IJECBE (2024), **2**, **2**, 153–178
Received (26 May 2024) / Revised (10 June 2024)
Accepted (10 June 2024) / Published (30 June 2024)
https://doi.org/10.62146/ijecbe.v2i2.50
https://ijecbe.ui.ac.id
ISSN 3026-5258

International Journal of Electrical, Computer and Biomedical Engineering

RESEARCH ARTICLE

Energy Management System using Evolutionary Mating Algorithms for Optimizing Energy Usage and User Comfort in Office Bulding

B. Alvin , F. Husnayain ,* B. Sudiarto , and R. Setiabudy

Department of Electrical Engineering, Faculty of Engineering, Universitas Indonesia, Depok, Indonesia
*Corresponding author. Email: faiz.h@ui.ac.id

Abstract

Indonesia has set a target to reduce emissions by 29% or 835 million tons of CO_2 by 2030. The building sector is one of the largest contributors to emissions in Indonesia. To reduce these emissions, the Indonesian government has issued energy conservation regulations requiring each sector to reduce energy consumption. According to Government Regulation No. 33 of 2023, energy conservation is mandatory for energy users in the building sector who use energy sources equivalent to or greater than 500 tons of oil equivalent. On the other hand, the comfort of the building's users must be considered in the energy conservation of a building. User comfort impacts their productivity and efficiency inside the building. Therefore, optimization is essential in order to find optimal values for energy use and user comfort. In this study, we used the evolution mating algorithm (EMA) to find optimal values for energy use and user comfort in office buildings in a tropical-climate country. The mathematical model from the previous research has been updated to perform optimization in tropical-climate countries. The temperature and lighting variables that will affect the thermal and visual comfort of the user inside the building are used to optimize the use of energy. The aim of this research is to determine and analyze the optimal values of temperature and lighting to generate the optimal value of energy use and user comfort in a tropical-climate country. This study compares the state of an office building before and after optimization. The results prove that conditions after optimization using EMA succeeded in reducing energy consumption and increasing user comfort inside office buildings in tropical-climate countries. The temperature and lighting variables after optimization are at the optimal point of 23 ^{o}C and 358.6 lux, which are in line with Indonesia Government Regulations.

Keywords: energy conservation, user comfort, evolution mating algorithm (EMA), energy efficiency.

1. Introduction

Indonesia has set a target to reduce emissions by 29% or 835 million tons of CO_2 under a business as usual (BAU) scenario by 2030 [1]. This target was increased in 2023 to 32% or 912 million tons of CO_2 by 2030. These targets align with the Nationally Determined Contributions (NDC) under the Paris Agreement, which emphasizes stronger commitments to mitigating climate change. The building sector is one of the largest emitters of greenhouse gases in Indonesia [2]. The Indonesian government is working to reduce these emissions by enacting energy conservation regulations, requiring each sector to conserve energy to support the government's efforts reducing CO_2 emissions [3]. According to Government Regulation No. 33 of 2023 on Energy Conservation, energy conservation activities are mandatory for energy users in the building sector who use energy sources equal to or greater than 500 Tons of Oil Equivalent (TOE). One way to conserve energy is by implementing energy-efficient technologies [4]. On the other hand, the comfort of building users must not be compromised when it comes to energy conservation in buildings. Factors determining user comfort include thermal comfort and visual comfort, which are part of indoor environmental quality (IEQ). User comfort directly impacts their productivity within the building. A 3% increase in productivity has been achieved with comfortable and high-performance buildings [5]. Building user productivity also increases with improved IEQ aspects such as thermal and visual comfort [6]. This indicates that building users are more enthusiastic, productive, and efficient when IEQ aspects are enhanced, leading to optimal user comfort [7].

This study aims to optimize energy use without compromising user comfort within the building. Optimization is performed using the Evolution Mating Algorithm (EMA), a part of the Evolutionary Algorithm (EA) developed based on natural selection and genetics. Previous research used EA to optimize the use of hybrid renewable energy systems (HRES), achieving optimal results in its application, where EA was used to determine multi-objective functions such as minimizing cost, maximizing performance, and maximizing reliability [8]. Previous studies also have tested energy use optimization using and comparing Genetic Algorithm (GA) with other algorithms such as Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO), and Biogeography-Based Optimization (BBO). It has been proven that GA has the best performance with optimal results [9]. Other studies also demonstrated that GA produces optimal results in energy consumption efficiency without compromising user comfort [10]. Recent studies have shown that EMA yields optimal results in optimizing energy consumption and user comfort in smart buildings [11] where EMA was compared with other EA algorithms like DE (Differential Evolution) and BBO. In recent studies [12][13], EMA has also been combined with deep learning to optimize the weight of parameters needed to provide optimal results.

Another study [14], EMA was combined with clustering, named as an adaptive clustering-based evolutionary algorithm (ACBEA), which was used to schedule energy usage and reduce electricity costs.

Previous studies [10], [11], using the EMA optimization algorithm were conducted in coldclimate countries. It is related to the temperature variable, where the optimal temperature inside the building will definitely be higher than the temperature outside the building (heating systems).

Further research on optimization using EMA in tropical-climate countries has not been done. Therefore, this study aims to determine and analyze the optimal values of temperature and lighting to generate the optimal value of energy use and user comfort in a tropical climate country using the EMA optimization algorithm. Mathematical models such as the formula for the calculation of energy and gain user comfort (GUC) have been updated to perform optimization with EMA in tropical climate countries. The gain user comfort (GUC) variable is used to indicate user comfort inside the building, and the gain energy saving (GES) variable is used to indicate the total use of energy. The temperature and lighting variables that will affect the thermal and visual comfort of the user inside the building are used to optimize the use of energy.

This research compares and analyzes two conditions of buildings, which are before and after optimization using EMA. Optimization will be done on energy use, lighting, temperature, GUC, and GES. The results of this study prove that conditions after optimization using EMA succeeded in reducing energy consumption and increasing user comfort inside office buildings in tropicalclimate countries. Discussions about how optimization using EMA is done will be discussed in the next section of this journal, which is structured as follows: Section 2 covers theories related to energy use optimization and user comfort in buildings using EMA. The mathematical model and optimization algorithm design are discussed in Section 3, followed by the discussion of research results in Section 4. The journal concludes with a summary in Section 5.

2. Energy Usage and User Comfort Optimization with Evolution Mating Algorithm

2.1 Building Energy Management System

Electric energy consumption in Indonesia for the years 2022, 2023, and 2024 are 1,173 kWh per capita, 1,285 kWh per capita, and 1,408 kWh per capita, respectively [15]. Similar to Indonesia, global electricity consumption has also been steadily increasing year by year, as shown in Figure 1 [2].

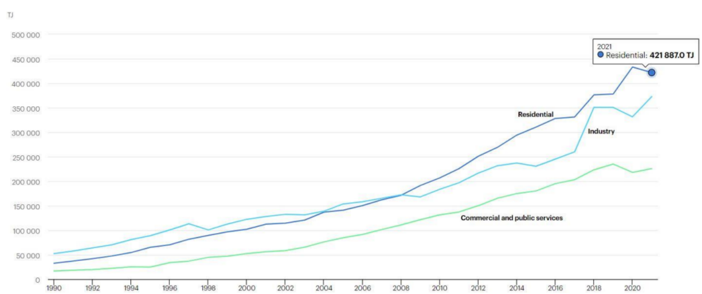


Figure 1. Global Electrical Energy Usage in Various Sectors

The three largest electricity-consuming sectors are the residential, industrial, and commercial sectors. The residential sector is one of the largest energy consumers, with a consumption of 421,887 Terajoules (TJ) or approximately 117,190 GWh. Buildings are a significant part of the residential sector, contributing about 36% of global electricity consumption [16].

Given the increasing electricity consumption, particularly in the building sector, buildings must implement energy management systems to ensure efficient energy use in accordance with Government Regulation No. 33 of 2023. The implementation of energy management systems in buildings, such as building energy management systems (BEMS), is considered an effective program to reduce electricity consumption in the residential, industrial, and commercial sectors [17].

Reducing electricity consumption has become very important, and energy consumption in the building sector plays a crucial role in energy efficiency [18]. Electricity consumers are also beginning to adopt energy management systems driven by several factors, such as rising electricity prices and potential financial incentives [19].

Over time, BEMS has evolved year by year. Today, smart buildings are becoming a target for new construction, especially in urban areas. The design concept of a smart building energy management system can be seen in Figure 2. The fundamental difference between BEMS and smart BEMS lies in the communication between building users and building equipment, such as cooling systems and lighting. Cooling systems consume a significant amount of electricity, making them critical for energy efficiency efforts [20].

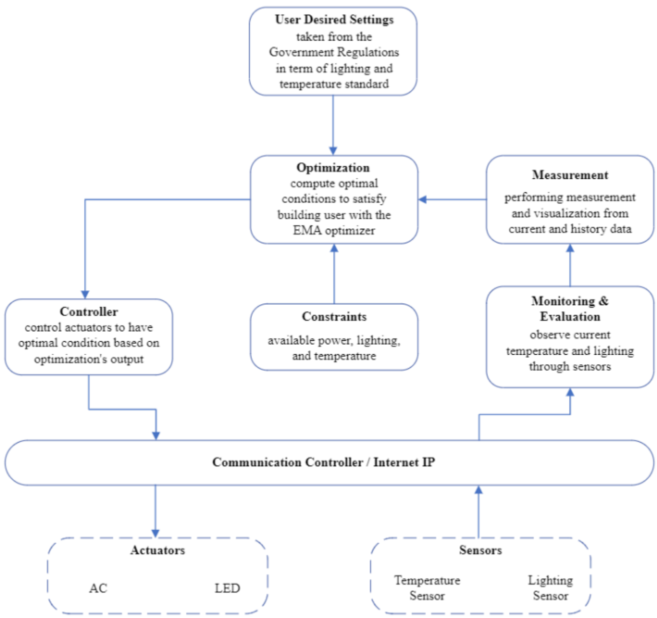


Figure 2. Conceptual Design of Smart Building Management System

This communication is facilitated through sensors, actuators, the internet (wireless communication), and an optimization system. In this study, the optimization system uses the EMA (evolution mating algorithm) optimizer, which considers user-desired parameters according to applicable standards. The optimization system collects historical and current data from sensors installed on electronic devices in the building and performs optimization based on constraints and user-desired parameters.

The optimization results are then sent to the control system, which then communicates with the actuators to produce outputs that align with the optimization results. The communication between actuators and controllers is wireless via the internet. This ensures that energy use in the building is more controlled and aligns with the comfort parameters of the building users.

2.2 Evolution Mating Algorithm

EMA is part of the Evolutionary Algorithm (EA), which is a nature-based algorithm inspired by natural processes. The structure diagram of EMA can be seen in Figure 3. The inspiration for the Evolution Mating Algorithm is also derived from the mating analogy of organisms, based on the Hardy-Weinberg principle. The mating analogy conceptualized in EMA is a general mating analogy and is not specific to any particular organism. In studies on specific organism mating behaviors [21], it has been found that it is very challenging to precisely follow mating behaviors due to the numerous natural strategies involved in the mating of each organism [11].

The Evolution Mating Algorithm (EMA) is chosen for several advantages over other evolutionary algorithms, including:

(a) Ability to effectively search for solutions. EMA achieves this by splitting the population size that enters the algorithm into two parts.
(b) Faster data processing capability. This occurs because evaluation is performed immediately after the mating process, eliminating the need for sorting.
(c) Lower complexity. The complexity of EMA only depends on the population size, the number of dimensions, and the number of iterations. In other words, the complexity can be adjusted according to the problem being optimized

EMA can be used for various optimization needs and is applied in this study to optimize energy usage and user comfort. The working mechanism of the EMA algorithm begins with the initiation process, selection of individuals for mating, and ends with the formation of new offspring. Each process in EMA's workflow requires variables and parameters discussed in Section 3. All input variables for temperature and lighting are divided into father and mother populations during the initiation phase. Identifying the best temporary offspring is done at the initiation stage by evaluating the objective function.

Mating is then carried out by combining the father and mother populations with their alleles, and the resulting offspring are evaluated and compared with the best temporary offspring from the initiation stage. The best offspring then undergo an exploration phase. If the number of iterations is fulfilled, the best offspring represent the optimal values for temperature and lighting. Energy consumption, GUC (Gain User Comfort), and GES (Gain Energy Saving) calculations will then be conducted using the optimal temperature and lighting values derived from the EMA optimization algorithm.

The phase of optimization using EMA until producing a new offspring will be described in the next subsection.

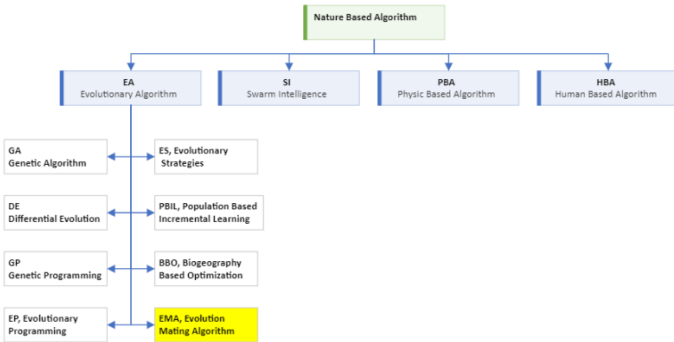


Figure 3. Structure Chart of Evolution Mating Algorithm

2.2.1 *Initialization Population*

The initiation stage is the initial phase in optimization using EMA. The input data, which constitutes the population in the EMA algorithm, will be organized into father and mother matrices. From these, the temporary best offspring will be determined by the existing population. The temporary best offspring are calculated by evaluating the objective function value for each population. The best population is the one that produces the optimal objective function value, depending on the research objective. The best population will be the optimal solution from the two groups of father and mother matrices and will be retained for subsequent processes [9]. The form of the father and mother matrices satisfies equations (7) and (8) in Section 3.

2.2.2 *Selection for Mating*

The next stage in optimization using EMA is population selection for mating. The population selection process for mating at this stage is conducted randomly according to the HardyWeinberg principle. This principle is used in the evolution mating algorithm, which relates the allele and genotype frequencies of male and female populations in random mating [22]. Figure 4 provides a simple illustration of the Hardy-Weinberg principle. The two alleles in Figure 4 represent alleles inherited from the father and mother, respectively. The expected genotype frequency from this mating is homozygous offspring. These offspring are obtained from the mating of the father's allele frequency with the father's allele frequency, represented by P^2 , or from the mating of the mother's allele frequency with the mother's allele frequency, represented by q^2 . In addition to homozygous offspring, there are also heterozygous offspring resulting from the mating of the father's and mother's allele frequencies, represented by p_q.

The EMA algorithm uses the Hardy-Weinberg principle approach to determine the best new offspring from each population, a process known as exploitation.

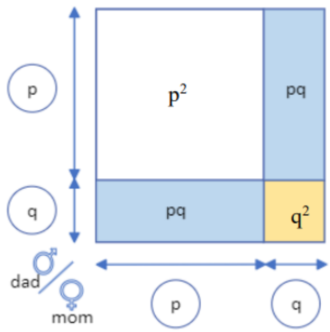


Figure 4. Ilustration of the Hardy-Weinberg Principle

The form of the population selection for mating equation meets equation (9) in Section 3. Imates in this equation can be interpreted as the total variation in mating success, representing separate selection probabilities arising from variations in sex ratio, mate availability timing, and spatial availability of mates [23].

2.2.3 Offspring Forming

After the new offspring are formed, they must be tested against the temporary best values stored during the initiation process and followed by the exploration process. The process of testing the offspring values against the temporary best values meets equation (11) in Section 3. Meanwhile, the exploration process on the offspring values meets equation (13) in Section 3. There are two parameters for testing with the temporary best values and the exploration process, namely Cr and r, where Cr is the crossover probability value that randomly decides whether to swap each component with the best solution or not [9].

After the new offspring are formed, they must be tested against the temporary best values stored during the initiation process and followed by the exploration process. The process of testing the offspring values against the temporary best values meets equation (11) in Section 3. Meanwhile, the exploration process on the offspring values meets equation (13) in Section 3. There are two parameters for testing with the temporary best values and the exploration process, namely Cr and r, where Cr is the crossover probability value that randomly decides whether to swap each component with the best solution or not [9]. The parameter r is used to determine whether exploration will be conducted in that iteration or not. Environmental effects in the evolution of mating, such as foraging and facing predators, cannot be avoided, which is then referred to as the exploration process [9], [24]. The decision whether an organism will flee or face a predator needs to be considered, where parameter r will play a role in this decision-making process. If the fitness function value is better after exploration, it can be concluded that the organism survived after facing the predator. Conversely, if the fitness function value is worse after exploration, it can be concluded that the organism died after facing the predator.

3. The Design of Evolution Mating Algorithms and Mathematical Model

This section will discuss how data is collected and processed into the EMA optimization algorithm to produce optimal temperature and lighting values. The imputation method will be used for data cleaning during the data retrieval and preparation stage. The results of the EMA optimization algorithm will be quantitatively analyzed by comparing the pre-optimization and post-optimization results. Data visualization in the form of graphs will be used to easily observe the differences between the research results.

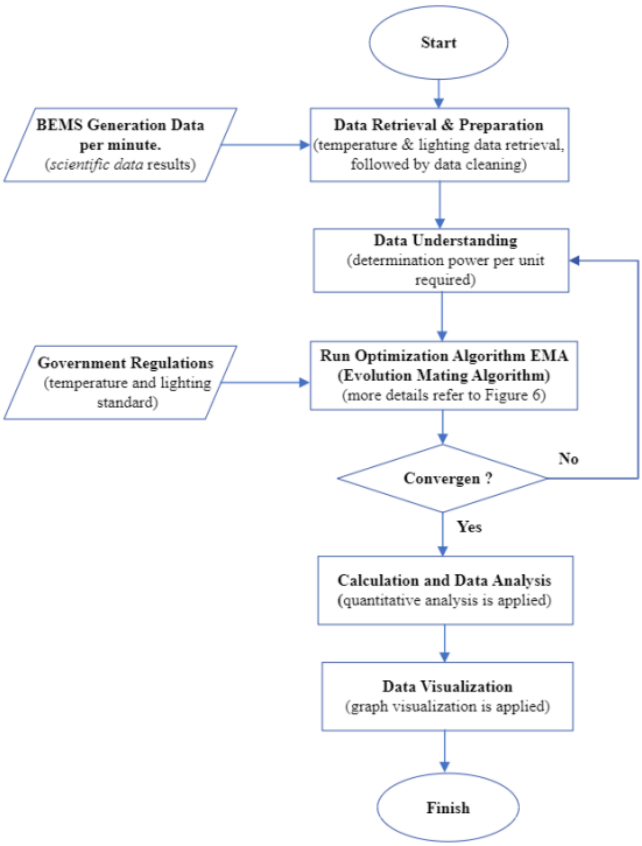


Figure 5. Research Flowchart

This study was conducted using quantitative analysis by comparing the values of energy consumption, temperature, lighting, GES (Gain Energy Saving), and GUC (Gain User Comfort) before and after optimization. The research began with data retrieval & collection. Data retrieval involves collecting the required data for this research from the obtained dataset, specifically focusing on temperature and lighting data. The dataset for temperature and lighting was sourced from measurement research conducted in an office building in Thailand [25]. The acquired dataset will then undergo cleaning using the imputation method, which is referred to as the data preparation stage.

After data retrieval and preparation, data understanding was performed, followed by the optimization of temperature and lighting. The optimal temperature and lighting values were obtained using the Evolution Mating Algorithm optimization algorithm, conducted with Matlab R2022A software. After obtaining the optimal values, a quantitative analysis was performed. The research flowchart is shown in Figure 5.

3.1 Data Retrieval & Processing

This section will discuss how data is collected and processed for subsequent optimization using the EMA algorithm. There are two stages of data processing before it is used for the EMA optimization algorithm in this study which are data retrieval & preparation, and data understanding.

The first stage in the data processing is data retrieval & preparation, which focuses on temperature and lighting data. The data was obtained from previously conducted measurements [25] which were conducted in a seven-story office building with a total area of 11,700 m2 , located in Bangkok, Thailand. The data measurements used in this research were from May 2019, focusing on the 7th floor of the building, where data on temperature, lighting, and electricity consumption were collected every minute. The dataset for May 2019 and the 7th floor was chosen because it had fewer missing values compared to other months and floors. The total missing values for May 2019 were 1.68%, or 752 minutes out of a total of 44,640 minutes in May 2019. After the data retrieval stage, data preparation is conducted by cleaning the data using the imputation method. Imputation methods were used to fill in these missing values since the missing values were below 30%[26]. Next, the average values were taken to produce hourly data for May 2019. A sample data snippet after the data retrieval & preparation stage can be seen in Table 1.

Table 1. Data Snippet after Data Retrieval & Preparation Stage

Time	Temperature (°C)	HVAC Load Consumption (kW)	Lighting (lux)	Lighting Load Consumption (kW)	Total Load Consumption (kW)
5/2/2019 8:00	21.9	36.6	294.1	3.1	39.66
5/2/2019 9:00	20.3	37.1	297.0	3.2	40.30
5/2/2019 10:00	20.3	37.7	295.0	2.4	40.02
5/2/2019 11:00	20.5	26.9	289.0	2.1	28.96
5/2/2019 12:00	25.2	0.6	285.0	1.9	2.47
5/2/2019 13:00	22.9	36.5	285.0	2.0	38.53
5/2/2019 14:00	21.4	36.3	289.0	2.1	38.36
5/2/2019 15:00	21.2	36.3	284.0	2.4	38.69
5/2/2019 16:00	20.5	36.6	281.8	3.1	39.72
5/2/2019 17:00	22.7	15.7	285.0	2.5	18.14
5/2/2019 18:00	20.1	37.0	280.0	2.1	39.06

The second stage in data processing is data understanding. In this stage, the average electrical power required for each increase or decrease in temperature and lighting will be determined for all hourly data in May 2019. The results of the data understanding stage are the PT and PL values in Table 4, which are 6.5 kW and 0.22 kW, respectively. It should be noted that the data required for the EMA optimization algorithm includes temperature, HVAC load consumption, lighting, lighting load consumption, and total lighting & HVAC load consumption, as shown in Table 1.

Another important aspect to consider is the missing values caused by sensor or communication network errors. Data cleaning methods using machine learning might be necessary if the missing value rate exceeds 30% [26].

3.2 Mathematical Model Design

The input and output variables in this study are shown in Table 2 and Table 3. The parameter values used in this study are provided in Table 4.

Table 2. Input Variables

Notation	Description
Tc	Temperature read by sensors (°C).
Lc	Lighting read by sensors (lux).
Td	Temperature based on user preference (°C).
Ld	Lighting based on user preference (lux).

Table 3. Output Variables

Notation	Description
To	Optimal Temperature (°C).
Lo	Optimal Lighting (lux).
Eo	Optimal Energy Consumption (kWh).
G_{UC}	*Gain user comfort* (user comfort value).
G_{ES}	*Gain energy saving* (energy efficiency value).

Table 4. Parameter Values

Notation	Value	Description
α_{UC}	0.5	Weight of user comfort.
α_{ES}	0.5	Weight of energy saving.
β_T	0.5	Weight of user temperature preference.
β_L	0.5	Weight of user lighting preference.
P_T	6.5 kW	Power per unit required for temperature.
P_L	0.22 kW	Power per unit required for lighting.

The values of PT and PL in Table 4 were determined during the data understanding stage, as shown in Figure 5. These values were derived from the average fluctuation in power needed for each degree of temperature and each lux of lighting. All the aforementioned variables and parameters will be processed into the algorithm model according to the objective function in this study, as shown in equation (1).

$$Maximize\{(\alpha_{UC} \times G_{UC}) + (\alpha_{ES} \times G_{ES})\} \epsilon [0, 1] \tag{1}$$

User comfort values and energy saving values will be balanced in this study, so the weight for user comfort (αUC) and the weight for energy efficiency (αES) in equation (1) are both 0.5. The most optimal GUC and GES values are those that make the objective function approach 1.0. To determine the user comfort value and energy saving value, the following mathematical model will be used:

$$G_{UC} = \beta_T x \left(\frac{Tmax - To}{\Delta T}\right) + \Delta\beta_L x \left(1 - \left(\frac{L_{max} - L_o}{\Delta L}\right)^2\right) \rangle [\mathbf{0}, \mathbf{1}] \tag{2}$$

Where:

T_{max} = Maximum temperature based on user preference (^{o}C).

L_{max}= Maximum lighting based on user preference (lux)

ΔT= The difference between the maximum and minimum values of the temperature preferences of building users (^{o}C).

ΔL = The difference between the maximum and minimum values of the lighting preferences of building users (lux)

$$G_{ES} = \left(1 - \left(\frac{E_O - E_{min}}{\Delta E}\right)^2\right) \rangle [\mathbf{0}, \mathbf{1}] \tag{3}$$

Where:

E_{min} = Minimum energy usage (kWh).

E_{max}E = Maximum energy usage (kWh).

ΔE= The difference between the maximum and minimum values of energy usage (kWh). To determine the values of Eo, Emin, and Emax, the following equations will be used:

$$E_O = P_T x (T_C - T_O) + P_L x (L_O - L_C) + P_A x (A_O - A_C) \tag{4}$$

$$E_{min} = P_T x (T_C - T_{Max}) + P_L x (L_{Min} - L_C) + P_A x (A_{Min} - A_C) \tag{5}$$

$$E_{max} = P_T x (T_C - T_{Min}) + P_L x (L_{Max} - L_C) + P_A x (A_{Max} - A_C) \tag{6}$$

Using equations (2) and (3), the objective function value in equation (1) can be determined.

3.3 Optimization Algorithm Design

Evolution mating algorithm (EMA) optimization design is based on the flowchart in Figure 6 below.

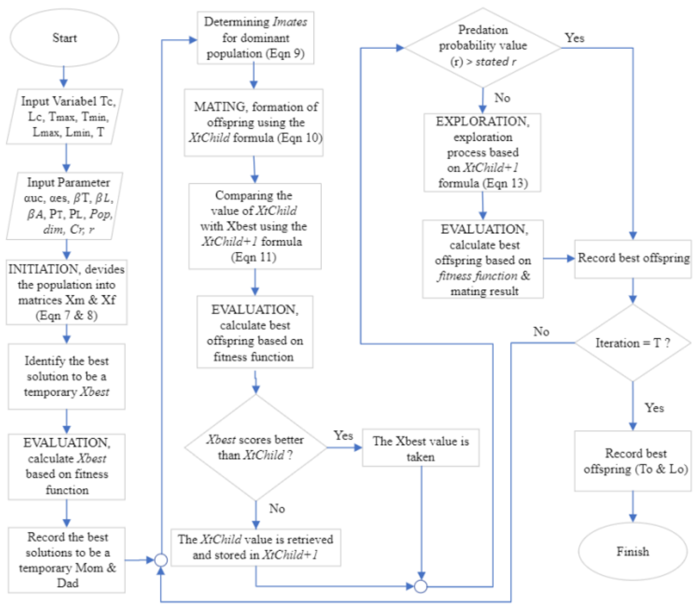


Figure 6. Evolution Mating Algorithm Flowchart

Broadly, the optimization process with EMA involves three stages: initiation, mating, and offspring formation. The offspring values are evaluated at each stage. Exploration is also carried out to ensure that the obtained optimal values remain more optimal compared to other temperature and lighting values. The output of the EMA optimization algorithm in this study is the optimal temperature and lighting values, which are 23°C and 358.6 lux, respectively. Each stage of the optimization process with EMA will be discussed in detail in the following sections.

3.3.1 Initiation Process

The input population will be divided into two groups: pop_dad for the father population and pop_mum for the mother population. These two groups will form matrices that satisfy equations (7) and (8) below:

$$pop\text{-}dad = \begin{bmatrix} x_1^1 \cdots x_d^1 \\ \vdots \ddots \vdots \\ x_{\frac{n}{2}}^1 \cdots x_{\frac{n}{2}}^d \end{bmatrix} \quad (7)$$

$$pop\text{-}mam = \begin{bmatrix} x^{1}_{\frac{n}{2}} + 1 \cdots x^{d}_{\frac{n}{2}} + 1 \\ \vdots \ddots \vdots \\ x^{1}_{n} \cdots x^{d}_{n} \end{bmatrix} \tag{8}$$

Where:
d = dimension of the problem.
n = number of populations.
Some initialized parameters can be seen in Table 5 below:

Table 5. Input Parameter

Notation	Value	Description
T	100	Number of iterations
SearchAgent	744	Number of populations
dim	2	Number of dimensions

Based on Table 5, the number of iterations in this study is 100, and 744 populations representing 744 hours in May 2019 will be tested. The number of dimensions refers to the number of variables to be optimized, which are temperature and lighting; therefore, the number of dimensions in this study is 2.

3.3.2 Offspring Selection for Mating

The matrices pop_dad and pop_mum obtained from the initiation process will be randomly mated based on the adoption of probability or the chance for sexual selection, denoted as Imates in equation (9) below [27].

$$I_{mates} = 1 + \left[var\left(X^{T}_{m,*}\right) - var\left(X^{T}_{f,*}\right)\right] \tag{9}$$

Where:
var$\left(X^{T}_{m,*}\right)$ = variance of the male that will be mated in iteration T.
var $\left(X^{T}_{f,*}\right)$= variance of the female that will be mated in iteration
X_{m*} *dan* $X_{f,*}$= selected male and female candidate individuals/solutions.

If var $\left(X^{T}_{f,*}\right)$ > var$\left(X^{T}_{m,*}\right)$, then Imates will be negative, meaning that the female's values $\left(X^{T}_{f,*}\right)$ will be dominant in producing offspring. Conversely, if var$\left(X^{T}_{m,*}\right)$ > var $\left(X^{T}_{f,*}\right)$, then Imates will be positive, meaning that the male's values $(X^{T}_{m,*})$ will be dominant in producing offspring [11].

$$x^{T}_{child} \begin{cases} p.*X^{T}_{m,*} + q.*X^{T}_{f,*}\, for\ I_{mates} \geq 0 \\ p.*X^{T}_{f,*} + q.*X^{T}_{m,*}\, for\ I_{mates} < 0 \end{cases} \tag{10}$$

Where: p = normally distributed random variable, alleles inherited from the father and mother. q = 1 - p, alleles inherited from the father and mother. If the fitness function value of the offspring is better than that of their parents, the offspring value (x^{T}_{child}) can be replaced by the values of their parents. Good offspring are also influenced by the best individuals stored during the initiation process.

Therefore, the results from equation (10) will be processed with the best solution at certain iterations according to equation (11) below.

$$X^{T+1}_{child} = K. * X^{T}_{child,j} + X^{best}_{j}. * (1 - K), j = 1, 2, ...d \tag{11}$$

Where:
$X^{T}_{child,j}$ = j-th offspring individual at iteration T.
X^{best}_{j} = j-th best individual.
K = random distribution.
The random distribution for the value K satisfies equation (12) below.

$$K = rand(1, d) < C_r \tag{12}$$

From equation (12), Cr is the algorithm's decision parameter for determining whether the algorithm produces the best solution. The offspring produced in equation (11) will be tested and compared with the fitness values of the parents. If the offspring's fitness value is better, the offspring will replace the parents. The parameter value Cr in this study is 0.8, which was obtained from testing Cr values ranging from 0 to 1, and a value of 0.8 resulted in fewer iterations and more optimal fitness function values.

In addition to being influenced by the best individuals and the Cr value, the offspring are also affected by the exploration process, which satisfies equation (13). This is intended to account for external factors, such as environmental effects when facing predators, in the evolution mating algorithm. This analogy is drawn from natural environmental conditions.

$$X^{T+1}_{child} = rand(1, d) . * X^{best}_{j} for\ r < \epsilon [0, 1] \tag{13}$$

In this study, the optimal parameter value r in equation (13) was found to be 0.2. This value was obtained from testing r values ranging from 0 to 1, where a value of 0.2 resulted in fewer iterations and more optimal fitness function values.

4. Results and Discussion

This section presents several key points, including a comparison of the office building conditions before and after optimization using the Evolution Mating Algorithm. The discussion section will compare the results of this study with previous research.

4.1 Pre-Optimization Conditions

This subsection discusses the conditions of the office area in the building before optimization, covering power consumption, temperature, lighting, Gain User Comfort (GUC) values, and Gain Energy Saving (GES) values.

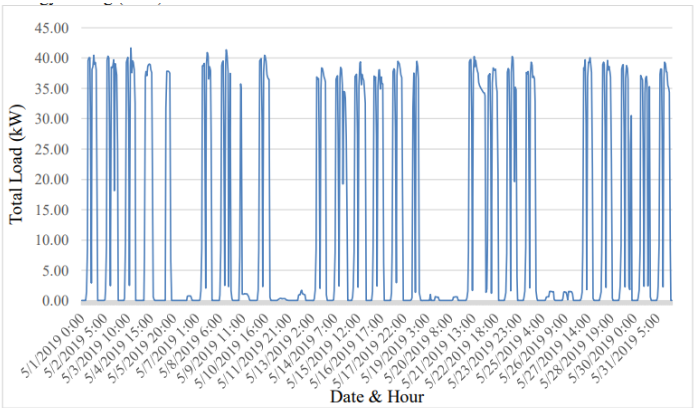


Figure 7. Power Consumption before Optimization

Figure 7 shows the power consumption of the 7th floor office area in May 2019. The building's operational hours are from 08:00 AM to around 08:00 PM. The power consumption measurements in Figure 7 are derived from the sum of the power consumption of the Air Conditioning (AC) and lighting. It can be seen that the highest energy usage on the 7th floor is 41.66 kWh. The power consumption pattern in this office area indicates low consumption during lunch hours and high consumption during working hours. Power consumption approaches 0 kWh on Sundays and holidays, with holidays in May falling on May 9 and May 20. The total power consumption in May 2019 for the 7th floor office area is 9775.6 kWh.

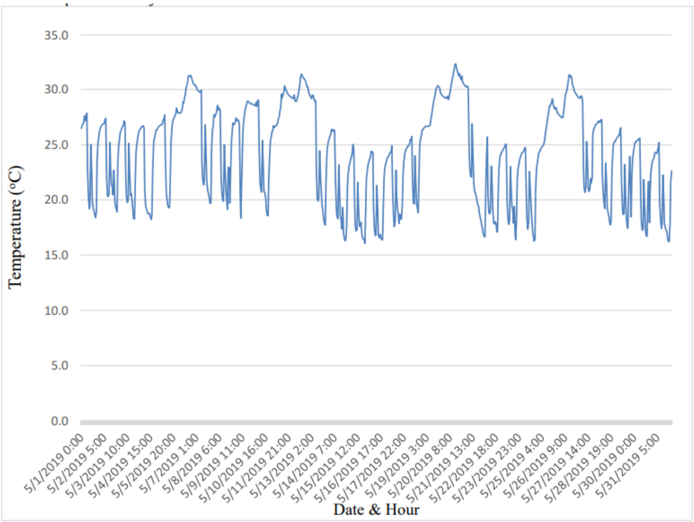


Figure 8. Temperature before Optimization

Figure 8 shows the temperature of the area before optimization. Based on the measurements in Figure 8, the average office area temperature ranges from 20°C to 25°C, with some weeks recording temperatures below 20°C. The lowest measured temperature is 16.05°C, and the highest is 32.39°C. The temperature fluctuation pattern in Figure 8 aligns with the power consumption pattern where during the lunch hours the cooling system is not being operational and causing room temperatures to rise to around 25°C. Additionally, room temperatures rise reaching up to 32.39°C when the office is not being operational, from approximately 08:00 PM to 08:00 AM each day.

According to the Indonesian Ministry of Manpower Regulation No.5 of 2018 concerning Occupational Safety and Health in the Work Environment, Article 40 Number 3 [28], he comfortable room temperature range should be maintained between 23°C and 26°C. This indicates that the office area temperature does not meet the standard at certain times which will disrupt the comfort of building users.

Figure 9 shows the lighting before optimization. Based on the measurements in Figure 9, the average office area lighting ranges from 200 to 300 lux during office hours. The lighting pattern in Figure 9 also aligns with the power consumption pattern where during lunch hours the lighting will be turned off causing the room lighting to drop below 20 lux. When the office is not being operational from around 08:00 PM to 08:00 AM the lighting also drops to 0 lux.

According to the Indonesian Ministry of Manpower Regulation No.5 of 2018 concerning Occupational Safety and Health in the Work Environment, Annex No. 2 [28], the lighting range 0.0 5.0 10.0 15.0 20.0 25.0 30.0 35.0 Temperature (*°C*) Date & Hour that must be maintained is between 300 and 500 lux. The measurements in Figure 9 show that lighting is below 300 lux almost all the time. This indicates that the office area lighting does not meet the standard, which will disrupt the comfort of building users.

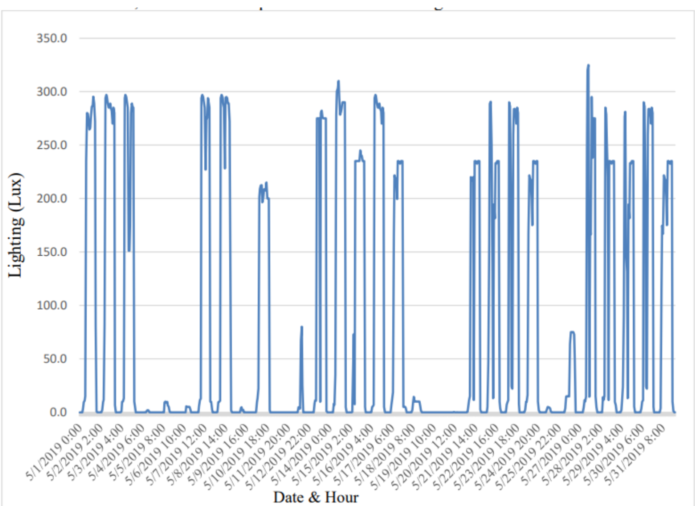


Figure 9. Lighting before Optimization

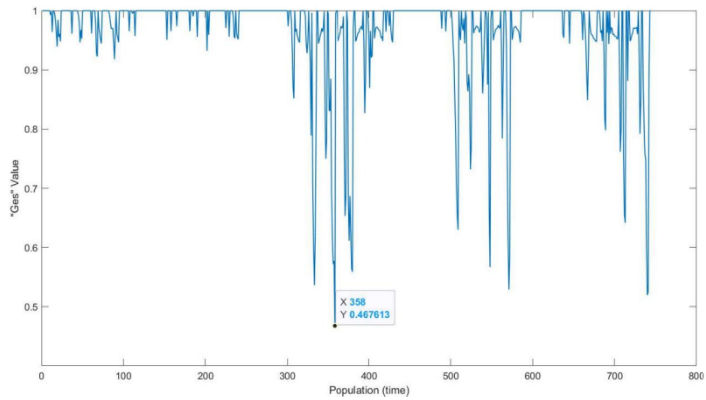


Figure 10. Gain Energy Saving (GES) Values before Optimization

Figure 10 shows the graph of population against GES (Gain Energy Saving) values, where the method to obtain the GES value is explained in Section 3. The optimal temperature and lighting values used to obtain GES are based on measured values. The X-axis in Figure 10 0.0 50.0 100.0 150.0 200.0 250.0 300.0 350.0 Lighting (Lux) Date & Hour represents the population size, corresponding to the number of hours in May 2019, which is 744 hours (31 days), making the maximum population size in this study is 744. The Y-axis in Figure 10 represents the GES values, which range from 0 to 1, with the maximum GES value being 1 and the minimum value being 0.

GES indicates the energy saving index. The GES values in Figure 10 show that the energy usage in the 7th floor office area ranges from 0.5 to 1.0. The GES value pattern in Figure 10 also follows the power consumption pattern in Figure 7, where during lunch hours and nonoperational hours, the GES value reaches 1.0. This indicates optimal energy use during these hours since the cooling and lighting systems are not turned off, resulting in power consumption dropping to around 0 kW to 5 kW. However, the GES value ranges from 0.5 to 0.9 during operational hours, from 08:00 AM to 12:00 PM and 01:00 PM to 08:00 PM. This occurs because the cooling and lighting systems are turned on during operational hours.

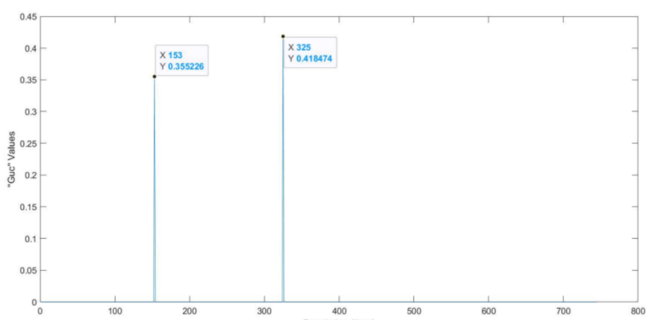


Figure 11. Gain User Comfort (GUC) Values before Optimization

Figure 11 shows the graph of population against GUC (Gain User Comfort) values, where the method to obtain GUC is explained in Section 3. The optimal temperature and lighting values used to obtain GUC are based on measured values. GUC indicates the user comfort index where values closer to the maximum of 1.0 indicate higher user comfort within the building. Conversely, values closer to the minimum of 0.0 indicate lower user comfort. The user comfort range for temperature and lighting adheres to the standards specified in the Indonesian Ministry of Manpower Regulation No.5 of 2018 [28] as previously mentioned.

The GUC values in Figure 11 are mostly at the minimum point of 0.0. There are only two points where the GUC values are not at the minimum which are at the 325th population on May 14 at 12:00 PM and at 153rd population on May 7 at 08:00 AM, with GUC values of 0.42 and 0.35 respectively. This is because, at these two times, the temperature and lighting values were within the specified standard range. Apart from populations 325 and 153, the GUC values remain at the minimum point of 0.0. This aligns with the room temperature values being below 23°C in Figure 8 and the lighting values being below 300 lux in Figure 9.

Because the temperature and lighting values are mostly below the standards, the GUC values are predominantly at the minimum point of 0.0. This indicates that the office building users are not experiencing optimal comfort levels. Therefore, an approach is needed to optimize user comfort without compromising energy usage in the building. Testing with EMA (Evolution Mating Algorithm) to optimize energy use and user comfort has been conducted, and the results will be discussed in the next section.

4.2 Post-Optimization Conditions

This section discusses the conditions of the office area in the building after optimization using EMA (Evolution Mating Algorithm) covering the results of optimizing temperature and lighting using EMA, the convergence curve, power consumption, temperature, lighting, Gain User Comfort (GUC) values, and Gain Energy Saving (GES) values. The post-optimization values will also be compared with the pre-optimization values.

EMA has been designed by incorporating the research variables and parameters as outlined in Section 3. Input data for 744 hours in May 2019 were fed into EMA, resulting in optimal temperature and lighting values to achieve balanced GUC and GES values. The optimal temperature and lighting values obtained are 23°C and 358.6 lux respectively. This optimal value is achieved with an objective function value of 0.74493. The equation to obtain this objective function value has been explained in Section 3. This objective function value was reached at the 26th iteration of the Evolution Mating Algorithm.

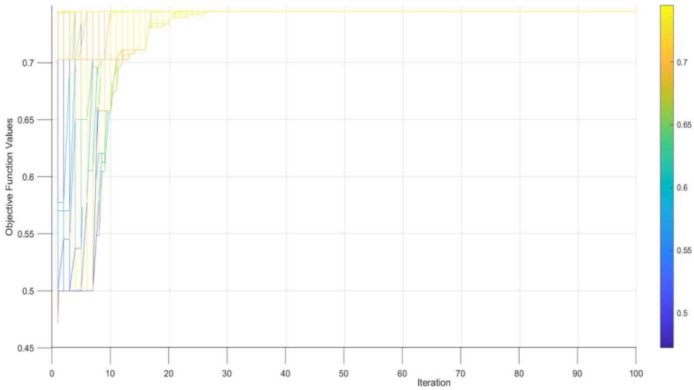
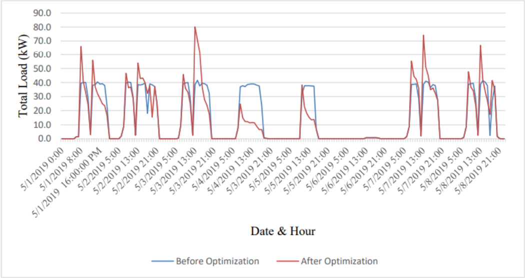


Figure 12. Convergence Curve

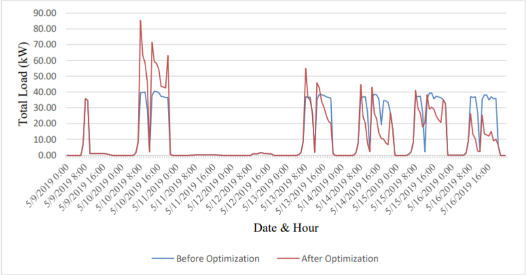
Figure 12 shows the number of iterations against the objective function value. This convergence curve demonstrates how the objective function value remains convergent from the 26th iteration to the 100th iteration at 0.74493. Each input data set of 744 hours represents the population size resulting 744 populations in this study. Each line on the convergence curve represents the 744 populations that fed into EMA to obtain the optimal objective function value, which subsequently determines the optimal temperature and lighting value.

Figure 13 shows power consumption before and after optimization. Figure 13 is divided into four subfigures, illustrating energy consumption for the first, second, third, and fourth weeks before and after optimization. In Figure 13(a), energy consumption before and after optimization for the first week of May 2019 is presented. The graph indicates that the optimization using EMA successfully reduced electricity usage on May 4th and 5th and at various other times throughout the week. The increase in energy consumption at other times is due to the algorithm's attempt to raise lighting consumption to the optimal point, resulting in increased energy usage at certain times. Overall, the optimization using EMA successfully saved 202.8 kWh in the first week, reducing energy consumption from 2,726.6 kWh before optimization to 2,523.9 kWh after optimization.

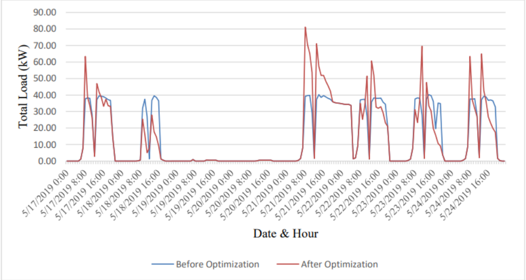
Figure 13(b) shows energy consumption before and after optimization for the second week of May 2019. The figure indicates that the EMA optimization successfully reduced energy consumption from May 13th to May 16th, 2019. However, it also shows an increase in energy consumption on May 10th, 2019, due to the recorded temperature being above the optimal point and the lighting level being below the optimal point on that day. As a result, the EMA optimization attempted to raise the temperature and lighting to optimal levels, leading to increased energy consumption on that day. Overall, the EMA optimization saved 273.2 kWh in the second week, reducing energy consumption from 2,332.5 kWh before optimization to 2,059.4 kWh after optimization.



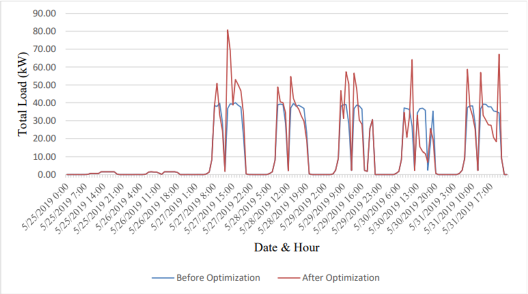
a). 1st Week



b). 2nd Week



c). 3rd Week



d). 4th Week

Figure 13. Energy Consumption Before & After Optimization (May 2019)

Figure 13(c) shows energy consumption before and after optimization for the third week of May 2019. The figure shows that the EMA optimization only successfully reduced energy consumption on May 18th, 2019, while on other dates such as May 21st, it increases energy consumption. This increase occurs because the recorded temperature during the measurement 0.00 10.00 20.00 30.00 40.00 50.00 60.00 70.00 80.00 90.00 Total Load (kW) Date & Hour Before Optimization After Optimization 0.00 10.00 20.00 30.00 40.00 50.00 60.00 70.00 80.00 90.00 Total Load (kW) Date & Hour Before Optimization After Optimization was above the optimal value, so the optimization attempted to lower it to the optimal temperature, which required more energy. In addition to temperature, lighting also contributed to the increase in energy consumption, as the average lighting in the third week was below 220 lux. Consequently, the EMA optimization increased the lighting to the optimal level resulting in higher energy consumption. Overall, the optimization increased energy consumption by 56.7 kWh in the third week, from 2,687.4 kWh before optimization to 2,744 kWh after optimization.

Figure 13(d) shows energy consumption before and after optimization for the fourth week of May 2019. The figure indicates that the EMA optimization successfully reduced energy consumption at certain times, while at most times, the optimization algorithm increased energy consumption. This was also due to the temperature and lighting values being below optimal levels, requiring more energy to reach the optimal point. In certain hours, the lighting level was even below 180 lux. Overall, the optimization increased energy consumption by 131.7 kWh in the fourth week, from 2,029 kWh before optimization to 2,160.7 kWh after optimization. In addition, the EMA optimization successfully reduced total energy consumption by 287.6 kWh for the entire month of May 2019.

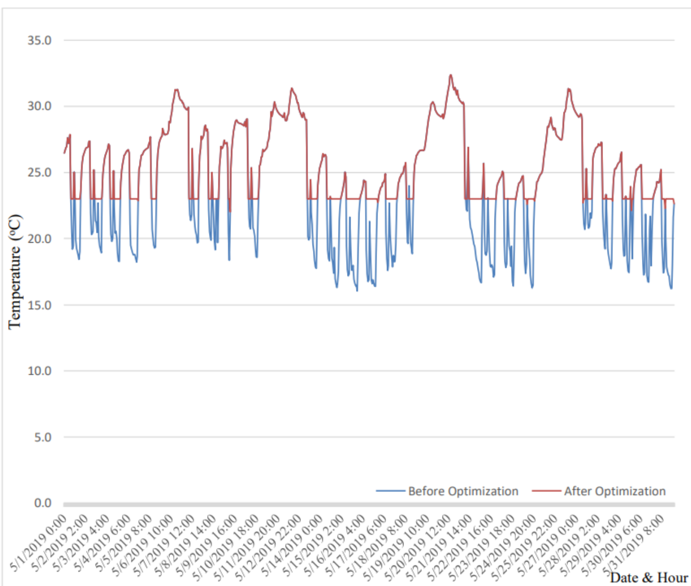


Figure 14. Temperature Before & After Optimization

Figure 14 shows the office area temperature before and after optimization. Based on the optimization results using EMA, it can be observed that any temperature value below the optimal point of 23°C is adjusted to maintain the optimal temperature of 23°C. This approach helps conserve electrical energy and increases user comfort (GUC). During lunch hours and when the building is not operational, the optimization is inactive resulting in the optimized temperature being the same as the sensor temperature, causing the pre- and post-optimization graphs to overlap. Overall, the EMA optimization successfully maintained the room temperature at 23°C during the building's operational hours.

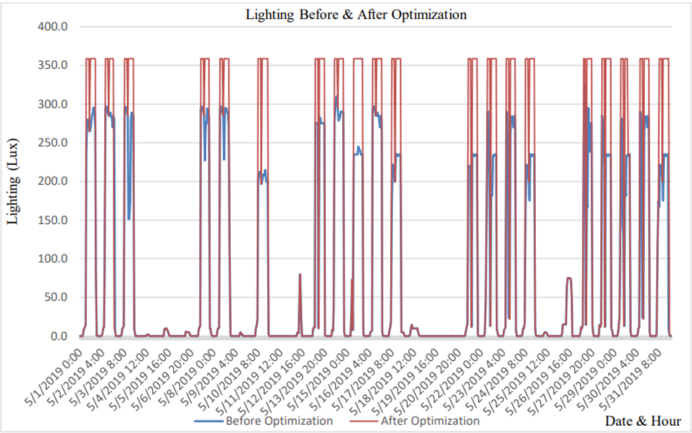


Figure 15. Lighting Before & After Optimization

Figure 15 shows the office area lighting before and after optimization. Based on the optimization results using EMA, it can be seen that any lighting value below the optimal value of 358.6 lux is adjusted to the optimal point. Raising all lighting values to the optimal point increases energy usage, which negatively impacts the GES value.

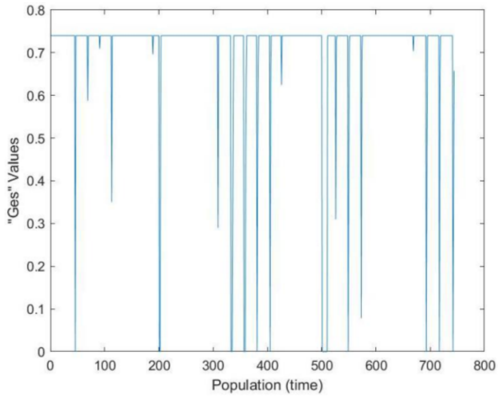


Figure 16. Gain Energy Saving (GES) Values after Optimization

This is inversely proportional to the GUC value, which increases as the lighting value rises to the optimal point, enhancing user comfort. Overall, the EMA optimization successfully maintained lighting at 358.6 lux during the building's operational hours.

Figure 16 shows the graph of population against GES values, where the method to obtain GES has been explained in Section 3. The optimal temperature and lighting values used to obtain the post-optimization GES are the optimal values derived from EMA, which are 23°C and 358.6 0.0 50.0 100.0 150.0 200.0 250.0 300.0 350.0 400.0 Lighting (Lux) Date & Hour Lighting Before & After Optimization Before Optimization After Optimization lux, respectively. The X-axis in Figure 16 represents the population size, corresponding to 744 hours in May 2019 (31 days). The Y-axis in Figure 16 represents the GES values, ranging from a minimum of 0 to a maximum of 1.

The maximum GES value after optimization, based on Figure 16, is 0.7398, which is lower than the maximum GES value before optimization. This decrease occurs because most lighting values were below the optimal point, requiring more electrical energy to raise the lighting to the optimal value.

Additionally, at certain times, the temperature was also above the optimal value, requiring more energy to lower the temperature to the optimal point. Figure 16 also shows that the minimum GES value touches 0.0 at certain times. This occurs because, at those points, the lighting measured by the sensor was below 10 lux (just before or after office hours). Consequently, the algorithm attempts to raise the lighting to the optimal point from a very low level, requiring significantly more electrical energy, resulting in the GES value dropping to 0.0.

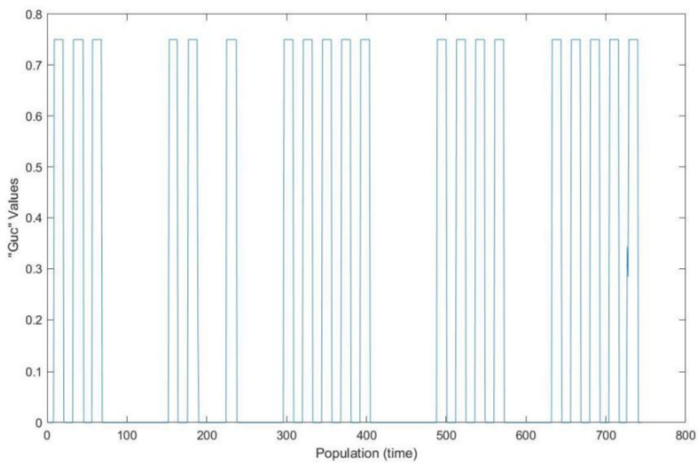


Figure 17. Gain User Comfort (GUC) Values after Optimization

Figure 17 shows the graph of population against GUC values, where the method to obtain GUC has been explained in Section 3. The optimal temperature and lighting values used to obtain the post-optimization GUC are the optimal values derived from EMA, which are 23°C and 358.6 lux, respectively. The X-axis in Figure 17 represents the population size, corresponding to 744 hours in May 2019 (31 days).

The Y-axis in Figure 17 represents the GUC values, ranging from a minimum of 0 to a maximum of 1. The maximum GUC value after optimization, based on Figure 17, is 0.75, which represents a significant increase compared to the pre-optimization state shown in Figure 11 (pre-optimization graph). It can be observed that when the building is operational, the GUC value reaches 0.75, and when the building is not operational, the GUC value drops to the minimum point of 0.0. Therefore, the graph of population against GUC values shows fluctuations.

This study demonstrates that the EMA optimization algorithm can optimize energy usage without compromising user comfort. Additionally, this research proves that the EMA optimization algorithm can effectively operate in tropical countries, where office buildings utilize cooling systems. This is consistent with results from studies in cold-climate countries where heating systems are used in buildings. The findings also show that the EMA optimization algorithm can optimize user comfort, energy consumption, temperature, and lighting [11]. Other studies in cold-climate countries have also shown similar results using EMA for optimization. The algorithm has been used to optimize temperature, lighting, air quality, energy consumption, and user comfort [10] demonstrating that EMA, as part of the Genetic Algorithm (GA), can achieve optimal optimization. Further research is needed to include additional optimization variables in tropical countries, such as air quality. Additionally, further studies are required for the EMA optimization algorithm to produce different optimal values for each input data set (multimodal), as the current study uses a unimodal optimization function, resulting in only one optimal temperature and lighting value.

5. Conclusion

The design of the Evolution Mating Algorithm (EMA) optimization algorithm has produced optimal temperature and lighting values of 23 °C and 358.6 lux, respectively. The optimization ran for 100 iterations and involved 744 populations, representing 744 hours in May 2019. The optimal values were obtained with a fitness function value of 0.74493, which converged at the 26th iteration out of the total 100 iterations conducted.

Electrical energy consumption after optimization decreased in the first and second weeks of May. In the first week, energy consumption was reduced by 202.8 kWh, from 2,726.6 kWh to 2,523.9 kWh, and in the second week, it was reduced by 273.2 kWh, from 2,332.5 kWh to 2,059.4 kWh. This trend was reversed in the third and fourth weeks, where energy consumption increased by 56.7 kWh, from 2,687.4 kWh to 2,744 kWh in the third week, and by 131.7 kWh, from 2,029 kWh to 2,160.7 kWh in the fourth week. The reduction in energy consumption occurred because, during these weeks, the average room temperature was below the optimal temperature value, so the algorithm reduced energy consumption by raising the room temperature to the optimal level. Conversely, the increase in energy consumption happened because, during these weeks, the average room temperature was above the optimal value, and the lighting was below the optimal value, so the algorithm worked to lower the temperature and increase the lighting, which required more energy. Overall, the optimization using EMA successfully saved 287.6 kWh of electricity in May 2019.

By improving energy efficiency, the comfort level of building users also increased. User comfort was measured using the GUC (Gain User Comfort) variable, where the GUC value ranges from 0 (minimum) to 1 (maximum). The closer to the maximum point, the more comfortable the building users are considered to be. The pre-optimization results showed a highest GUC value of 0.42, while the post-optimization GUC value was consistently 0.75 when the building was operational. This indicates that building users felt comfortable with the optimal temperature and lighting values produced by the EMA optimization algorithm.

The energy efficiency achieved from this research is also in line with government policy according to Government Regulation No. 33 of 2023 on energy conservation. Energy efficiency technology is applied through optimization using the EMA optimization algorithm. Policymakers, especially in the building sector, can implement optimization technology using EMA to enhance energy efficiency. Further research is needed on the application of the EMA optimization system to a control system that will manage actuators to regulate the cooling and lighting systems. It is hoped that the control of the cooling and lighting systems by actuators will output the optimal temperature and lighting values from the EMA optimization system. With further research, the EMA optimization system could be applied to achieve energy efficiency in buildings without compromising user comfort. Additionally, the long-term goal is for the EMA optimization system to be monetized.

Acknowledgement

This research was supported by Indonesia Education Scholarship (LPDP).

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