Rethinking Passive Cooling Strategies with Artificial Intelligence for Sustainable Building Design in Malaysia

Gopisetty Pardhavika1, a), Naveen Palanichamy 2, 3, b), Subhashini G4, c), Allin Geo A.V1, d) and R Priscilla1, e)

1Department of Artificial Intelligence and Data Science, St. Joseph’s Institute of Technology, Old Mahabalipuram Rd, Kamaraj Nagar, Semmancheri, Chennai, Tamil Nadu, 600119, India.

2Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, Cyberjaya, Selangor, 63100, Malaysia.

3Centre for Digital Innovations, CoE for Immersive Experience Multimedia University, Persiaran Multimedia, 63100, Cyberjaya, Malaysia.

4Department of Information Technology,St.Joseph’s Institute of Technology, Old Mahabalipuram Road, Semmencherry, Chennai 600119, India.

b) Corresponding author: p.naveen@mmu.edu.my

a) pardhavika.gopisetty@gmail.com  
c) gopal.subha191@gmail.com  
d) seemeallin@gmail.com  
e) hodads@st.josephstechnology.ac.in

**Abstract.** Artificial intelligence (AI) is transforming a number of industries, including building architecture, by modifying design procedures and operating strategies. With Malaysia’s rapid expansion, modern technology must be incorporated into key areas, especially the built environment. Sustainable and energy-efficient architectural solutions are required because of the country’s tropical climate, which is facing rising temperatures and rising energy demands. To improve energy efficiency and occupant comfort, this study investigates the potential theoretical integration of AI with Passive Cooling Systems (PCS) in midrise buildings. The study investigates AI-based techniques, such as Long Short-Term Memory (LSTM) networks, reinforcement learning (RL), and genetic algorithms (GA), for the prediction and application of real-time cooling measures. Furthermore, the study examines the role of Demand Response Programs (DRPs), such as Time-Based Rate Programs (TBR) and Incentive-Based Programs (IBP), can optimize energy use by combining intelligent energy management techniques with passive cooling. The suggested framework seeks to preserve thermal comfort in buildings, promote natural daylighting, and decrease cooling demands. MATLAB is used to build theoretical assessment and prediction models that evaluate performance and feasibility. Even though this research is still theoretical, it offers a solid basis for further empirical research and real-world applications. By discussing how AI might enhance passive cooling in Malaysia’s climate, this work advances energy-efficient architecture and sustainable building design in tropical areas.

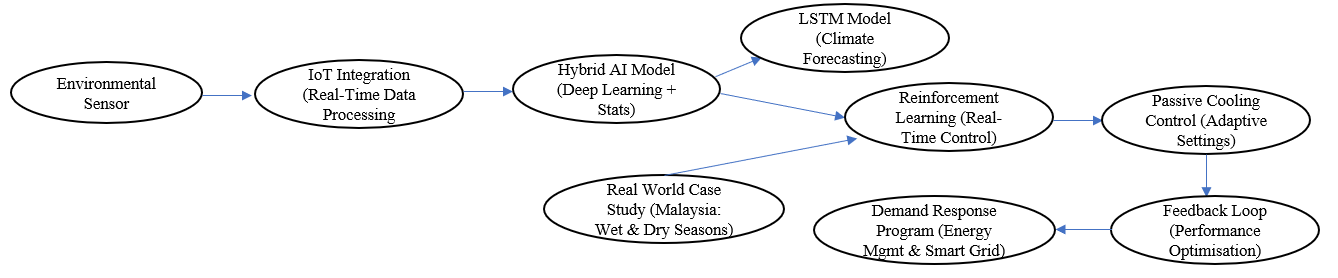
# INTRODUCTION

Global attention on sustainability and energy efficiency has increased significant interest in adopting Artificial Intelligence (AI) technologies in various fields. AI has greatly influenced building architecture, resulting in improvements in energy management, design, and construction. Due to its tropical climate and rapid industrialization, Malaysia has particular problems, including rising temperatures and rising energy consumption [1], [2]. Solving these issues and maximizing building performance while preserving sustainability requires innovative thinking. These buildings, which are frequently found in crowded places, have to strike a balance between the conflicting needs of environmental impact, energy efficiency, and thermal comfort [3]. Conventional mechanical cooling methods demand more energy usage and emit more greenhouse gas (GHG) emissions, despite being the industry standard. This highlights the need for alternative energy-saving solutions that support Malaysia’s goals under the Green Building Index (GBI) and the Sustainable Development Goals (SDGs). Passive cooling systems (PCS) are a practical and effective option to address these challenges, as they help reduce energy use and CO2 emissions while improving indoor comfort. One of the key challenges in advancing PCS is the lack of advanced materials that can support their optimal performance. The absence of such materials limits the full potential of PCS [3]. While the potential of radiative cooling as a PCS strategy has been widely studied, however, Recent studies have shown that traditional passive cooling is often inadequate in warm and humid climate like Malaysia, especially without real time adaptability or forecasting capabilities [4], [5]. This work mainly focuses on how AI can be used to overcome these limitations and improve PCS performance. By integrating advanced AI algorithms-such as Machine Learning (ML) for predicting climate patterns, Reinforcement Learning (RL) for real-time system adjustments, and Genetic Algorithms (GA) for optimizing multiple performance factors, PCS can become more efficient [6]. The case study includes theoretical calculations done using MATLAB code. It compares the energy usage, thermal comfort, and carbon emissions of a conventional PCS with a smart AI-integrated PCS [7]. Limits of traditional PCS: Conventional PCS- such as fixed shading, natural ventilation, and thermal mass- Malaysia struggles to maintain thermal comfort in the tropical climate of Malaysia, where day temperature is often more than 30 ° C and relative humidity is more than 70% around during the whole year [7]. For example, large, fixed shedding devices can reduce the benefit of heat but may be ineffective during the wet season (October to February) of Malaysia or under the overcast, i.e, cloudy skies [8]. These demonstration issues show that standalone traditional PCS solutions are often ineffective in Malaysia's climatic conditions and highlight the need for adaptive, AI-operated systems [9].

## Case-Study: Midrise Buildings in Malaysia

In the hot and 70 % exceeding humid climatic conditions of Malaysia, especially in urban cities like Kuala Lumpur (KL), the energy requirements of the buildings are deeply affected. This case study looks at the typical 12-story building, which is in the KL area, considered in this paperwork. This building uses conventional air conditioning and PCS, like natural ventilation and shading devices. The initial building’s baseline data is assumed to be 15,000 kWh/month of energy consumption, costing $3,000/month (too high). The pre-manufactured value (PMV) score is 0.45, representing average thermal comfort, and CO₂ emissions are 7.2 tons/month, indicating significant environmental consequences. Moreover, another drawback is that the PCS cannot effectively adapt to Malaysia's wet season (October to February) and dry season (March to September). Furthermore, PCMs used in the building are also affected by inefficient energy management, as they are not supported by intelligent energy allocation systems [8]. Thus, the main purpose of the present paper is to make use of AI smart algorithms for the transition of these futuristic energy strategies and for the reduction of the total energy consumption and the integration of it properly.

# ROLE OF AI ALGORITHMS AND THEIR INTEGRATION WITH MATLAB

The proposed optimization framework, which integrates multiple AI algorithms, is shown in Figure 1. Each algorithm’s role—LSTM for forecasting, RL for control, and GA for optimization—is described in the following section. Through the usage of tools such as MATLAB, a collection of AI algorithms can be trained smartly, including AI and ML, LSTM networks, RL, and GA, to enhance the efficiency of PCS. As for the efficiency of cooling energy needed, ML handles data from the previous weather, the diligence of the building, and the energy that has been consumed in the past. This is done in order to save energy. As a pattern, LSTM networks, a kind of deep learning model, can predict the temperature and the level of humidity in the future. This allows the system to better adapt to alterations in weather conditions LSTM networks [9].

**FIGURE 1.** PCS optimization framework scenario using AI

## AI Implementation Methodology in MATLAB

To ensure that this research is transparent and reproducible, it explains how AI algorithms were applied strategically to MATLAB (R2025a) to adapt to PCS. The study used three main AI techniques: LSTM network, RL, and GA. LSTM was used to forecast time-series, which helps the system to identify and learn from patterns in temperature and humidity data. To support these algorithms, the input data was carefully prepared. Historical weather data was collected from the Malaysian Metrological, Department, while energy consumption benchmarks were obtained from literature at the typical 12-story buildings in Kuala Lumpur. This data was normalized between 0 and 1, and the missing values were filled using linear projections. The LSTM model was trained with 70% data, which was validated with 15%, and the remaining 15% was tested. The RL model was trained using simulated feedback, and GA was started with values obtained from traditional PCS settings. LSTM network has proved effective in predicting future weather conditions in the tropical environment, improving the accountability of the PCS [4],[10]. The RL has been successfully implemented in the manufacture of energy control systems to dynamically manage indoor comfort and energy use [5]. All the AI models worked together within the Matlab environment and to simulate and improve the performance of the PC. The LSTM model predicted weather conditions; RL optimized the system in real time based on those predictions; And GA adapted the overall configuration. Matlab then used these AI outputs to calculate important parameters (see Table 1) using Equation (1) shown below.

(1)

|  |  |  |  |
| --- | --- | --- | --- |
| **TABLE 1.** Output values: conventional PCS vs smart AI PCS integration | | | |
| **Parameter** | **Baseline value** | **Optimised value** | **Improvement (%)** |
| Cooling energy consumption | 15,000 kWh/month | 11,700 kWh/month | 22% |
| Thermal comfort | 0.45 | 0.15 | 66.67% |
| Energy cost | $3,000/month | $2,580/month | 14% |
| Carbon footprint | 7.2 tons CO₂/month | 5.6 tons CO₂/month | 22.22% |

The AI insights derived by MATLAB provide efficiency factors that enable energy usage reduction by 22%, along with energy cost reduction by 14% through mathematical models to baseline data. The Figure 2 represents baseline performance through red dashed lines, but shows AI- AI-optimised via red dashed lines but shows the AI-optimized results with blue solid lines. The energy requirements of this AI-improved system are 11,700 kWh lower than 15,000 kWh, and it operates at a reduced cost of $2,580 compared to $3,000/month, with a resulting CO2 emission reduction of 5.6 tons below 7.2 tons/month. Thus, AI technology consistently improves PCS system performance through enhanced efficiency and sustainable operation according to these results.

A graph with numbers and lines

AI-generated content may be incorrect.

**FIGURE 2.** Key parameters, energy usage, cost, and CO2 reduction over 12 months without and with AI PCS comparison

## Predicting Temperature and Humidity Levels by the LSTM Method

Recurrent Neural Networks (RNNs) contain the LSTM AI model, which specifically processes sequential data while successfully anticipating environmental measurements with irregular time-dependent patterns [11], [12], [13]. PCS makes use of LSTM models for testing historical climate information, which includes hourly temperature measurements and humidity data to generate future condition predictions (shown in Figure 3). This predictive ability helps PCS adapt cooling approaches ahead of time, thus leading to better energy results while maintaining comfort indoor temperatures. Temperature predictions from the LSTM model can be seen in the first chart, along with recorded 24-hour temperature data presented through orange lines and predicted data shown as blue dashed lines. The prototype accurately predicts the temperature patterns while accurately replicating peak daytime and nighttime patterns, while showing some variations because of unanticipated meteorological shifts. The second graph presents LSTM - humidity predicting that displays actual humidity levels as green and the LSTM predictions as red dashed lines. This model exhibited excellent capabilities in evaluating humidity patterns because it senses early morning peaks and evening peaks as well as midday lows. PCS optimization is certainly improved through temperature and humidity forecasting, which allows for the preparation of ventilation strategies in advance and the implementation of shading and cooling plan systems that minimize both expenses and energy use, plus achieve better thermal comfort levels. Through MATLAB implementations, the LSTM models smartly use historical data from training that enables predictions to merge into energy management AI algorithms for producing optimized results between cooling energy usage and energy costs, and PMV score and carbon footprint calculations. Therefore, the incorporation of LSTM model with AI establishes new innovation possibilities to enhance PCS operations, thus achieving more energy-efficient buildings with reduced operational expenses and environmental degradation.

## Real-Time Adaptive Cooling Control

Figures 3a and 3b show the AI-powered Systems PCS, which operates through real-time adjustments of cooling methods based on temperature and humidity fluctuations spanning a whole day. A typical day temperature pattern appears from the real-time temperature data that appears as the red line while the environment becomes cooler during the evening. The blue graph represents the humidity presence in the environment, which reaches its peak during cold hours before sinking as day temperatures rise. Such variations significantly affect how people experience thermal comfort, together with their cooling requirements.

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| --- | --- |
|  |  |
| (a) | (b) |

**FIGURE 3.** Predicting (a) temperature and (b) humidity trends using an LSTM model

Real-time adaptive cooling control by the system is shown in Figures 4a and 4b through the AI adjustments that control adaptive shading factor and ventilation rate parameters. The cyan line (see Figure 4) elements control adaptive shading factors at higher levels during morning and evening when solar light entry is permitted, while descending during peak temperatures to reduce solar heat gain, thus maintaining interior temperatures stable. The green line controls ventilation rate by maximizing it during cooler periods to bring efficient fresh air, then decreasing it while avoiding hot outdoors air intake that elevates cooling loads.

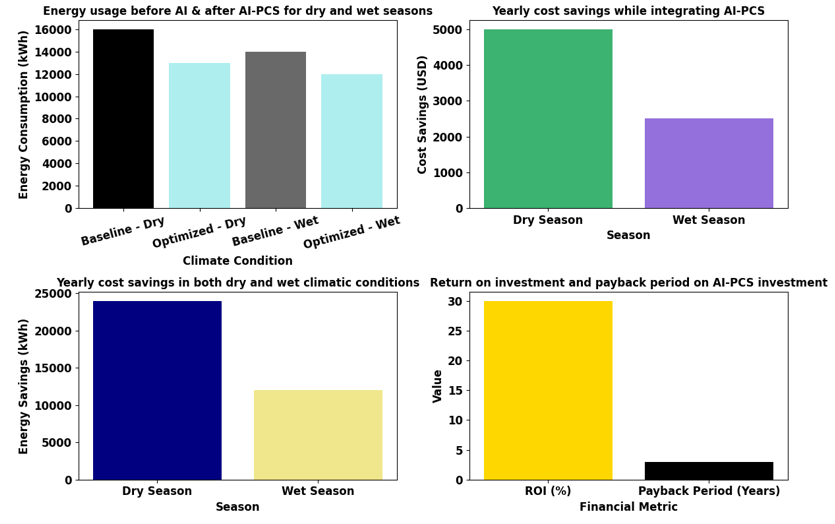
|  |  |
| --- | --- |
|  |  |
| (a) | (b) |

**FIGURE 4.** AI a) Real-Time Temperature & Humidity and b) Real-Time adaptive cooling control for 24 hours’ time

The real-time performance management of the system depends on AI algorithms, including both GA for balance optimization and RL for adjusting to environmental changes. The system uses ML model to analyze historical data, thus enabling it to make forward adjustments before environmental changes happen. MATLAB organizes the simulation of all framework processes through which it analyzes real-time data while performing AI calculations to optimize system performance. Therefore, AI technology applications improve both energy efficiency and management costs, together with better indoor environmental comfort, because they optimize PCS. The AI model was applied with key settings in Matlab: LSTM used 3 layers, 100 units and 0.01 learning rates. RL used Q-learning with α = 0.1 (learning rate) and Rate = 0.9 (discount factor) to balance short-term comfort and long-term energy savings. GA was configured with 50 persons, 0.05 mutation rates and 100 generations. Data for training, verification and testing were normalized, launched and divided (70/15/15). While simulation results are promising, the lack of overfitting and uncertainty analysis is accepted as future research requirement.

# RETURN ON INVESTMENT (ROI) AND PAYBACK PERIOD OF AI-PCS INVESTMENT

So far, research-based theoretical analysis verified that AI-optimized PCS provide superior performance to conventional PCS through minimal energy use combined with minimal expenses as well as better comfort levels in all aspects. An important evaluation factor exists when examining the effectiveness of implementing these intelligent system solutions. The key financial metrics for proper analysis include ROI and the payback period. Additionally, this study further analyzes the system's performance by dividing the weather conditions into two seasons: dry and wet months. The Figure 5 (top left) thoroughly examines how AI-Optimized AI-PCS perform and generate value across Malaysia's contrasting dry and wet seasons. AI optimization results in substantial energy savings shown by the chart which depicts a drop from 16,000 kWh to 12,500 kWh during the dry season and from 14,000 kWh to 11,500 kWh across the wet season. AI-PCS obtained an overall energy reduction of 22% while delivering better savings during the dry season because cooling demands are higher. The second chart (top right) demonstrates the yearly financial savings enabled by AI-PCS which amount to $4,800 during dry periods and $2,500 throughout the wet months. Energy cons-umption reductions demonstrate AI's effective management of cooling loads during extreme heat and humidity conditions which leads to these savings. The third chart (bottom left) shows annual energy savings data where the dry season accounts for 24,500 kWh and the wet season contributes about 12,500 kWh which underscores AI's ability to manage energy needs throughout all seasons. The final chart (bottom right) evaluates the financial viability of AI-PCS investments by demonstrating a significant Return on Investment of 30% with a payback period of three years, which shows that initial investment costs will be recovered swiftly through energy savings. The financial advantage of AI-PCS together with its enhanced energy efficiency, establishes it as a cost-efficient method for sustainable cooling. AI-PCS provides a viable solution to decrease energy consumption while reducing operational costs and carbon emissions within the hot and humid climate of Malaysia, where cooling systems use significant energy. The system supports Malaysia’s sustainable development plans while backing initiatives such as the Green Building Index (GBI) to enhance energy efficiency and climate resilience.



**FIGURE 5.** Energy usage before and after AI, yearly cost savings using AI-PCS, and ROI

# LIFE CYCLE COST ANALYSIS

The Lifecycle Cost Analysis (LCCA) of costs associated with the traditional CS and an AI Optimize PCS over a 10-year time frame that includes installation cost, annual energy costs and maintenance expenses (refer to Table 2 for calculations). Equation (2) given below is used to calculate the life cycle cost in full.

(2)

The initial cost is assumed to be $10,000 for the traditional PCS with annual energy costs of $3,000 and maintenance of $500 yearly. Over the span of 10 years, this will add up to 10 times of mean annual cost, i.e, $30,000 energy cost or $500/year maintenance, then LCCA to $45,000. In contrast, AI-optimized PCS starts with a higher initial cost of $15,000 because of advanced AI smart technologies, but cuts energy costs down to just $2,400 annually and maintenance down to $300, owing to predictive maintenance in the long run. Over 10 years, this is $24,000 in energy and $3,000 in maintenance for a total lifecycle cost of $42,000. The AI-PCS saves $3,000 net compared to the traditional PCS due to $6,000 in energy savings and $2,000 in reduced maintenance (a higher upfront investment of $10k). The lower the LCCA, the faster it will pay off to transfer to an AI-PCS. Therefore, this analysis demonstrates the cost-benefits and financial value proposition of AI-OCS, signaling a higher upfront investment but the cost savings advantage of long-term energy efficiency on maintenance and net lifecycle cost.

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| **TABLE 2.** LCCA comparison between traditional PCS and AI-optimised PCS | | | | |
| **System** | **Initial cost** | **Total energy cost** | **Total maintenance cost** | **Total LCCA** |
| Traditional PCS | $10,000 | $30,000 | $5,000 | $45,000 |
| AI-optimised PCS | $15,000 | $24,000 | $3,000 | $42,000 |

# FUTURE WORK: INTEGRATION OF RENEWABLE ENERGY SOURCE WITH AI-PCS

This observation from case study inspires the next stage: integrating renewable energy sources (RES) in AI-PCS framework to reduce dependence on grid and increase stability [14]. RL can make real -time decisions on energy use and storage, and GA can get the optimal balance between energy consumption, cost, comfort and RES use [15]. Energy management system will coordinate RES, battery storage and grid interactions using the formula: Etotal = Egrid + Ebattery - ERES, where Etotal is the total energy used, and ERES is the energy generated from renewal. The purpose of this setup is to reduce Egrid (grid dependency), and to maximizing ERES. Integrating renewable in AI-PCS directly manufactures the success of the case study and provides a clear route towards achieving non-zero energy buildings (NZEB) in Malaysia. It is not a random expansion but is a logical and data-operated progress based on the proven benefits of AI-PCS to reduce the use of energy and improve comfort. Note that, AI-Enhanced Inactive Cooling Experimental Verification has demonstrated promising consequences, especially in climate similar to Malaysia [5].

## Technical Challenges

Combining AI-Optimized (AI-PCS) with (RES) faces many technical challenges, including data availability and quality. As AI algorithms e.g., RL, LSTM, demand precise real-time data which is not always available or may be inaccurate. High computational training complexity of AI model and overfitting risk along with renewable variability makes it difficult to match variable solar or wind power with cooling demands. System integration complication like hardware difficulty, communication delays and scalability issues while deploying AI models in various environments [16]. Energy storage system management, cybersecurity, economic and policy barriers including high upfront cost and regulatory constraints are other implementation issues. These challenges can be overcome by well-defined data strategies combined with advanced AI algorithms; architectural design considering security for future scalability; as well as energy policy helping to address these economic issues [17].

# CONCLUSION

This research analyzed the effectiveness of a standard Passive Cooling System (PCS) versus an AI Optimized Passive Cooling System (AI-PCS) on a 12-story commercial and residential building located in Kuala Lumpur, Malaysia. AI-PCS uses modern Artificial Intelligence technologies like Reinforcement Learning (RL), Genetic Algorithms (GA), and Long Short-Term Memory (LSTM). This allows AI-PCS to change cooling approaches based on real-time environmental and occupancy conditions, while PCS's have no ability to do this because they are static. The case study found that AI-PCS provided the best energy performance, where it achieved over 22% energy savings and cost reduction of over 20%. A payback period of 3 years was expected. Traditional PCS did not operate efficiently, providing a greater level of energy consumption while increasing less efficient temperature control, adapting to Malaysia's hot and humid tropical climate during the changing weather conditions. The introduction of AI brings with it several barriers, such as data quality issues, the complexity of AI models, and system integration. However, these premised challenges will be surpassed in light of the enhanced level of operational efficiency that can be achieved, alongside the increased overall cost-effectiveness. Although this study demonstrates the ability of AI-Integrated PCS through MATLAB simulation, it is theoretical.

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