Optimization of hybrid GA–PSO-based energy management with Six Sigma penalty in buildings

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ABSTRACT

This study proposes the optimization of a hybrid genetic algorithm-particle swarm optimization (GA-PSO) building energy management combined with Six Sigma for quality control. The main problems include high energy consumption, large carbon emissions, and performance variability. Six Sigma is applied through control limits (UCL/LCL) and process capability index (Cpk) so that the solution is not only efficient but also stable. Using 30 days of operational data, the model evaluates daily energy consumption (kWh) and carbon emissions, then compares the baseline with pure GA, pure PSO, and GA-PSO+Six Sigma. The results show that GA-PSO reduces average energy consumption by 5.1% compared to GA and 3.5% compared to PSO. When combined with Six Sigma, the savings increased to 7.5% compared to GA and 6.6% compared to PSO, while reducing carbon emissions without compromising operational comfort. These findings present a measurable, sustainable, low-carbon building energy management model that is aligned with the decarbonization framework and ISO 50001 best practices.

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1. INTRODUCTION

Indonesia has strengthened building-sector energy management and carbon-emission reduction through a mix of green building standards, renewable energy integration, and incentives that encourage low-carbon technologies [1]-[4]. As a result, many commercial and public buildings have begun adopting smart energy management systems, solar PV, and environmentally responsive design to reduce energy use while maintaining occupant comfort [5], [6]. These efforts support Indonesia's commitments under the Paris Agreement and its Net Zero Emissions 2060 target [7], [8].

Nevertheless, buildings remain a major driver of global energy demand and emissions, largely due to heating, ventilation, and air conditioning (HVAC), lighting, and plug loads such as computers [9], [10]. The International Energy Agency (IEA) reports that buildings account for over 30% of total global energy use, and Indonesia's rapid urbanization and expansion of commercial/office buildings have further increased electricity demand domestically [11]-[13]. Consequently, robust energy management is needed to curb operating costs and mitigate carbon emissions in the building sector [14], [15].

To address this, many studies apply metaheuristic optimization—especially genetic algorithms (GA) and particle swarm optimization (PSO)—because they can handle complex, large-scale, multi-objective building energy problems [16]-[18]. GA provides strong exploration via selection and crossover, whereas PSO often converges faster through swarm dynamics [19]. However, GA can be computationally intensive, and PSO may stagnate in local optima, motivating hybrid GA–PSO schemes that balance exploration–exploitation and improve solution quality and convergence [20], [21]. Even so, much prior work emphasizes efficiency or cost objectives while giving limited attention to performance stability and energy service quality [22].

Six Sigma offers a complementary, quality-oriented lens using control charts and the capability index (Cpk) to reduce variability and enforce consistency [23]. Embedding Six Sigma penalties into the optimization objective—through constraints such as upper control limit (UCL)/lower control limit (LCL) for energy consumption and carbon emissions—can push solutions to be not only efficient but also reliable and operationally stable, supporting sustainable energy management goals [24]. Because integration of Six Sigma penalties within hybrid GA–PSO for building energy management remains limited, this study positions its novelty in developing such a model to close the gap between purely technical optimization and quality-controlled, comfort-aware, and ISO 50001-aligned energy management [25].

2. METHOD

2.1. Research design

This study employs a quantitative approach based on simulation and numerical experiments. The building energy management system is modelled by considering the main loads, namely HVAC, lighting, and electrical equipment [26], [27]. The optimization objective is to minimize energy consumption and carbon emissions, while maintaining energy performance quality through Six Sigma penalties. The research framework consists of four main stages: i) data collection, ii) building energy system modelling, iii) application of the GA–PSO hybrid optimization algorithm with Six Sigma penalties, and iv) performance evaluation.

Figure 1 is a picture of a building that is powered by PLN, which is connected to an existing building own several sensors, such as CO_2 sensors for validating comfort, a 3-phase power meter, and Modbus RTU for measuring voltage, current, and kWh. In addition, equipped with an HVAC controller, a lighting controller, and communication devices that the Raspberry Pi 4 uses for running GA-PSO and Six Sigma, as well as an RS-485 Gateway device, whereas level stability uses electricity using an MCB with a type-shielded cable separate to control and monitor; all devices or components have already been selected and carried out calibration. GA–PSO + Six Sigma optimization not only changes the set-point but operate actuation on the device electronics power on the side supply, and loads such as LCL filter as supply, HVAC pump as burden controlled, and power factor as quality power. GA–PSO minimizes J (energy, CO_2, cost) while Six Sigma enforces process limits (comfort and quality) power through penalties: CVR, Cpk, THD, switching limits, and rate-limits. As for the advantages of GA-PSO + Six Sigma optimization compared with optimization that previously only used GA-PSO optimization, as in Table 1.

Based on Figure 1, an asymmetric building energy management system was developed to improve energy management effectiveness. This requires a holistic approach through carbon emission reduction in the building sector using GA and PSO optimization. The Six Sigma algorithm was also applied to determine the standard deviation, as illustrated in Figure 2.

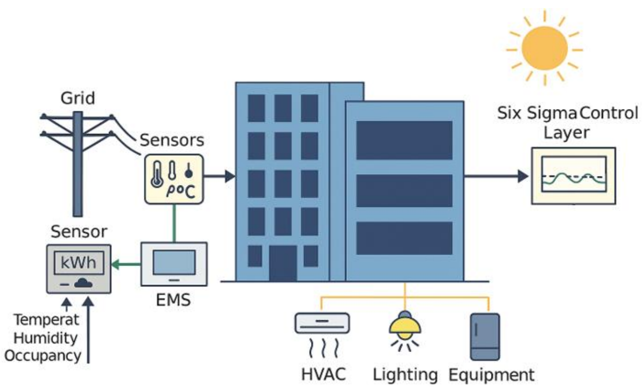


Figure 1. Energy management system in buildings

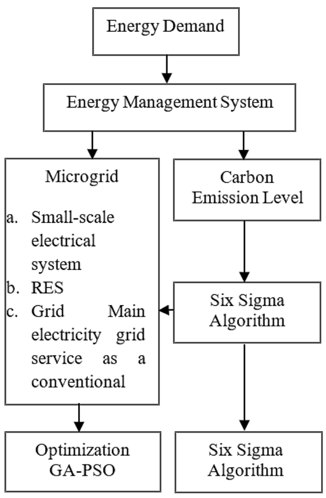


Figure 2. Asymmetric energy management using GA-PSO and Six Sigma algorithm

Table 1. Comparison of GA-PSO optimization and GA-PSO + Six Sigma optimization

Aspect comparison	Conventional GA–PSO	GA–PSO + Six Sigma (new innovation)
Optimization goals	Just looking for the best combination to minimize energy and emissions based on the double objective function.	Adding constraint layers based on process quality parameters (Z-score, σ level, and tolerance) deviation.
Characteristics algorithmic	Merger exploration (GA) and exploitation (PSO) for fast convergence.	Inserted Six Sigma DMAIC cycle as a control for quality results iteration, with a penalty for the solution that came out of the process boundary.
Handling operational data variation	Not taking into account fluctuations in daily /hours of operation and noise sensor.	Enter variability as the parameter σ and set the upper/lower control limit (UCL/LCL).
Additional output	Minimum value of the function objective.	Additional: value Z_upper, sigma level, penalty, and prediction process quality (Cp, Cpk).

2.2. Data sources and research variables

The data used includes: i) Building electricity load profiles; ii) Hourly electricity rates (time-of-use/TOU) from PLN; iii) Carbon emission factors (kg CO_2/kWh); and iv) Energy quality limits defined in the form of upper control limit (UCL) and lower control limit (LCL). Meanwhile, the optimized decision variables include: i) HVAC operating schedule; ii) Lighting intensity; and iii) Equipment power settings.

Roadmap for implementation research, including: i) Develop and validate GA-PSO + Six Sigma models based on experimental data, through collection of electricity consumption data, developing GA-PSO models and GA-PSO + Six Sigma models to compare convergence and deviation for lower energy use and CO_2 emission levels; ii) Integrate algorithm to the simulation system such as IoT Gateway, with real-time feedback simulation with load scenarios dynamic each the day; iii) Operating algorithm in real time on the building energy dashboard; and iv) Make GA-PSO + Six Sigma algorithm as module continuous energy optimization standard, with multi-location testing, integrating with external data and learning adaptive.

2.3. Optimization formulation

Several optimizations will be carried out, and formulas will be used to conduct the research.

2.3.1. Objective function

The multi-objective function states that ω1 is the weight used to determine energy consumption, while ω2 is the weight used to determine carbon emissions, where ω1 and ω2 must add up to 1 or 100%. This is formulated in (1).

$$\mathrm{M}\min_{x_{1:T}} F(x) = \omega_1 E(x) + \omega_2 C(x) + \lambda \pi_{6\sigma}(x) \quad (1)$$

With

$$E(x) = \sum_{t=1}^{T} e_t(x_t) \quad C(x) = \sum_{t=1}^{T} c_t(x_t) = \gamma \sum_{t=1}^{T} e_t(x_t) \quad (2)$$

Where E is total energy consumption (kWh), C is total carbon emissions (kgCO_2), ω_1, ω_2 is the weight of importance of each objective, and $\pi_{6\sigma}$ is the Six Sigma penalty based on the process capability index (Cpk).

2.3.2. Six Sigma penalty

Penalties are imposed if the optimization results fall outside the set UCL–LCL limits. There are two options, namely:

i) Control chart-based penalties:

$$\pi_{cc}(x) = \sum_{t=1}^{T} \left[\alpha_+ (e_t(x_t) - UCL_t)_+^2 + \alpha_- \left(LCL_t - e_t(x_t)\right)_+^2\right] \quad (3)$$

With $(z)_{(+)} = \max(0,z)$, $\alpha_{(\pm)} > 0$.

ii) Penalty based on process capability index (C_{pk}):

As a tool for monitoring and controlling how much variation a process experiences regarding its specification limits, statistical measurements based on standard deviation offer in-depth information about how well a process is operating and what actions may be necessary to make improvements.

$$\mu(x) = \frac{1}{T}\sum_{t=1}^{T} e_t(x_t) \quad \sigma(x) = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(e_t(x_t) - \mu(x)\right)^2} \quad (4)$$

Index:

$$C_{pk}(x) = \min\left\{\frac{UCL-\mu(x)}{3\sigma(x)}, \frac{\mu(x)-LCL}{3\sigma(x)}\right\} \quad (5)$$

Cpk considers how centered the process is relative to the specification limits. A higher Cpk value indicates a more capable and centred process. Levels in Cpk values:
Cpk < 1: The process is incapable, often producing output outside the specification limits.
Cpk = 1: The process is just capable of operating well, with 99.73% of output within specification limits.
Cpk > 1: The process is capable, with 99.73% of output within specification limits.
Cpk ≥ 1.33: The process is highly capable, with 99.99% of output within specification limits.

Penalty (quadratic with respect to quality deficiency) is given by (6).

$$\pi C_{pk}(x) = \beta\left(C^*_{pk} - C_{pk}(x)\right)^2_+, \quad C^*_{pk} \geq 1.33 \quad (6)$$

We can choose one of ($\pi_{6\sigma} = \pi_{cc}$ or πC_{pk}). For smooth derivatives, π_{cc} is easier (differentiable almost everywhere), while π_{cc} requires handling at the minimum point.

2.4. Determination of sensitivity, parametric and convergence diagnostics

Sensitivity and convergence analyses were conducted to assess the robustness and stability of the proposed framework. The following aspects were evaluated:

a. Parameters tested include sleep objective: ω1 (kWh) and ω2 (CO_2), penalty Six Sigma, and control devices like lights, HVAC, time control period, weight inertia (PSO), and population size (GA).
b. Determine LCL and UCL with LCL = μ - kσ and UCL = μ + kσ formulas.
c. Perturbation operational, such as building and weather scenarios.
d. Sensitive output such as kWh, CO_2, Cpk, and the number of actuator switching/day.
e. Curves and key indicators, such as diversity, iteration maximum.

2.5. Experimental and simulation stages

The following are the stages of the experiment conducted:

2.5.1. Data acquisition and baseline construction

Load profile data were collected continuously for 24 h per day over 30 consecutive days from the case-study building. The monitored load categories comprised HVAC, lighting, and equipment (plug loads). All measurements were time-stamped to ensure temporal alignment across signals. When available, environmental and operational variables such as temperature, humidity, and occupancy proxy were recorded to represent operating conditions and to support constraint checking or supplementary analysis. Output of this stage: a 30-day baseline dataset representing daily demand variability and operational patterns.

2.5.2. Data pre-processing and normalization

Prior to optimization, the dataset was pre-processed to ensure numerical stability and comparability across variables. First, signals were resampled to a uniform interval (Δt) and synchronized by timestamp. Second, normalization was applied so that optimization variables and objective terms were mapped to a comparable scale. Third, baseline statistics required for the Six Sigma layer were established from the 30-day dataset to define the initial control limits and to enable stability evaluation. Output of this stage: a normalized dataset and baseline statistics (μ, σ) used for control-limit construction.

2.5.3. Comparative optimization scenarios

Optimization was executed using four comparative approaches to quantify the contribution of hybridization and Six Sigma stability control: pure GA, pure PSO, hybrid GA–PSO without Six Sigma penalty, and hybrid GA–PSO with Six Sigma penalty. For each approach, the optimizer generated candidate operating decisions (e.g., schedules or set-points for HVAC, lighting, and equipment control) that minimize energy use and associated carbon emissions, while respecting operational constraints. Output of this stage: optimal solutions and convergence traces for each approach.

2.5.4. Algorithm parameterization and calibration

To ensure fair comparison and reproducibility, GA and PSO parameters were determined through initial trials and then fixed for all subsequent runs. GA parameters included population size, crossover probability, mutation probability, and number of generations/iterations. PSO parameters included number of particles, inertia weight, acceleration coefficients (c1, c2), and iteration count. The hybrid GA–PSO configuration additionally specified the integration rule (e.g., GA for exploration followed by PSO refinement or interleaved updates), and the Six Sigma scenario activated a penalty mechanism when stability criteria were violated. Output of this stage: a locked parameter set used consistently across all experiments.

2.5.5. Performance evaluation metrics and multi-run protocol

All approaches were evaluated using the following metrics: energy consumption (kWh), carbon emissions (kg CO_2), average computation time (per optimization run), convergence speed (iterations/time to reach best fitness or convergence threshold), process capability index (Cpk) (stability indicator), and multi-run optimization success rate (percentage of runs meeting the predefined acceptance criteria, including stability constraints). A multi-run protocol was used to reduce stochastic bias inherent in population-based metaheuristics. Summary statistics (e.g., mean and standard deviation) were reported across runs. Output of this stage: comparative performance table and stability/quality assessment for each method.

Figure 3 shows the hybrid GA–PSO optimization framework with Six Sigma stability control for building energy and emission reduction. The framework starts with data acquisition (HVAC, lighting, equipment loads, optional environmental/occupancy signals) and emission-factor definition, followed by pre-processing and normalization. A hybrid GA–PSO optimizer generates candidate operating schedules/set-points and evaluates them using a fitness function that jointly minimizes energy use and carbon emissions. A Six Sigma control layer then assesses stability through control limits (UCL/LCL) and the process capability index (Cpk); solutions that violate limits or yield $C_{pk} < 1.33$ are penalized to guide the search toward stable, reproducible policies. The final decision layer dispatches HVAC, lighting, and equipment set-points, producing an optimization schedule with improved efficiency, reduced emissions, and stable performance $\left(C_{pk} \geq 1.33\right)$.

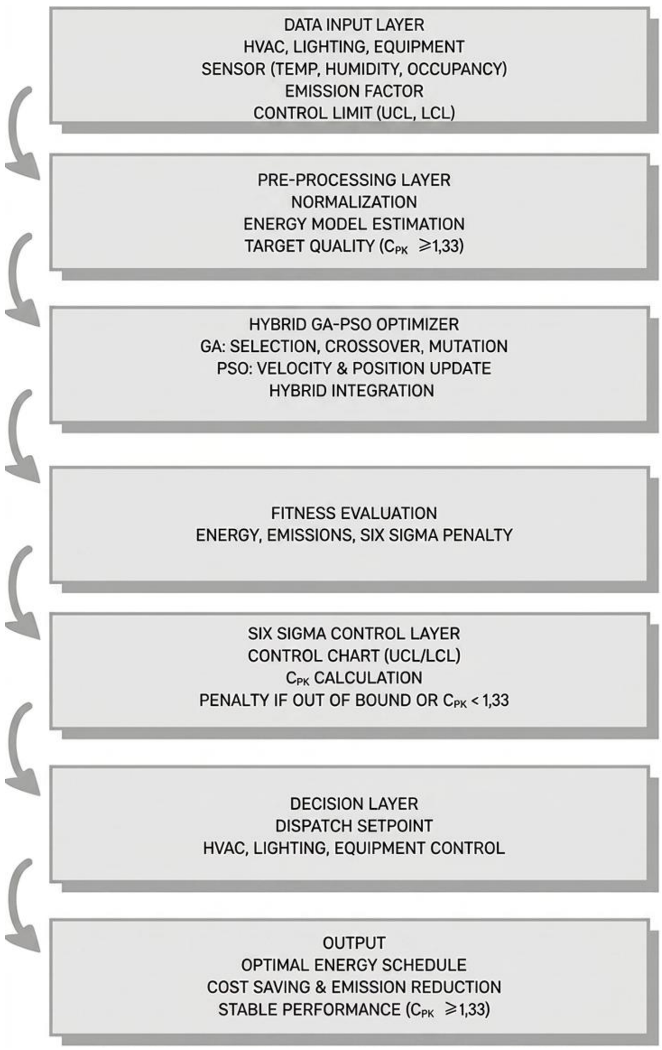


Figure 3. Optimization framework

3. RESULTS AND DISCUSSION

This study uses a quantitative approach based on simulation and numerical experiments. The building energy management system is modelled by considering the main loads, namely HVAC, lighting, and electrical equipment. The optimization objective is to minimize energy consumption and carbon emissions, while maintaining energy performance quality through Six Sigma penalties.

The research framework consists of data collection, building energy system modelling, application of GA–PSO hybrid optimization algorithms with Six Sigma penalties, and performance evaluation. The data sources and research variables are as follows: building electricity load profile: daily/hourly consumption data for HVAC, lighting, and equipment loads, hourly electricity rates (time-of-use/TOU) from PLN, carbon emission factors (kg CO_2/kWh), and energy quality limits defined in the form of upper control limits (UCL) and lower control limits (LCL). The optimized decision variables are the HVAC operating schedule, lighting intensity, and equipment power settings. A derivative equation model for the non-linear HVAC model on the penalty derivative. The derivative of F with respect to $x_{t,}$ because $C(x) = \gamma E(x)$.

$$\frac{\partial F}{\partial x_t} = (\omega_1 + \gamma\omega_2)\frac{\partial e_t}{\partial x_t} + \lambda\frac{\partial \Pi_{6\sigma}}{\partial x_t} \tag{7}$$

$\partial et/\partial xt$'s derivative depends on the form of et, such as a simple non-linear HVAC model:

$$e_t(x_t) = p^{fan}|x_t^{air}|_1 + p^{ch}(\Theta_t - \Theta_t^{set}) \tag{8}$$

derivative of the Π_{cc} penalty control chart, for each t:

$$\frac{\partial \pi_{6\sigma}}{\partial x_t}\begin{cases} 2_{\alpha+}(e_t - UCL_t)\frac{\partial e_t}{\partial x_t}, e_t > UCL_{t,} \\ -2_{\alpha-}(LCL_t - e_t)\frac{\partial e_t}{\partial x_t}, e_t > LCL_{t,} \\ 0, \qquad \text{others} \end{cases} \tag{9}$$

Meanwhile, for the penalty derivative C_{pk}:

$$\frac{\partial \mu}{\partial x_t} = \frac{1}{T}\frac{\partial e_t}{\partial x_t} \tag{10}$$

for $\sigma(x) > 0$:

$$\frac{\partial \sigma}{\partial x_t} = \frac{1}{T\sigma}(e_t - \mu)\frac{\partial e_t}{\partial x_t} \tag{11}$$

$$C_u = \frac{UCL-\mu}{3\sigma}, \qquad C_l = \frac{\mu-LCL}{3\sigma}, \qquad C_{pk} = \min\{C_u, C_l\} \tag{12}$$

If $C_u < C_l$ (binding upper bound), then $C_{pk} = C_u$ and,

$$\frac{\partial C_{pk}}{\partial x_t} = \frac{\partial C_u}{\partial x_t} = \frac{1}{3}\left[-\frac{1}{\sigma}\frac{\partial \mu}{\partial x_t} + \frac{UCL-\mu}{\sigma^2}\frac{\partial \sigma}{\partial x_t}\right] \tag{13}$$

If $C_l < C_u$ (binding upper bound), then $C_{pk} = C_l$ and,

$$\frac{\partial C_{pk}}{\partial x_t} = \frac{\partial C_1}{\partial x_t} = \frac{1}{3}\left[\frac{1}{\sigma}\frac{\partial \mu}{\partial x_t} - \frac{\mu-LCL}{\sigma^2}\frac{\partial \sigma}{\partial x_t}\right] \tag{14}$$

The derivative of the penalty πC_{pk} , if $\pi C_{pk} < \pi C *_{pk}$, then:

$$\frac{\partial \Pi_{C_{pk}}}{\partial x_t} = -2\beta\left(C_{pk}^{\star} - C_{pk}\right)\frac{\partial C_{pk}}{\partial x_t} \tag{15}$$

and if $\pi C_{pk} \geq \pi C *_{pk}$, then $\partial\mu$, $\partial\sigma$ are replaced by $\partial e_t/\partial x_t$ from the energy model.

3.1. Initial simulation results

The experiment was conducted on 24-hour building energy consumption profile data over 30 days with variations in HVAC load, lighting, and electrical equipment. Four optimization scenarios were tested, namely pure GA, pure PSO, hybrid GA–PSO without penalty, and hybrid GA–PSO with Six Sigma penalty. The algorithm parameters were set with a population size of 50, a maximum number of iterations of 200, a crossover probability of 0.8, a mutation of 0.1 (for GA), and an inertia weight of 0.7 and a cognitive–social coefficient of 1.5 (for PSO). The data obtained are shown in Table 2 for each method.

The results show that GA–PSO integration is capable lower consumption average energy up to 5.1% compared to pure GA and 3.5% compared to pure PSO. The application of Six Sigma penalty increases performance more significantly, with energy savings of 7.5% compared to GA and 6.6% compared to PSO. At the same time, reducing carbon emissions in a significant way.

If seen from side economy hybrid method GA-PSO + Six Sigma is seen that use lowest kWh/day energy compared to method others, so that if converted to in rupiah it really affects expenditure cost use electricity per month and more low use energy so the more low-level CO_2 emissions, hybrid method GA-PSO + Six Sigma in side operational guard Cpk ≥ 1.33 level comfort users building guaranteed. Need the existence of economic analysis plus comfort with display kWh and CO_2 usage vs baseline and Cpk level per zone with decision threshold as follows: If Cpk < 1.33 for > 2 consecutive hours → increase the comfort setpoint (automatic), or switch to balanced mode and if economical fee < 5% for 7 days → reduce aggressiveness optimization (energy cheap ≈ not worth it).

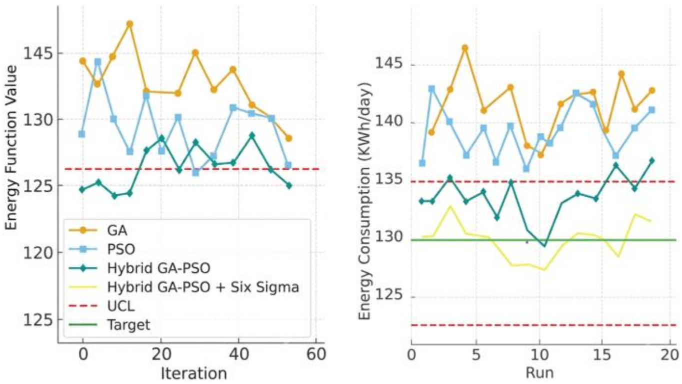
Table 2. Results of energy and carbon emission optimization

Method	Energy (kWh/day)	CO_2 emissions (kg)	Computation time (s)	Success rate (%)	Cpk (≥1.33 target)
Pure GA	142.8	98.7	12.3	76.7	1.08
Pure PSO	139.5	96.2	10.4	81.3	1.15
GA–PSO hybrid	135.6	93.1	14.2	88.5	1.25
GA–PSO+Six σ hybrid	130.2	89.8	15.7	93.4	1.41

3.2. Convergence analysis

The convergence curve shows that pure PSO has a high convergence speed in the first 50 iterations, but tends to stagnate afterwards and is prone to getting stuck at local optima. In contrast, pure GA is slower but more stable in exploring solutions. The integration of GA–PSO results in a balance between exploration and exploitation, with faster convergence than GA, but without losing final accuracy.

Figure 4 shows the variations in optimised energy consumption across several runs. The GA and PSO algorithms still produce solutions that exceed the control limits (UCL and LCL), whereas the hybrid GA–PSO with Six Sigma remains stable within these limits, with values close to the target. The Six Sigma penalty also smooths the convergence path by penalising solutions outside the control limits and redirecting them toward the feasible region that satisfies the energy quality standards.



(a) (b)

Figure 4. Optimization results: (a) convergence optimization results curve and (b) Six Sigma control chart

The process capability index (Cpk) is used to measure the consistency of solutions against control limits. Simulation results show that pure GA and PSO only achieve Cpk values below 1.2, which means that energy consumption variation is still quite high and often exceeds the target. The GA–PSO hybrid increased to 1.25, but only reached the industrial quality standard value of ≥1.33 after being combined with the Six Sigma penalty (Cpk = 1.41). This proves that the Six Sigma penalty is effective in stabilizing system performance, making it not only efficient but also reliable.

Figure 5 compares four metaheuristic energy management patterns in buildings. It can be seen that only the hybrid GA–PSO + Six Sigma method is between the UCL and LCL lines while reaching the green Target line. Figure 5 also illustrates the lowest objective function value achieved by the hybrid GA–PSO + Six Sigma optimization, approaching zero.

Figure 6 shows that the hybrid GA-PSO + Six Sigma method produces the lowest objective function value and fastest convergence compared to GA, PSO, and hybrid GA-PSO. This demonstrates that the addition of the Six Sigma approach can increase optimization effectiveness by producing more optimal and more stable solutions.

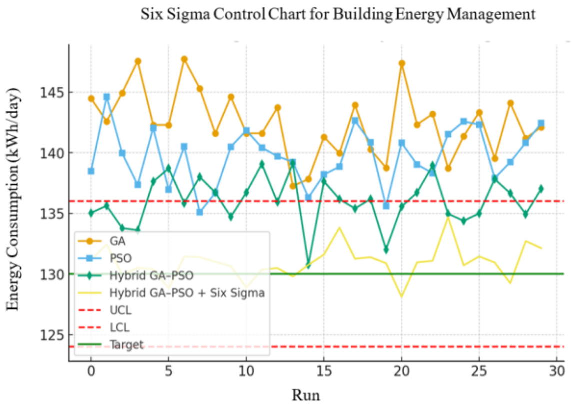


Figure 5. Six Sigma control chart for building

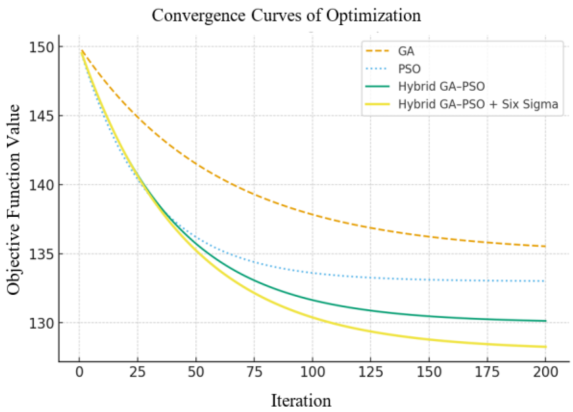


Figure 6. Convergence curves of 4 optimizations

Using a contour plot graph will show the distribution of energy consumption (kWh) and emissions throughout the iterations. Before optimization (red), the values are higher and more scattered. With hybrid GA–PSO optimization (green), kWh and emissions are reduced, while optimization using Six Sigma (blue) produces more stable results and falls within stricter quality limits, as shown in Figure 7.

Meanwhile, Figure 8 is a bar chart comparing average kWh and emissions. Before optimization, both were at their highest levels. The GA–PSO hybrid significantly reduced kWh and emissions, and the addition of Six Sigma control further improved stability and ensured quality targets (Cpk ≥ 1.33). Figure 9 is a 3D surface plot illustrating how kWh and emissions evolve with optimization iterations. The surface becomes flatter as optimization progresses, indicating convergence towards a more efficient and low-emission operating point.

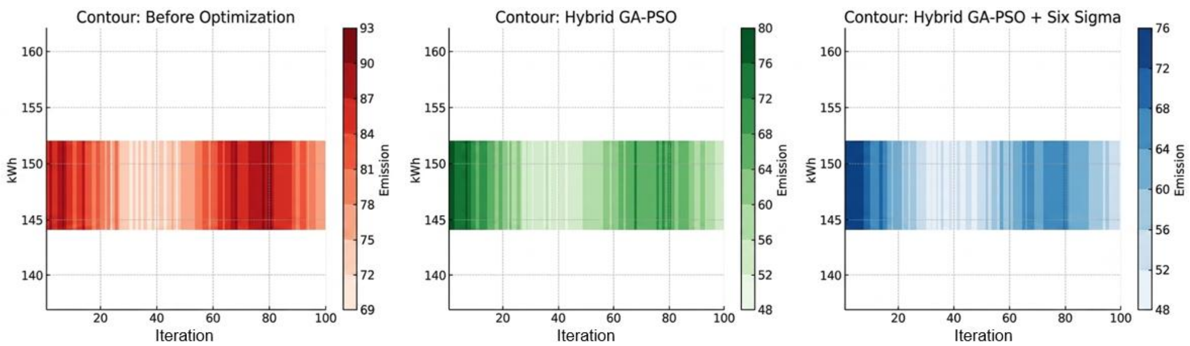


Figure 7. Distribution of kWh and emissions across iterations

Figure 10 is a graph showing the relationship between iterations, energy consumption (kWh), and carbon emission levels, where the results are more stable and controlled using the hybrid GA-PSO + Six Sigma method. As seen from the figure, which shows the relationship between iterations, energy consumption (kWh), and emissions using hybrid GA-PSO + Six Sigma optimization. The results are more stable and controlled compared to using hybrid GA-PSO optimization alone.

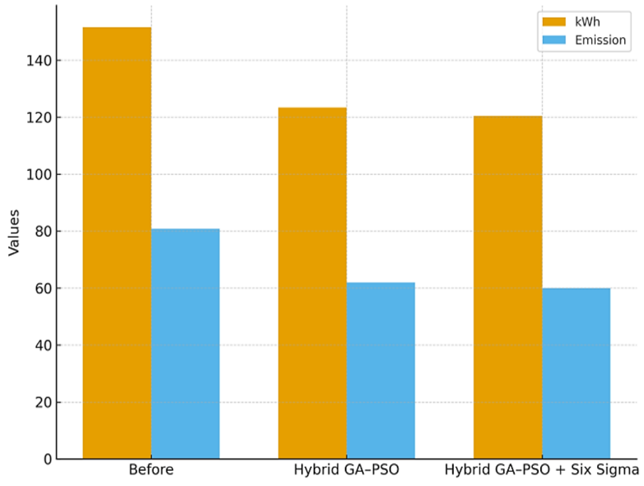


Figure 8. Average kWh and emissions before/after optimization

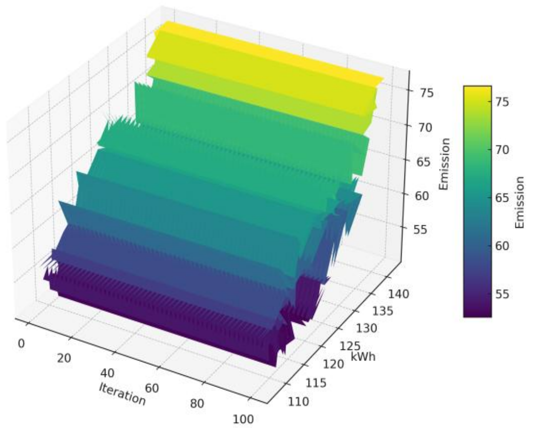


Figure 9. 3D surface: iteration vs. kWh vs. emission (hybrid GA-PSO)

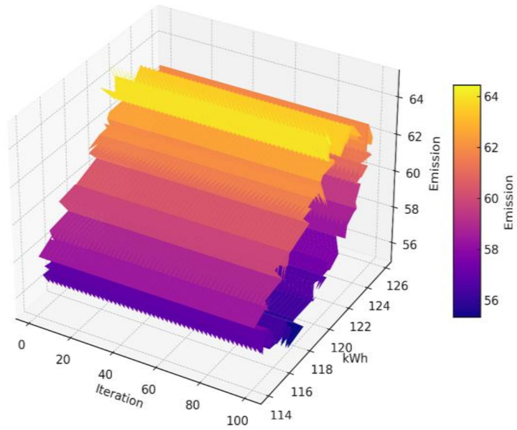


Figure 10. 3D surface: iteration vs. kWh vs. emission (hybrid GA-PSO + Six Sigma)

3.3. Reliability, comfort, and quality metrics environment

In looking at the comfort level need to pay attention to CVR temperature and Cpk room temperature and lighting system, with paying attention to lux adequacy (≥300 lx office; night ≥500 lx), basic uniformity, CVR lux and Cpk lux, humidity level of RH ≤ 65%, CVR RH, and Cpk RH. For system reliability takes into account the MTBF/MTTR of the key device (meter, gateway, controller) and tolerance error, such as packet loss simulation 1–5%, sensor dropout 5–10 min, actuator denial, measuring KPI degradation and time recovery, with threshold operational CVR ≤ 5%, Cpk ≥ 1.33 around ≥90% of operational hours.

3.4. Conformity with standard

Approach management energy in research this use Six Sigma methodology, namely DMAIC [28], to optimize the use and consumption of energy, can integrate Lean Six Sigma methodology with standard system management ISO 50001 [29], which implements plan, do, check, and act (PDCA) cycle of framework ISO work for improvement efficiency energy ongoing measurable, documented, and sustainable [30]. To achieve the target in kWh savings and transparently reduce CO_2 emissions, measured with validated energy performance indicators, analyzed using statistical process control tools, then followed up through action improvement and operational standardization so that economic and environment achieved as well as awareness.

Following the DMAIC ↔ PDCA in ISO 50001:

a. Define ↔ Plan: to determine the energy baseline scope, goals, savings targets, and aligned CO_2 reduction targets and policy energy.
b. Measure ↔ Do: implement plan measurement and verification, metering data collection, and efficiency program execution early on key equipment.

c. Analyze ↔ Check: analyze deviation performance with Pareto and root cause analysis to validate gaps against usage targets, energy, and emissions factors.
d. Improve ↔ Do/Act: implement process improvements such as setpoint optimization, scheduling load, and automation control data-based that reduce kWh and CO_2 consumption.
e. Control ↔ Act: to do standardization, control plan, internal audit, and review management for improvement united in ISO 50001 procedures, as well as guard achievements efficiency, and reduction emission in a way consistent.

4. CONCLUSION

The GA–PSO hybrid approach is proven to be superior to single methods in building energy management optimization, because it is able to balance exploration and exploitation in the solution space. The integration of Six Sigma penalties ensures that the optimization results are not only efficient (kWh and emission reduction) but also consistent with strict quality limits (UCL, LCL, and Cpk ≥ 1.33). Simulations show a significant reduction in energy consumption and emissions, with more stable and controlled results when Six Sigma is used in buildings, this is in accordance with the ISO 50001 standard as an international standard for energy management systems, due to the integration of DMAIC–PDCA in reducing energy intensity and carbon footprint to obtain energy cost savings that show measurable environmental performance and are in line with decarbonization targets.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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