. Department of Energy, EnergyPlus, (2023). https://energyplus.net/.
[33] U.S. Department of Energy, Commercial Reference Buildings., (2023). https://www.energy.gov/eere/buildings/commercial-reference-buildings.
[34] American Society of Heating, Refrigerating and Air-Conditioning Engineers,

ANSI/ASHRAE/IES Standard 90.1-2019: Energy Standard for Buildings Except Low-Rise Residential Buildings, 2019. https://www.ashrae.org/technical-resources/standards-and-guidelines/read-only-versions-of-ashrae-standards.
[35] U.S. Department of Energy, Engineering Reference, U.S. Department of Energy, 2022. https://energyplus.net/assets/nrel_custom/pdfs/pdfs_v22.2.0/EngineeringReference.pdf.
[36] J.H. Cha, J. Park, S.H. Yeon, C.H. Kim, K.H. Lee, A Study of Optimal Operating Conditions for Multiple Chiller Control Strategy: Energy Consumption and COP variation Evaluation Based on Number of Chillers and Partial Load Settings, in: The Society of Air-Conditioning and Refrigerating Engineers of Korea, Pyeongchang, n.d.: p. 635~638.
[37] U.S. Department of Energy, Input Output Reference, U.S. Department of Energy, 2023.
[38] Treksplorer, Best Time to Visit Baltimore, MD: Weather by Month and Season, Treksplorer (2023). https://www.treksplorer.com/best-time-to-visit-baltimore-md-usa/ (accessed February 27, 2024).