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Energy Internet In Building Energy Management System (Ei-Bems)

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Malaysia's National Energy Transition Roadmap (NETR) identifies Energy Efficiency as one of the six key levers for achieving a sustainable energy future. Commercial buildings account for approximately 26–27% of national electricity consumption, mainly due to lighting and air-conditioning systems. Conventional Building Energy Management Systems (BEMS) commonly employ Proportional–Integral–Derivative (PID) controllers because of their simplicity. However, PID controllers are less effective in handling the nonlinear and dynamic characteristics of real building environments. To address this limitation, this paper proposes an Artificial Neural Network (ANN)-based controller integrated into an Energy-Internet Building Energy Management System (EI-BEMS). ANN and PID controllers were developed and evaluated in MATLAB Simulink for lighting and HVAC subsystems. The results show that the ANN controller achieved superior predictive accuracy, with regression coefficients R = 0.94 for HVAC and R = 0.99 for lighting, while also providing faster response times, lower overshoot, and improved control stability compared to PID control. The novelty of this study lies in demonstrating ANN as an intelligent alternative to PID for EI-BEMS applications, enhancing both energy efficiency and indoor comfort. These findings support Malaysia's NETR energy efficiency initiative and align with United Nations Sustainable Development Goal (SDG) 7.3, which aims to double the global rate of energy efficiency improvement by 2030.

Keywords: energy transition; energy efficiency; cost-effectiveness; AI integration; sustainable future; building energy management system

I. INTRODUCTION

With the continuous growth of the global population and increasing energy demand in buildings, environmental pressures have become increasingly significant. Malaysia has pledged to reduce the greenhouse gas (GHG) emissions intensity of its Gross Domestic Product (GDP) by 45% by 2030 under its Nationally Determined Contributions (NDCs) to the Paris Agreement (International Energy Agency, 2020a). Among the major end-use sectors, commercial buildings are the second-largest electricity consumers in Malaysia, accounting for approximately 26–27% of the nation's total electricity consumption. According to (Al-Ghasem & Ussaleh, 2012; Paulauskaite-Taraseviciene *et al.*, 2015), this high

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energy usage is mainly driven by air-conditioning systems (64%) and lighting systems (12%).

This trend highlights the urgent need for smart energy management systems that can optimise building loads while ensuring comfort. The emerging Energy Internet–based Building Energy Management System (EI-BEMS) integrates internet technologies, smart sensors, and intelligent control to manage lighting, air-conditioning, and ventilation more efficiently (Sun *et al.*, 2015; Ntafalias *et al.*, 2024; Mischos *et al.*, 2023). However, the effectiveness of such systems strongly depends on the selected control strategy. Traditionally, Proportional–Integral–Derivative (PID) controllers have been widely adopted due to their simplicity and reliability. However, PID controllers often struggle to handle the nonlinear and dynamic characteristics of building environments, leading to reduced control accuracy, overshoot, and unstable system performance. These limitations reduce energy efficiency, comfort, and equipment lifespan. To address this gap, intelligent approaches such as Artificial Neural Networks (ANNs) have been explored. ANN can learn from data, adapt to environmental variations, and provide smoother, more stable control actions than PID (Ang *et al.*, 2005; Al-Mashakbeh, 2009; Park *et al.*, 2014).

The novelty of this study lies in the development and evaluation of an Artificial Neural Network (ANN)-based control strategy within an Energy-Internet Building Energy Management System (EI-BEMS) for Malaysian commercial buildings. Unlike most existing ANN-based BEMS studies, which primarily focus on energy forecasting or single-subsystem optimisation, this work implements ANN as a direct control mechanism for both lighting and HVAC subsystems. In addition, a technical comparison with conventional PID controllers is conducted within MATLAB/Simulink software to evaluate not only prediction accuracy but also dynamic control performance, including response time, stability, and overshoot. The study further demonstrates the applicability of ANN-based control in improving both energy efficiency and indoor comfort under realistic building operating conditions. Finally, the proposed approach aligns with Malaysia's National Energy Transition Roadmap (NETR) and supports SDG 7.3, which aims to improve global energy efficiency.

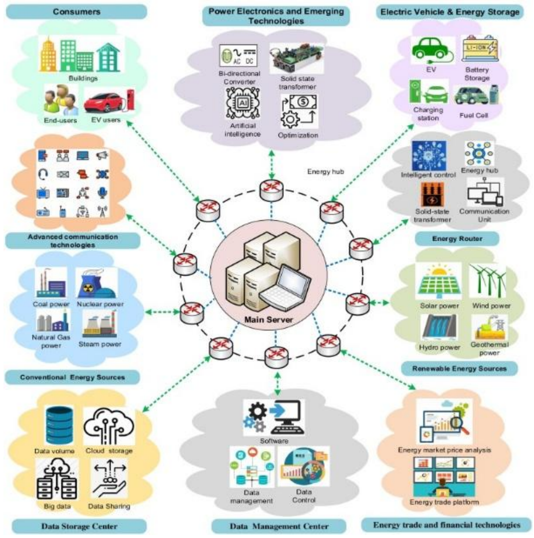

Figure 1. The key features of the Energy Internet (EI) framework

A. *Current Development of Building Energy Management Systems in Malaysia*

Globally, buildings account for a substantial proportion of electricity demand, with lighting and air-conditioning systems contributing approximately 50–70% of total energy consumption in residential and commercial sectors (International Energy Agency, 2020b). China has emerged as a leading country in the deployment of Building Energy Management Systems (BEMS), supported by strong policy frameworks targeting energy efficiency and carbon emission reduction. By 2015, building operations were estimated to represent nearly 20% of China's total energy consumption (Jingyun & Ping, 2017), driving extensive efforts toward large-scale building energy retrofits and system upgrades. Empirical studies on retrofit performance, such as those conducted by (Dubois *et al.*, 2015), have demonstrated the economic feasibility of efficiency improvements, with the integration of energy-efficient lighting systems and occupancy-based control achieving energy savings exceeding 45%, with a payback period of less than three years.

In Malaysia, the implementation of smart, low-carbon Building Energy Management Systems (BEMS) is still in its early stages. Due to the hot, humid climate, air-conditioning systems account for the largest share of building energy consumption, typically 40–60%, while lighting accounts for an additional 12–15% (Al-Ghasem & Ussaleh, 2012; Paulauskaite-Tarasevicione *et al.*, 2015). Although several pilot projects have been implemented in government facilities and major commercial buildings, their adoption has not yet been widely scaled. This gap indicates a clear demand for more intelligent, economically viable, and locally optimised Energy-Internet BEMS (EI-BEMS) solutions, particularly targeting air-conditioning and lighting as the primary energy-consuming subsystems.

B. Malaysia's Energy Efficiency Policy and SEDA Initiatives

The Malaysian government has introduced several frameworks to accelerate energy efficiency in buildings. The Sustainable Energy Development Authority (SEDA) is the primary body overseeing the implementation of energy efficiency and renewable energy (SEDA Malaysia, 2021). It enforces Minimum Energy Performance Standards (MEPS) for lighting and HVAC systems, while promoting financing tools such as the Green Technology Financing Scheme (GTFS). Under the National Energy Transition Roadmap (NETR) and the Eleventh and Twelfth Malaysia Plans, energy efficiency is emphasised as a key contributor to energy security and carbon reduction (Fernandez *et al.*, 2024). The Minimum Energy Performance Standards (MEPS) implemented by SEDA set regulatory benchmarks for lighting and HVAC efficiency in commercial buildings (Isa, Salleh & Roslan, 2023). Key national initiatives include the National Energy Efficiency Action Plan (NEEAP), the Green Technology Master Plan (GTMP), and the Green Building Index (GBI), all of which promote energy audits, building retrofits, and sustainability certification. The NEEAP provides a coordinated framework for implementing energy efficiency measures across multiple sectors, while the GTMP outlines Malaysia's long-term strategy for a low-carbon, resource-efficient economy through the adoption of green technologies. Meanwhile, the GBI serves as the country's primary green building rating system, encouraging the adoption of sustainable design principles and energy-efficient practices in the built environment (Hafez *et al.*, 2023). Despite these efforts, most existing BEMS still rely on PID-based controls, which lack adaptability to dynamic indoor environments. This gap highlights the need for ANN-based intelligent control strategies that can address nonlinearity, improve stability, and fully realise the benefits of Malaysia's energy efficiency policies.

C. Alignment with Global Goals (UN SDG 7)

Malaysia's energy efficiency agenda closely aligns with United Nations Sustainable Development Goal 7 (SDG 7), which aims to "ensure access to affordable, reliable, sustainable, and modern energy for all." In particular, Target 7.3 emphasises the need to double the global rate of improvement in energy efficiency by 2030 (Elavarasan, Nadarajah & Shafiullah, 2024). The implementation of intelligent and cost-effective Building Energy Management Systems (BEMS) directly supports this objective by reducing building energy intensity, lowering operational electricity costs, and contributing to national carbon reduction commitments under the Paris Agreement (Hafez *et al.*, 2023).

II. ENERGY-INTERNET SMART BUILDING ENERGY MANAGEMENT SYSTEM

In this project, the control system is designed to regulate the building's lighting and ventilation systems, including fans and air-conditioning units. Its primary objective is to optimise energy consumption while maintaining a comfortable indoor environment. The overall EI-BEMS architecture can be classified into three main components: the lighting subsystem, the air-conditioning (ventilation) subsystem, and the control unit. Each component plays a distinct role in regulating energy usage while ensuring optimal indoor environmental conditions.

First, it integrates Artificial Neural Network (ANN) controllers into an Energy-Internet-based framework, targeting both lighting and air ventilation subsystems simultaneously. Second, the study compares the performance of ANNs and traditional PID controllers directly, clearly demonstrating the limitations of PID in nonlinear and dynamic building environments. Through MATLAB/Simulink implementation, ANN shows superior predictive accuracy, faster dynamic response, reduced overshoot, and more stable control actions.

A. Lighting System

As shown in Figure 2, the illumination range is set between 300 lux and 500 lux. This range ensures sufficient brightness for common indoor tasks such as reading, writing, and computer usage, without causing eye strain or fatigue.

Illumination below 300 lux makes prolonged reading difficult. In contrast, levels above 500 lux can cause glare and reflections, which reduce comfort and efficiency.

Energy efficiency is also a key factor in selecting this range, as it prevents over-illumination and unnecessary electricity consumption. The control logic is implemented using relational operators and switches in MATLAB/Simulink. The relational operator compares real-time illumination with the defined range (300–500 lux) and outputs a Boolean signal ('1' for true and '0' for false).

Two relational operators and switches are used in the design. The first triggers when illumination falls below 300 lux, while the second triggers when illumination exceeds 500 lux. The corresponding switches then determine the appropriate lighting output. The system produces three possible brightness states:

- **'1' = FULL BRIGHTNESS,**
- **'0.5' = MEDIUM BRIGHTNESS,**
- **'0' = LIGHTS OFF.**

This control strategy maintains illumination within the optimal range, enhancing both energy efficiency and user comfort.

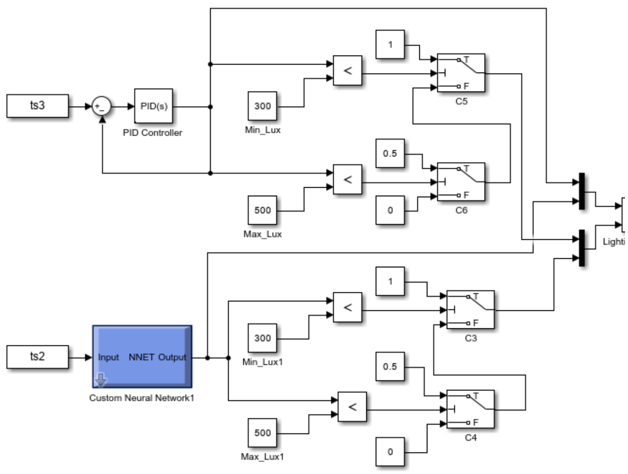

Figure 2. Lighting control system in Matlab Simulink

B. *Air Ventilation System*

The air ventilation system, shown in Figure 3, consists of two subsystems: fans and air-conditioning units (ACs). In Malaysia's hot-humid climate, where outdoor temperatures range from 28°C to 34°C, these systems maintain an indoor temperature of 20°C–25°C, achieving both thermal comfort and energy efficiency.

Cooling 20°C below significantly increases electricity consumption in large buildings, while maintaining temperatures above 25°C can compromise comfort. The predefined range therefore prevents overcooling and minimises unnecessary energy use, addressing a major shortcoming of conventional buildings where indoor conditions are not automatically regulated.

The control design uses relational operators to compare real-time indoor temperature with the thresholds (20°C and 25°C). An AND logic gate evaluates whether the measured temperature is within or above the range. Based on these conditions:

- Fans operate at '1' (full speed) or '0.5' (medium speed),
- Air-conditioning units switch 'ON' (1) or 'OFF' (0).

This logic ensures that ventilation devices operate only when necessary, reducing both electricity cost and energy waste.

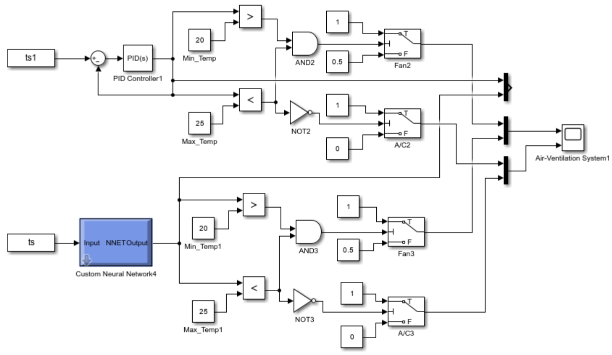

Figure 3. Air ventilation control system in Matlab Simulink

C. *Controller Unit*

The controller unit forms the core of the proposed EI-BEMS, responsible for executing intelligent decisions for both lighting and air ventilation systems. Two types of controllers are implemented and compared:

1. Proportional-Integral-Derivative (PID) controller

The PID controller operates based on three parameters: Proportional (P), Integral (I), and Derivative (D) gains.

- **P** increases the speed of system response,
- **I** eliminate steady-state error over time, though high values may cause oscillations,
- **D** provides damping, reducing overshoot and improving stability.

Figure 4 illustrates the block diagram of the PID controller. Despite its widespread use in industrial systems due to simplicity and reliability, PID tuning is challenging in nonlinear, variable environments such as building operations.

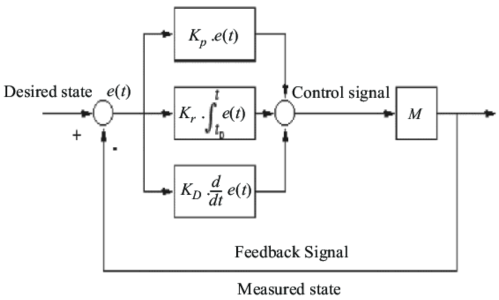

Figure 4. The block diagram of PID controller

2. Artificial Neural Network (ANN) controller

The Artificial Neural Network (ANN), illustrated in Figure 5, is an intelligent controller inspired by the structure of the human brain. It consists of interconnected processing units (neurons) arranged in three layers:

- **Input Layer:** Receives environmental and system data,
- **Hidden Layer(s):** Learns internal relationships and nonlinear patterns,
- **Output Layer:** Produces control actions for lighting and HVAC subsystems.

The ANN is trained using historical and simulated data to recognise patterns in building energy demand. Once trained, it adapts to new conditions, making it more robust than PID in nonlinear environments. This capability enables ANN to deliver smoother control actions, improved stability, and higher accuracy in regulating both lighting and HVAC loads.

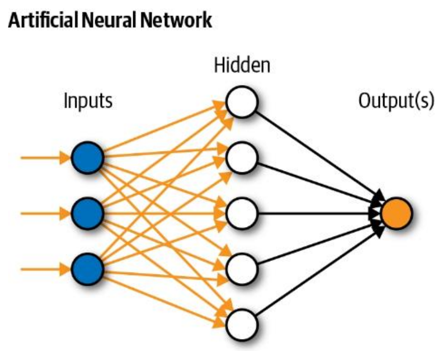

Figure 5. The algorithm of Artificial Neural Network (ANN) controller

III. RESULTS AND DISCUSSION

A. ANN Controllers

In this project, the ANN model is constructed using programming code. Since the BEMS consists of two subsystems, two separate ANN models are required. The first model, ANN1, is designed for the air ventilation system, while the second model, ANN2, is used to control the lighting system.

1. ANN1 (Air ventilation system)

For the ANN model training, both input and output data are required. In this case, three input parameters are used: maximum indoor temperature, minimum indoor temperature, and indoor humidity. These parameters are selected because they significantly influence the indoor thermal environment. The output data is the average indoor temperature, which serves as the target variable for prediction. As shown in the ANN1 network diagram in Figure 6, the model includes three hidden layers between the input and output layers. The network consists of three hidden layers with nine neurons of feed forward neural network (3–5–1 configuration), allowing it to capture nonlinear dependencies among input parameters.

The model was trained for 1,000 epochs, achieving a regression value of R = 0.9445 as shown in Figure 7, indicating a strong correlation between predicted and actual temperature. This result confirms that ANN1 can reliably estimate indoor thermal conditions, making it suitable for adaptive control of the ventilation system.

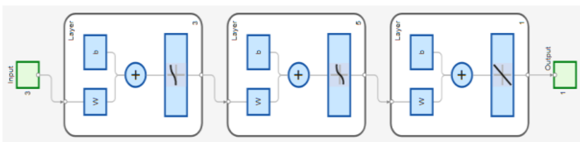

Figure 6. The network diagram of ANN1

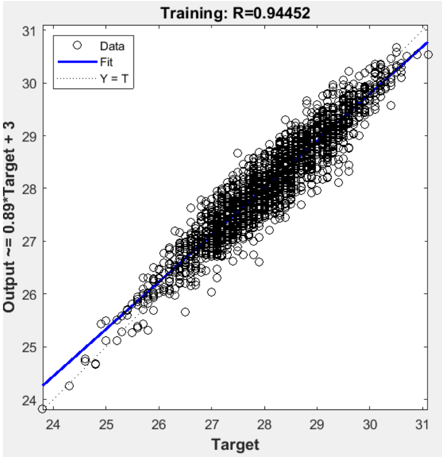

Figure 7. The regression training results of the ANN1 model

2. ANN2 (Lighting System)

This second ANN model, as shown in Figure 8, is designed for the indoor lighting system. It can predict the illumination level in lux within a space based on several environmental factors. This helps in achieving proper lighting control and energy savings. In this model, five input parameters are selected from the input dataset and significantly affect the indoor brightness level, including the number of lights, the space area (m^2), the lumens per light, the ceiling height, and the surface reflectivity. These input factors are measured or estimated based on actual indoor conditions. The network comprises two hidden layers with a total of 15 neurons (5–10 configuration), enabling accurate mapping of nonlinear input-output relationships as shown in Figure 8.

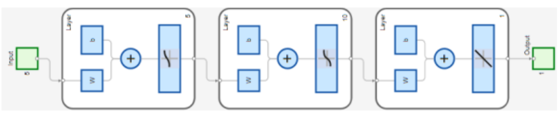

Figure 8. The network diagram of ANN2

The training results in Figure 9 yielded an R value of 0.9959, indicating very high prediction accuracy. The ANN2 model thus provides a reliable basis for intelligent lighting control, capable of maintaining illumination within the desired 300–500 lux range with minimal error.

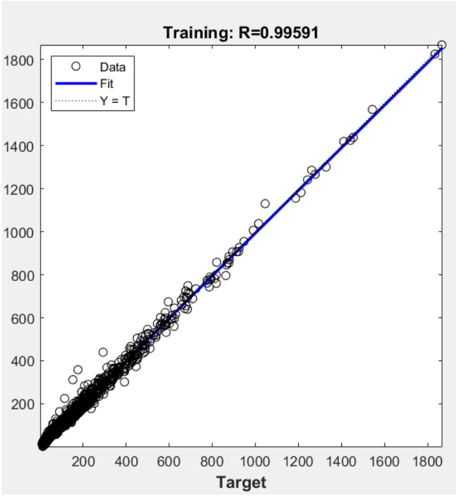

Figure 9. The regression training results of the ANN2 model

B. Comparison of PID and ANN Performances

Both PID and ANN controllers were implemented in the lighting and ventilation subsystems. The performance was assessed based on accuracy, stability, dynamic response, and energy efficiency.

1. Air ventilation system

The comparison of controller responses in the air ventilation subsystem in Figure 10 shows that both PID and ANN1 generally follow the desired trajectory. However, the PID controller responds more slowly during both rising and falling transitions. This delay is mainly due to its reliance on present and past error values, which limit its ability to react quickly to sudden changes. In addition, the ventilation system exhibits nonlinear behaviour, such as rapid temperature changes when the air-conditioning system is switched on or off. Because the PID controller is based on a fixed linear control law with constant gains, it struggles to capture these nonlinear dynamics, leading to slower, less accurate regulation. Furthermore, since the PID gains are fixed after tuning, its performance is acceptable only within a limited operating range (approximately 20–25°C). Outside this range, or under varying environmental conditions, its performance becomes less reliable. These limitations highlight the PID controller's limited adaptability, making it less suitable for dynamic building environments. In contrast, ANN1 adapts to nonlinear system behaviour through data-driven learning, enabling faster response and more stable temperature regulation. This makes ANN more suitable for intelligent building energy management applications.

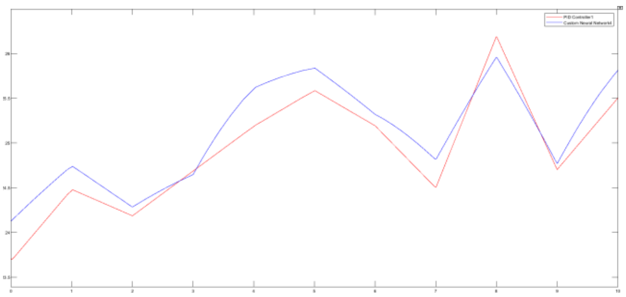

Figure 10. Output responses of both controllers in the air ventilation system

2. Lighting system

A similar pattern is evident in the lighting subsystem in Figure 11. The PID controller overshoots the target illumination, reaching up to 635 lux, exceeding the desired 500 lux, indicating poor steady-state accuracy. This overshoot stems from PID's reactive nature, as proportional and derivative gains tend to overcorrect when responding to nonlinear or rapidly changing inputs. Modern LED lighting systems further complicate control due to their inherently nonlinear relationship between input voltage/current and illumination output, compounded by factors such as ceiling height, reflectivity, and lumen rating. Consequently, PID produces delayed responses and unstable control under these conditions. By contrast, ANN2 achieves smoother transitions with minimal overshoot and consistently stable illumination outputs. Its ability to learn from training data enables it to capture the complex relationships among lighting parameters and deliver more precise control. The smoother curves observed in ANN2's responses are particularly beneficial for user comfort and energy efficiency, underscoring ANN's superiority in managing modern building lighting systems.

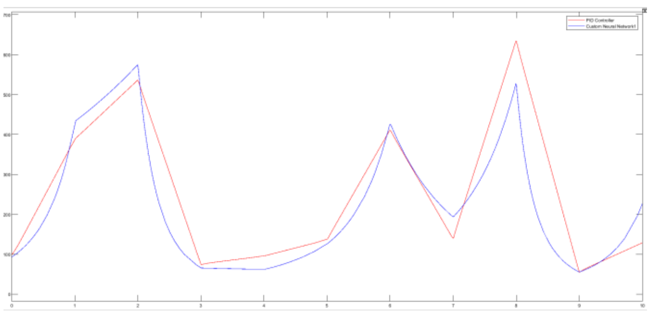

Figure 11. Output responses of both controllers in the lighting system

C. Output Responses of Both Control Systems using PID and ANN Controllers

Both the lighting and air ventilation systems connected are fully controlled by the signals generated from the PID and ANN controllers. The output responses previously discussed are further analysed in this section.

1. Lighting system

Figure 12 below shows a comparison of the system responses from the two controllers: the PID controller (red line) and the ANN controller (blue line) for a lighting control system. The values 0, 0.5, and 1 represent the control output levels where:

- '0' : light off or minimum brightness
- '0.5': medium brightness
- '1' : full brightness

The integrated lighting and air ventilation systems were tested under PID and ANN control to evaluate switching behaviour, stability, and overall system reliability. As shown in Figure 12, the PID-controlled lighting system exhibited frequent switching within short time intervals due to its high sensitivity to small error signals. This produced a noisy response, resulting in visible flicker and unstable brightness. Such behaviour is undesirable in office environments, as it can reduce worker comfort and productivity while also causing long-term eye strain. Frequent switching further accelerates the wear of components such as relays, leading to higher maintenance costs and reduced system reliability. In contrast, the ANN controller demonstrated a more stable switching pattern, maintaining longer periods at fixed states. By filtering out small disturbances and avoiding unnecessary corrections, ANN provided smoother and more reliable illumination control, thereby improving both comfort and equipment lifespan.

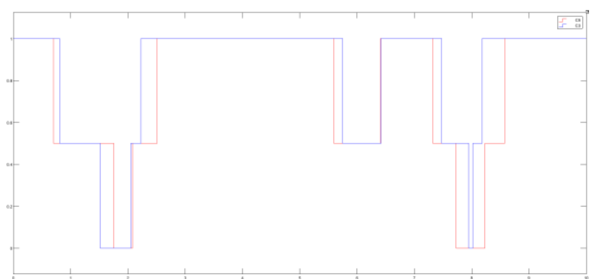

Figure 12. Output responses of the lighting system using PID and ANN controllers

2. Air ventilation system

Figures 13 and 14 below compare the system responses of the two controllers: the PID controller (red line) and the ANN controller (blue line) for an air ventilation system. The values 0 and 1 represent the control output levels where:

- '0': device is OFF
- '1': device is ON

A similar outcome was observed in the air ventilation subsystem for Figures 13 and 14. The PID controller responded to even minor temperature fluctuations, causing frequent ON/OFF switching of the fan and air-conditioning units. This behaviour not only increased energy consumption but also placed additional mechanical stress on motors and compressors, shortening the operational lifespan. Furthermore, the excessive switching sometimes delayed the restoration of comfortable indoor conditions, reducing user satisfaction. In contrast, the ANN controller operated in a more intelligent and adaptive manner. Trained with historical data, it identified when corrective action was truly necessary and ignored minor fluctuations. As a result, the ANN reduced unnecessary switching, stabilised the indoor temperature more effectively, and improved energy efficiency. These advantages also translate into extended equipment durability and lower maintenance costs.

Overall, the output responses confirm that while PID control can maintain basic functionality, it is prone to instability, oversensitivity, and inefficiency in dynamic environments. ANN control, by contrast, achieves smoother and more reliable system operation, delivering improved energy savings, greater user comfort, and enhanced long-term system reliability.

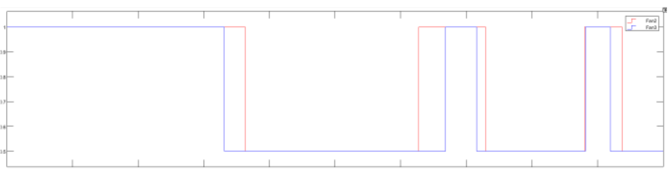

Figure 13. Output responses of the fan system using PID and ANN controllers

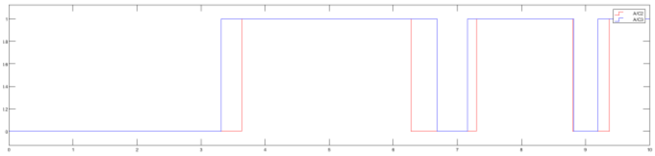

Figure 14. Output responses of the air conditioning system using PID and ANN controllers

IV. CONCLUSION

This study introduces a new building concept, the Energy-Internet Smart Building Energy Management System (EI-BEMS), to replace traditional commercial building models. As commercial buildings account for a substantial share of Malaysia's total energy consumption, there is a clear need for smarter and more efficient management systems. By implementing EI-BEMS, energy use can be optimised and electricity costs significantly reduced. Within this framework, two control strategies, Proportional-Integral-Derivative (PID) and Artificial Neural Network (ANN), were evaluated. The analysis of system responses revealed that ANN is better suited for managing lighting and air ventilation in complex, real-world environments. Compared with PID controllers, which rely on fixed parameters and are prone to overshoot, frequent switching, and poor noise handling, ANNs provide a more intelligent and flexible approach.

ANN's ability to learn from usage patterns, adapt to environmental changes, and deliver smoother, more stable system responses makes it a superior choice for intelligent building energy management. This adaptability reduces unnecessary switching, extends equipment lifespan, and enhances overall energy efficiency. In contrast, the static nature of PID controllers limits their effectiveness in dynamic, nonlinear systems such as those in modern smart buildings. Therefore, for applications that demand precision, adaptability, and intelligence, ANN emerges as the more effective solution.

In conclusion, the results demonstrate the benefits of integrating ANN-based intelligent control strategies into Building Energy Management Systems (BEMS) for improved building performance. In addition to enhancing system responsiveness and reducing energy consumption, ANN-based control also improves operational efficiency, equipment reliability, and long-term sustainability. These outcomes are consistent with Malaysia's National Energy

Transition Roadmap (NETR) and support the United Nations Sustainable Development Goal 7 (SDG 7), particularly in improving energy efficiency. Future work should consider incorporating cost–benefit analysis and financial modelling to further evaluate the economic feasibility of implementing intelligent BEMS at scale. By combining intelligent control with cost-effective system design, Malaysia can accelerate the transition toward a low-carbon, resilient, and sustainable energy future.

V. ACKNOWLEDGEMENT

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