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Research article

Optimal control of cooling management system for energy conservation in smart home with ANNs-PSO data analytics microservice platform

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ABSTRACT

An intelligent cooling management system with a smart home application is proposed to evaluate optimal target temperatures and air conditioner fan modes, thereby maximizing energy efficiency while ensuring residents' comfort. The proposed system integrates a home energy management system with a sophisticated backend infrastructure designed to enable seamless hardware connectivity for real-time data acquisition from various sensors, a gateway, internet of things (IoT) devices, and servers. Furthermore, it serves as a platform for implementing a software data analytics model, structured upon a microservice architecture, aimed at providing optimal feedback control. The data analytics platform utilized in this research integrates two sets of artificial neural networks (ANNs) and a particle swarm optimization (PSO) algorithm for computation and control. This platform is designed not only to gather real-time ambient data and air conditioner usage records but also to regulate the air conditioner's operation autonomously. By considering aprevailing ambient air condition, the ANNs accurately predict power consumption, indoor temperature, and indoor humidity following adjustments in target temperature and fan mode. The PSO-based data analytics model efficiently selects the most suitable target temperature and fan mode, thereby achieving a dual purpose of enhancing energy conservation while minimizing potential occupant discomfort. This optimization is driven by utilizing the predicted mean vote (PMV) calculated through the analysis performed by the ANNs. Validation of the developed intelligent cooling management system was conducted in a real smart home environment inside a single detached two-story house, using an 8,000 BTU air conditioner as the testbed within an 8×5 m^2 space accommodating four occupants. The implementation results indicate that the proposed intelligent cooling management system can reliably predict the behavior and ambient data of the air conditioner and give the best-operating settings in any different environment scenarios and therefore shows potential for energy savings in smart home applications.

1. Introduction

In the contemporary digital landscape, the seamless integration of technology, digital services, and online platforms reflects individuals' pursuit of convenience and efficiency in everyday life. This integration firmly establishes technology as an indispensable

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facet of routines across personal and professional domains. The profound impact of the COVID-19 pandemic has necessitated unprecedented global adaptation, compelling government and private sectors worldwide to help their people change the ways they work and live with technological support. This concerted effort has fostered increased acceptance and reliance on technology for communication and daily activities. Consequently, individuals are progressively embracing technology, leading to its pervasive adoption across diverse demographics at an unprecedented scale.

The pandemic has acted as a transformative force for reshaping societal dynamics, particularly attitudes toward technology. In response to stringent social distancing measures, numerous organizations have implemented remote work arrangements, allowing their employees to operate from home. As a result, they have gradually adapted and have been getting accustomed to this new normal working lifestyle. Remarkably, this transition has been met with positive reception due to savings in travel costs and time without significantly compromising productivity. Therefore, the house is no longer just a place to live but can also be a place to work, hold meetings, or do leisure activities. This transformative shift emphasizes a growing reliance on technology and online platforms to facilitate home-based activities, thereby leading to a new lifestyle trend and economic model called the "stay-at-home economy," which is fundamentally based on people doing things at home.

An illustrative example of the stay-at-home economy exhibits the increasing prevalence of online communication, meetings, and business transactions facilitated by application services. These activities require the perfect combination of technology for the convenience of living in the home, and smart home technology offers an attractive solution to achieve the objectives. Within this context, home energy management systems represent a key application domain for smart home technology, leveraging a suite of components such as sensors, multimedia devices, and communication protocols [1]. Home energy management has recently been in greater attention, and most of the research and development has been focused on enabling the integration of a wide range of devices and sensors to increase residents' comfort. Another significant and indispensable feature is the integration of energy savings into smart home applications because cost savings, in particular, emerge as a compelling factor driving the widespread adoption of smart home technology, especially in scenarios where prolonged periods of home occupancy are anticipated.

Addressing the challenges above, utilizing energy within households most effectively and ensuring widespread access to this solution becomes imperative, explicitly targeting residential electricity consumers. This objective demands a keen focus on developing innovative technologies leveraging the functionalities of internet of things (IoT) devices commonly installed within contemporary smart homes. For instance, with IoT functionalities, smart home devices can be programmed to preset operating schedules and detect occupancy within the home. These devices possess the capability to autonomously regulate energy usage by automatically powering off lights, air conditioners, fans, or other electrical appliances when unoccupied, and subsequently restoring them to operation upon detecting human presence.

One significant research challenge lies in the development of adaptive home energy-saving systems capable of adjusting to residents' habits and behaviors. These systems can include features like automatically adjusting air conditioner settings or controlling window openings to reduce heat buildup in the house. Thailand, like many other regions, has experienced rising temperatures due to climate change, particularly during the summer months. Consequently, there is a heightened demand for air conditioning in households, with a significant portion of electricity costs attributed to air conditioner usage. Technological solutions such as sensors and smart controllers have been extensively studied for their potential to enhance energy efficiency and reduce electricity expenses. The current market offers a range of smart home products at competitive prices, making them accessible to households of varying economic means. Furthermore, these products are designed to be user-friendly and can often be installed by homeowners themselves, further increasing their appeal for achieving energy savings.

Numerous studies have investigated the affordability and accessibility of current smart home products, including sensors and smart controllers. These studiesare emphasized on how these products can enhance energy efficiency and reduce electricity expenses. The user-friendly design and easy installation of these products make them attractive to consumers from diverse economic backgrounds, increasing their potential for widespread adoption in home energy conservation efforts. The adoption of modern technology, digital services, and online platforms has significantly increased, making technology an indispensable part of daily life. Artificial intelligence (AI) and machine learning (ML) have demonstrated remarkable versatility across various disciplines. In electrical engineering, they are utilized in the smart grid and energy internet [2]. Energy science leverages AI and ML for energy prediction, using historical data to forecast future consumption under different constraints [3]. In structural engineering, AI and ML improve design by overcoming traditional model limitations, employing pattern recognition (PR) and deep learning (DL) [4]. Agriculture benefits from AI and ML through real-time detection of plant diseases [5], such as using deep-learning methods to detect and categorize leaf diseases in tomatoes [6], and even in medical analysis for diabetes diagnosis [7]. Additionally, AI has seamlessly integrated with IoT systems, enhancing efficiency and security in various industries [8].

This research proposes an intelligent cooling management system integrated into a home energy management system. The system includes backend infrastructure developed to enable hardware connectivity for real-time data acquisition from sensors, a gateway, IoT devices, and servers. Additionally, it facilitates a software data analytics model based on microservice architecture for optimal feedback control. The key advantage of the microservice design is its flexibility to scale and independent modification of functionality. The data analytics platform embedded in the system features two main processes: artificial neural networks (ANNs) [9,10] and particle swarm optimization (PSO) [11,12]. The ANNs serve for parameter predictions by analyzing ambient conditions, the air conditioner's usage behavior, and the air conditioner's specific performance data. For a given prevailing ambient air condition, the PSO algorithm selects the optimal target temperature and fan mode to maximize energy savings while ensuring occupants' comfort or minimizing possible impacts on occupants using the predicted mean vote (PMV) [13,14]. The PMV, an industry-standard index for assessing thermal comfort, is calculated from the room's temperature and humidity by the ANNs.

The research places a strong emphasis on the practical implications and applications of its findings. To achieve this, particular attention is given to developing budget-friendly hardware and software solutions, as well as conducting real experiments for validation. The cost-effectiveness of the platform's design allows for easy replication in various contexts. While the methodology is adaptable to different customer sectors, the primary focus is on the residential domain, highlighting the utilization of budget hardware and software implementation. By prioritizing the residential sector, the aim is to showcase the feasibility and practicality of the approach in everyday settings, using a real smart home environment. This approach makes it more accessible and beneficial to a broader range of users within the context of a testing environment in Thailand.

The subsequent sections of the paper are organized as follows. Section 2 provides related research work on cooling management systems. The research contribution is given in Section 3. The architecture design of the proposed cooling management system is described in Section 4. Section 5 details the implementation results of the intelligent cooling management system tested in a real smart home environment with analysis and discussion. Section 6 concludes the paper.

2. Related research work

In the domain of air conditioning systems, achieving optimal energy efficiency typically involves adopting one of three primary approaches. The first approach focuses on enhancing hardware components and entails investigating the impact of incorporating complementary accessories, such as smart curtains, to improve the efficiency of air conditioning systems. For example, Mohammed et al. [15] proposed a split air conditioning system tailored for energy savings in hot and arid climates. This innovative system utilized a hybrid proportional integral derivative (PID) controller to effectively manage fan and mist generation. Recent advancements have introduced novel methodologies for evaluating and predicting energy savings in air conditioning systems. One such technique employs the refrigeration operation energy saving effect ratio (ROEER) as a key parameter, used in conjunction with ANNs. This methodology, exemplified by relevant research [16], provides a comprehensive evaluation of the energy efficiency of the system and enables precise forecasts of energy conservation. Another emerging approach is a data-driven methodology that underlines forecasting energy consumption patterns in air conditioning systems. This method utilizes meteorological data and historical records of energy consumption to leverage the capabilities of Gaussian process regression, ensuring accurate and dependable forecasts of energy consumption patterns [17].

The second approach centers on implementing load control strategies during periods characterized by elevated energy demand. This approach has been extensively studied by Ilic et al. [18] and Singaravelan et al. [19] as a crucial component of smart home systems. These strategies allow users to tacticallyadjust the operation of electrical appliances during peak demand periods, when energy prices are high, to off-peak periods when energy costs are lower. However, direct load control is more suitable for non-air conditioning appliances due to their greater flexibility in modifying usage schedules. In contrast, applying direct load control solely to air conditioning systems during periods of high energy demand could significantly impact the comfort and well-being of residents. Therefore, it is advisable to adopt a comprehensive approach that combines direct load control with other energy-saving methodologies while minimizing any potential user discomfort.

The third approach to achieving optimal energy efficiency in air conditioning systems revolves around considering occupancy and ambient factors. Researchers have proposed innovative methods to optimize air conditioning system operation based on real-time occupant presence and environmental conditions. For example, Cheng and Lee [20] introduced a smart air conditioning control system with a mobile phone interface. Motion sensors installed in the area detected occupant activity, and a proportional integral derivative (PID) system intelligently regulated the air conditioning operation based on temperature variations and user activity data. In a related study, Erickson et al. [21] presented an air conditioning control predictive demand model to estimate the number of occupants in a room accurately. The model used occupancy-based system for efficient reduction of heating, ventilation, and air conditioning energy (OBSERVE)trained on data from various sensors in the environment to obtain a real-time count of the number of persons present, enabling the air conditioning system to optimize its settings accordingly. Additionally, Yang [13] explored the use of an ANN to determine the optimal pre-cooling time in an office building. By analyzing environmental data such as ambient temperature, outdoor sunlight, and temperature variations within the room, the ANN model estimated the projected room temperature and the time required to achieve optimal cooling. This proactive approach ensured energy efficiency by pre-cooling the space as needed, minimizing energy wastage during high-demand periods.

Models in the third category offer potential solutions for controlling air conditioning systems to optimize energy efficiency while maintaining users' comfort. To achieve this goal, the PMV index [22] has been adopted as an effective tool for evaluating an individual's perception of their ambient climate. Hawila et al. [23] investigated the energy-saving potential and thermal comfort in glass-fronted buildings during European winter conditions, using a PMV index as a criterion for verifying comfort levels. Simplifying resident comfort assessments, Zhang and Lin [24] proposed the utilization of model-derived skin temperature instead of measured skin temperature in PMV index calculation. Additionally, Yamada et al. [25] addressed the dynamic setting of target temperatures for office workers based on the environment, employing a PMV index to gauge comfort levels effectively.

The success of such comfort assessments critically depends on accurate environmental data collection. Consequently, when adjusting air conditioning systems, it is crucial to consider both energy consumption and its impact on occupant comfort. Numerous studies have explored these aspects. For instance, Yonezawa [26] presented an air conditioning control system that utilized ANNs and a PMV index to dynamically adjust the target temperature, ensuring both comfort and energy savings. Chinnakani et al. [27] conducted a comparative study on air conditioner energy consumption under three distinct comfort control scenarios: maintaining temperature and humidity within predefined ranges, predicting the duration for heaters and humidifiers to sustain optimal conditions, and controlling temperature and humidity within the PMV comfort criteria.

In an alternative approach, Mei et al. [28] utilized a model predictive control (MPC) to regulate multiple components of an conditioning system, including compressors, fans, and valves. By predicting the indoor environment and energy consumption, optimal configurations were determined to improve energy efficiency. Similarly, Xu et al. [29] proposed a collaborative control approach for heating, ventilation, and air conditioning (HVAC) systems that integrated natural ventilation during the initial phase in a meeting room to reduce the overall energy consumption of the building. They devised a rule-based framework to approximate the optimal control policy for the joint control of an HVAC system and natural ventilation, employing threshold policies for this purpose.

In a study conducted by Ref. [30], the application of a PSO process in conjunction with a generalized regression neural network (GRNN) was investigated for forecasting a PMV index in office environments concerning air conditioning utilization. The PSO optimized the parameters of the GRNN model, resulting in improved learning accuracy and speed. The GRNN predicted the PMV index using multiple data variables, including indoor temperature, humidity, wind speed in the shade, tube temperature, average radiation temperature, and clothing surface temperature. The study demonstrated that using the PSO with the GRNN produced superior predictive capabilities compared to using a radial basis function network and a non-optimized GRNN, while also reducing both training and prediction time. In a separate investigation [31], a PSO model was applied in conjunction with an MPC to regulate the air flow rate and establish the desired temperature of the air conditioning system. This approach aimed to mitigate energy consumption and ensure optimal user comfort amid changing environmental conditions and occupancy patterns. The PSO determined the optimal parameters of the MPC strategy to maximize the efficiency of a variable air volume (VAV) air conditioning system.

A significant body of research has been devoted to energy savings, load control, and the determination of optimal settings for air conditioning systems. Innovations in this area include the use of PID controllers, the ROEER, and ANNs for energy predictions. Load control schemes, which are components of smart home systems, aim to shift energy demand from high to low-cost periods. Various strategies have been developed to determine optimal air conditioning settings based on occupancy and ambient factors, with many studies utilizing the PMV index to evaluate comfort levels. Comparative studies on energy consumption under different comfort control conditions have been conducted, and MPC has been applied to find optimal settings [26–29].

These studies collectively emphasize the importance of the PMV index and advanced control strategies in attaining a harmonious equilibrium between energy efficiency and occupant comfort within air conditioning systems. Through the integration of advanced modeling techniques and data-driven approaches, these methodologies play a significant role in the progression of intelligent and environmentally friendly building management practices. Further investigation in this field is essential to enhance and optimize the efficiency of air conditioning systems, thereby promoting a balanced integration of energy preservation and the comfort of occupants.

Despite the advancements achieved in the domain, there is a pertinent area of inquiry regarding the feasibility of integrating cost-effective hardware and sensors into machine learning and optimization algorithms to facilitate the reduction of energy consumption in practical scenarios, specifically concentrating on air conditioning systems. Therefore, there remains an unaddressed issue concerning the application of artificial intelligence to define the optimal target air temperature using PMV data. Furthermore, the practical implementation of this approach with budget-friendly hardware to improve its accessibility and applicability in everyday scenarios remains largely unexplored and challenging. The central highlight is on leveraging affordable hardware components and sensors with advanced machine-learning techniques and optimization algorithms to improve the energy efficiency of air conditioning operations. Although previous studies have made significant progress in investigating different approaches to energy conservation, there exists a research gap on how the integration of budget-friendly technologies can effectively contribute to this endeavor remains generally unaddressed.

This research seeks to formulate several critical research questions related to the integration of budget-friendly hardware components, sensors, sophisticated machine learning techniques, and optimization algorithms to enhance energy efficiency in air conditioning operations. Firstly, we aim to investigate how the combination of these cost-effective technologies can effectively contribute to improving energy efficiency in air conditioning systems. This exploration will show the potential benefits of utilizing budget-friendly solutions to energy conservation. Secondly, the study's objective is to identify viable means to optimally regulate air conditioning settings using ANNs and a PSO algorithm based on data from PMV assessments. By doing so, we intend to achieve reduced energy consumption without compromising the thermal comfort of the occupants. This investigation will offer insights into the practicality and effectiveness of employing advanced AI techniques for enhancing energy efficiency in air conditioning operations. Furthermore, a key focus of this research is on the practical implementation and testing of the proposed approach in real-world settings using budget hardware. The significance of this aspect is to ensure the feasibility and viability of the energy-saving approach across various conditions and dynamic situations. By conducting thorough testing and experimentation, our ultimate goal is to establish the validity of the proposed approach in real-life scenarios, thus bridging the gap between theoretical advancements and practical application.

3. Research contribution

The methodology developed and experiments conducted herein have made the following noteworthy contribution.

- **Intelligent cooling management system:** In this study, an advanced intelligent cooling management system has been developed, which effectively utilizes backend infrastructure to integrate hardware components and employs a combined ANNs-PSO data analytics platform. The system is fully automated, enabling real-time data gathering and demonstrating remarkable adaptability to changing conditions, including user behavior and environmental variations. Leveraging the predictive capabilities of the ANNs and the optimization competence of the PSO, the system ensures optimal energy conservation without compromising user comfort. The effectiveness of this system was validated through practical experiments conducted in a real smart home environment.

- **Microservice-based architecture platform:** The implementation of a microservice-based architecture enhances the flexibility and scalability of the data analytics model. This framework enables seamless customization to meet specific requirements and facilitates easy expansion to accommodate a growing user base. Moreover, the microservice-based approach demonstrates remarkable compatibility with automated demand response programs, which aim to optimize electricity consumption in response to price incentives. Utilizing a cloud-based server system, the proposed architecture ensures effortless and cost-effective implementation, operation, and maintenance, making it highly suitable for large-scale deployment in practical scenarios.
- **Economically efficient design**: Previous studies on smart homes have highlighted the potential energy savings of air conditioning systems that can be adjusted based on occupancy or user activity. Existing discussions have explored various approaches to control air conditioning systems based on factors like the number of occupants or users' activities. However, the development of such models often necessitates the use of more costly and specialized sensors, surpassing the affordability of common household ones typically available. To address this concern, the hardware and software design of the intelligent cooling system in our research was thoughtfully tailored to align with commonly accessible and economical IoT devices or sensors, including temperature and humidity sensors, smart meters, and an infrared (IR) blaster, commonly found in embedded systems and readily available in the market. This deliberate implementation approach was aimed at promoting practical adoption among smart home users, facilitating energy savings, and encouraging sustainable practices.
- **Advanced comfort prediction model:** While most existing models use only future temperature forecasts to estimate room comfort, our research introduces an advanced data analytics model capable of predicting both temperature and humidity for the PMV comfort indicator as well as power consumption as a key indicator of energy conservation. These predictions are used to determine the optimal settings for the cooling management system, thus enabling a more accurate and holistic evaluation of the system's performance.
- **Balancing energy conservation and comfort**: The system's utilization of the PMV index, an industry-standard index for thermal comfort assessment, features its commitment to minimizing occupants' potential discomfort while enhancing energy conservation. This dual objective highlights the system's adaptive nature.

4. Proposed methodology for intelligent cooling management system

4.1. Hardware and software development for data analytics microservice platform

The intelligent cooling management system has been designed based on the microservices architectural concept. This approach involves segmenting a comprehensive application into smaller, self-contained modules, each with specific and well-defined responsibilities. By adopting this methodology, the system achieves a higher level of modularity, scalability, and flexibility in its development process. An illustrative example of this concept is the implementation of containers, which allow developers to focus independently on individual services without being hindered by interdependencies with other modules. This approach enhances the agility and efficiency of system development. In contemporary practices, cloud-based applications predominantly adopt containers and microservices as fundamental building blocks. Containers provide an environment where applications can run consistently across various platforms, thus simplifying deployment, and ensuring consistency. The system architecture of the proposed cooling energy management system with a data analytics model in a smart home environment is depicted in Fig. 1, consisting of three main parts.

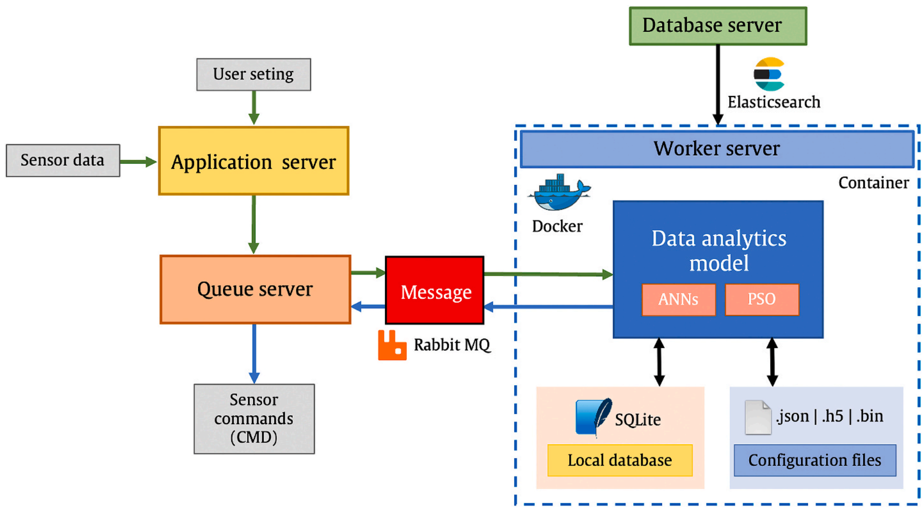


Fig. 1. Proposed intelligent cooling management system with a data analytics model in a smart home system.

- The Application Server serves as a central hub within the system, playing a pivotal role in efficiently receiving commands from various sources, including mobile applications, web admin applications, and IoT gateways, achieved by utilizing a REST API. The server aggregates and analyzes essential user data including significant data elements such as user identification, home identification, gateways, and sensors. These data elements collectively contribute to the efficient functioning and coordination of the entire cooling energy management system.
- The Worker Server functions in a supplementary role, enhancing the capabilities of the Application Server by actively monitoring and responding to instructions transmitted via the Queue Server. The range of duties it undertakes encompasses various tasks such as the gathering of sensor data, which is then intended for archival purposes or storage within the database. The data that have been gathered assist the system in understanding the prevailing conditions within the home and making informed decisions regarding cooling management. The system consistently receives real-time data from multiple sensors, and the Worker Server stores this information for future reference and analysis. The utilization of historical data is a significant process for system optimization, allowing for insights into long-term patterns and trends related to cooling energy consumption and indoor environmental conditions.
- The Queue Server plays an important role in effectively distributing sub-tasks to a variety of servers after receiving data from the Application Server. The system effectively manages the task allocation process by efficiently directing assignments to the Worker Server for optimal data storage. Additionally, the Queue Server is responsible for issuing control commands to sensors and other internet of things (IoT) devices deployed within the home environment. The Queue Server ensures an efficient data storage mechanism through well-organized management of the task allocation process.

The home energy management system was architecturally structured to function as a microservice, and by this design, the data analytics model was developed as a microservice platform. The data analytics models operate on separate servers, distinct from a single home energy management system server, and run on Docker with the Python interpreter in Python 3.8. Utilizing a container makes the data analytics model easily implementable and scalable to accommodate future user groups [32]. The data analytics model is equipped with necessary Python packages comprising pika 1.2.0 for retrieving data through RabbitMQ [33], elasticsearch 7 7.17.2 for retrieving data [34], keras 2.4.3 for ANNs [35], scikit-learn 1.2.0 for splitting datasets and calculating the mean squared error [36], and pythermalcomfort 2.1.0 for evaluating the PMV index of the ambient conditions in the room from temperature and humidity [37].

The data connection, as outlined in Fig. 1, is divided into two primary components: real-time data transmission and historical data retrieval. The real-time data transmission involves acquiring current temperature or humidity data from sensors and dispatching control commands to the IoT devices. This process is facilitated by transmitting data in the form of messages, utilizing the RabbitMQ messaging platform. In the second component, historical data is retrieved from the database server via Elasticsearch. Additionally, a local database is instantiated using SQLite to store essential data. Configuration files are generated and saved in the.json file format to store connection settings. The trained data acquired from the analytical model are saved in either the.h5 file format or the.bin file format. All the files are stored within the model's container.

Fig. 2 illustrates the operational framework of the data analytics model within the context of the cooling energy management system. Central to this model is the collection of crucial environmental air condition data from deployed sensors. The model acquires data on ambient air conditions through sensors, capturing vital variables such as indoor temperature, indoor humidity, and outdoor temperature before any alterations are made to the air conditioning system. Subsequently, the data analytics model utilizes the gathered information to evaluate the process of adjusting the air conditioning system, giving priority to both energy conservation and occupant comfort factors.

After collecting ambient data, the data analytics model conducts a comprehensive analysis for adjusting the air conditioning setting. The model's primary goal is to achieve an optimal balance between two fundamental factors: energy conservation and occupant comfort. By analyzing the collected data, the model investigates the relationship among multiple variables, enabling the identification of the most efficient and comfortable air conditioning settings.

The data analytics model performs a comprehensive evaluation of the potential effects of various cooling adjustments on both energy consumption and indoor comfort levels. It considers a range of variables, including ambient temperature, humidity, and outdoor conditions. Prioritizing energy conservation while maintaining occupant comfort, the model ensures the optimal operation of the cooling energy management system. This approach effectively achieves the dual goals of improving energy efficiency and meeting

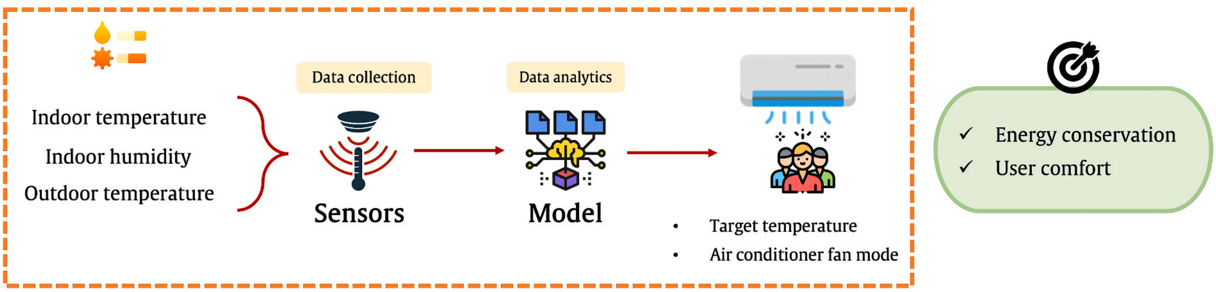


Fig. 2. Control process of the proposed intelligent cooling management system.

user needs. By achieving an optimal equilibrium between energy conservation and occupant comfort, the data analytics model contributes significantly to the system's ability to enhance cooling efficiency and maintain a desirable indoor environment within the smart home setting.

4.2. Prediction of power consumption and indoor environment by ANNs

ANNs are a mathematical model with learning capabilities [9,10]. In the context of this study, two sets of ANNs are utilized within the intelligent cooling management system: one for predicting power consumption and the other for predicting indoor temperature and indoor humidity. The development process of the ANNs in this research comprises two stages: learning and evaluation. During the learning phase, data that have been collected and stored in the local database are used to train the ANNs. This enables the ANNs to learn and retain information about weights and biases, generating an activation function that is then employed in the evaluation phase. The training process is based on a comprehensive set of data that includes patterns of the indoor environment and how the air conditioning unit is used by occupants. The objective is to give enough examples so that appropriate weights can be set for the different situations that can happen during use. For this study, the training data include the typical weather conditions of Thailand, which are hot and humid, as well as the actual usage patterns of occupants in the smart home, which are typically between 23 °C and 27 °C and range from 0 (low) to 2 (high) for the air conditioner fan mode. For other weather conditions, like a cold climate with the use of heating devices, correct and accurate predictions of energy use and indoor conditions require collecting the right data for training, which should matchthe behavior of the population in using heating devices.

During the evaluation phase, the current data from the sensors and the activation function created during the learning phase are utilized as input data. These data points serve as the basis for the ANNs to conduct their predictive analysis. The output of the ANNs includes three key predictions: power consumption, indoor temperature, and indoor humidity. These predictions are activated whenever changes occur in the target temperature and the fan mode of the air conditioner in response to the ambient conditions in the room.

As shown in Fig. 3, the prediction of power consumption by the first ANN involves the utilization of five key input data points: air-conditioner fan mode, indoor temperature, differential temperature, indoor humidity, and outdoor temperature. The differential temperature is the difference between the indoor temperature and the target temperature. When these different types of data are combined, the ANN can make accurate estimates about the power consumption of the air conditioner. For these calculations, the ANN architecture has two hidden layers, each with 150 nodes. These hidden layers are a key part of the model's ability to find useful patterns and relationships in the data it receives, facilitating the model's ability to recognize complex dependencies and correlations. Through this layered design, the ANN can do complex computations and improve its predictions iteratively to achieve a high level of precision and accuracy.

Fig. 4 illustrates three key input data points of the second ANN: indoor temperature, indoor humidity, and predicted power consumption, which collectively serve as the basis for estimating the predicted indoor temperature and the predicted indoor humidity. The neural network architecture employed in this estimation process consists of two hidden layers, each comprising 150 nodes. This configuration ensures a robust and comprehensive data analysis capability, enabling sophisticated pattern recognition and data processing. The hidden layers of the ANN are designed to extract meaningful features and relationships from the input data, enabling the model to identify and capture significant dependencies among the variables. Through this iterative and dynamic process, the model refines its estimations iteratively, achieving greater accuracy and precision in its predictions. The ability of this ANN to estimate the indoor temperature and the indoor humidity is important to improve the cooling energy management system's overall performance, allowing for more informed decisions and precise control of the indoor environment.

4.3. Predicted mean vote for air comfort measurement from air conditioner adjustment

PMV is an established index widely used to assess the overall thermal comfort experienced by individuals in a specific environment [13,14]. In the context of the data analytics model, the PMV index serves as a useful indicator of the ambient air condition within the

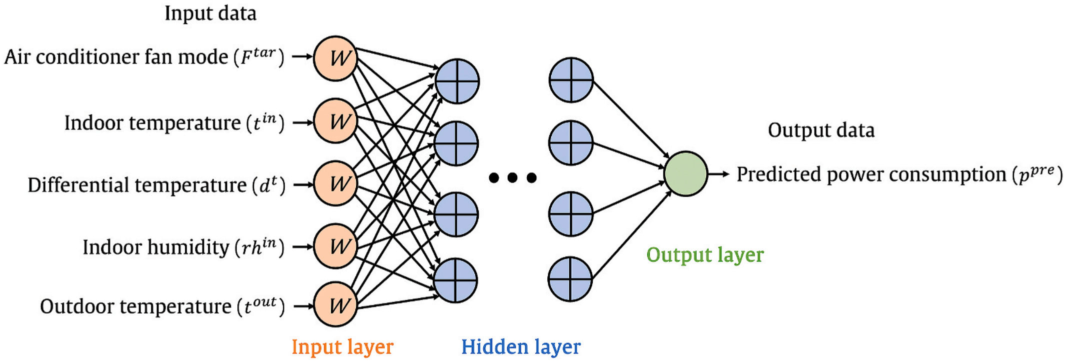


Fig. 3. ANN architecture for predicting power consumption.

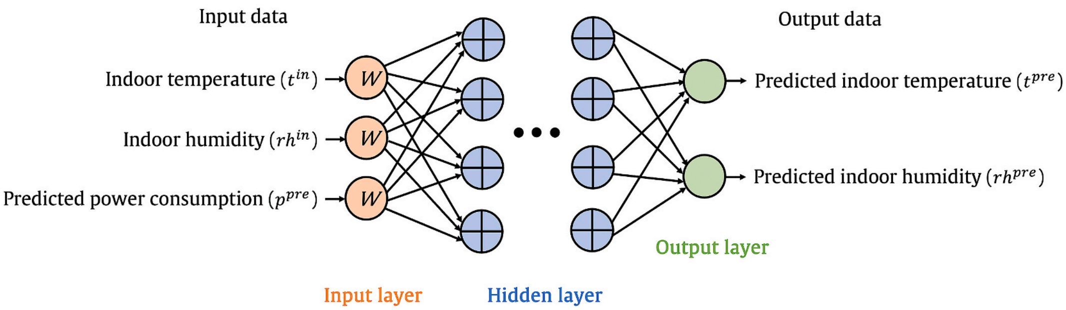


Fig. 4. ANN architecture for predicting indoor temperature and indoor humidity.

room with its variation directly influenced byair conditioning control settings selected by users. The PMV index is derived from predicted temperature and predicted humidity data, reflecting the prevailing air quality that should ideally fall within a range ensuring users' comfort. For a 7-stage PMV scale, the index is evaluated as an integer value from −3 to +3, indicating the average person's perception of the environment from very cold to very hot, respectively [38,39]. It is generally recommended that the PMV index should be between −0.5 and 0.5 to ensure occupants' comfort in confined spaces.

Fig. 5 identifies the shaded region representing the comfort zone for users, along with the correlation between temperature and humidity. For instance, a combination of indoor temperature at 27 °C and indoor humidity at 61 rh corresponds to a room environment with which the user feels comfortable. However, maintaining the same temperature while increasing indoor humidity leads to a decrease in user comfort. Both temperature and humidity jointly influence the optimal adjustments required. While air conditioners enable users to control the temperature, the level of dehumidification remains beyond their direct control. Consequently, each instance of activating the air conditioner results in varying reductions of humidity within their homes.

In the data analytics model, the Pythermalcomfort Python package [37] is employed to calculate the PMV index from six key parameters. The four indoor parameters that reflect the indoor ambient condition are air temperature, mean radiant temperature, air velocity, and relative humidity. The other two parameters that indicate the personal condition are metabolic rate and thermal resistance of clothing. The parameters used in the PMV calculation and the relationship of PMV to the thermal sensation scale as shown in Fig. 6 are assigned as follows: the human body has a metabolic rate of 1 for minor activities like sitting or lying [40,41], an air velocity of 0.3 for small, enclosed rooms or bedrooms, and the thermal resistance of clothing is 0.42 for short-sleeve pajamas [35]. The air temperature and mean radiant temperature are set at the predicted indoor temperature, and the humidity is set at the predicted indoor humidity. Note that adjustment of the air conditioner determines the predicted indoor temperature and the predicted indoor humidity.

4.4. PSO for selecting optimal air conditioner adjustment

PSO is a well-known optimization technique based on the collective foraging behavior of bird flocks and fish schools. This metaheuristic algorithm has proven to be useful for a wide variety of optimization problems, as it employs a swarm of particles to navigate

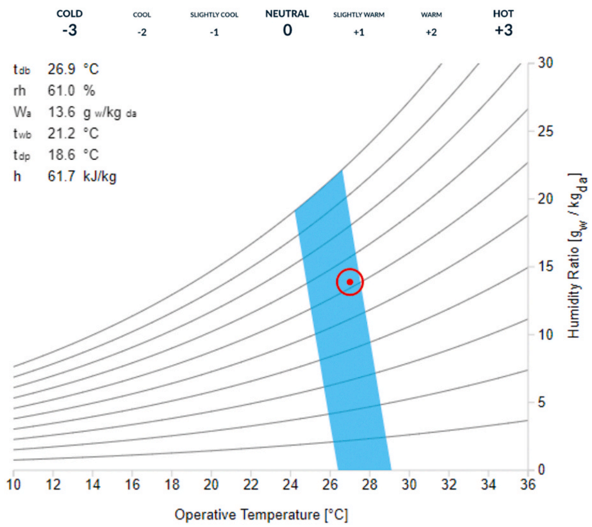
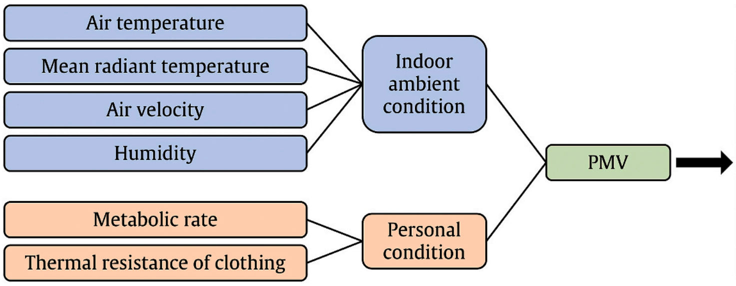


Fig. 5. Temperature and humidity correlation in PMV analysis.



PMV	Thermal sensation scale
3	Hot
2	Warm
1	Slightly warm
0	Neutral
-1	Slightly cool
-2	Cool
-3	Cold

Fig. 6. Parameters used in PMV calculation and the relationship of PMV to thermal sensation scale.

the search space and identify the best solution. Each particle represents a viable alternative [11,12]. PSO is competitive with other algorithms with comparable objectives, including genetic algorithms (GAs) [42], ant colony optimization (ACO) [43], and simulated annealing (SA) [44]. One of its primary advantages is its implementation simplicity, which facilitatesproblem-solving in comparison to the complex crossover and mutation operations of GA. PSO frequently outperforms other methods in terms of speed and efficiency, making it ideal for real-time applications and situations with limited computational resources. PSO enables particles to exchange information regarding the best solution, thereby accelerating convergence to the optimal solution. In this research, the PSO algorithm was employed with 30 particles (n) and 4 particle movements (k). It was developed to optimally select the target temperature and the air conditioner fan mode based on the pseudocode of the PSO algorithm given in Table 1. This decision aimed to conserve energy while minimally impacting user comfort.

$$penalty_i(t) = \begin{cases} 100 \times |PMV_i(t)| & , -0.5 < PMV_i(t) < 0.5 \\ 0 & , PMV_i(t) < -0.5 \text{ or } PMV_i(t) > 0.5 \end{cases} \quad ; \quad i = 1,2,...,n, t = 1,2,...,k \tag{1}$$

$$P_i(t) = p_i^{avg}(t) + penalty_i(t) \quad ; \quad i = 1,2,...,n, t = 1,2,...,k \tag{2}$$

$$Pbest_i = \min[P_i(t)] \quad ; \quad i = 1,2,...,n, t = 1,2,...,k \tag{3}$$

$$Gbest(t) = \min[Pbest_i(t)] \quad ; \quad i = 1,2,...,n, t = 1,2,...,k \tag{4}$$

$$\vec{V}_i(t+1) = w\vec{V}_i(t) + n_1 r_1 \left[Pbest_i - \vec{X}_i(t)\right] + n_2 r_2 \left[Gbest_i - \vec{X}_i(t)\right] \quad ; \quad i = 1,2,...,n, t = 1,2,...,k \tag{5}$$

$$\vec{X}_i(t+1) = \vec{X}_i(t+1) + \vec{V}_i(t+1) \quad ; \quad i = 1,2,...,n, t = 1,2,...,k \tag{6}$$

where.

Table 1
Pseudocode of the PSO algorithm for determining the optimal air conditioner adjustment.

Input data	Current ambient weather information is obtained from sensors that measure indoor temperature, outdoor temperature, and indoor humidity.
Output data	Best target temperature and best air conditioner fan mode
1	**For** $i = n$, work from the first particle to the n^{th} particle.
	Random $\vec{X}_i(1)$ and $\vec{V}_i(1)$ of each particle in the swarm with two dimensions: $t_i^{tar}(1)$ and $F_i(1)$.
	End For
2	**For** $t = k$, work from the first particle movements to the k^{th} particle movements.
2-1	**For** $i = n$, work from the first particle to the n^{th} particle.
2-1-1	Predict $p_i^{pre}(t)$, $t_i^{pre}(t)$, and $rh_i^{pre}(t)$ from $\vec{X}_i(t)$ (comprising $t_i^{tar}(t)$ and $F_i(t)$) and obtain the current ambient weather information from the sensors using the ANNs.
2-1-2	Calculate the average predicted power $p_i^{avg}(t)$ from $p_i^{pre}(t)$.
2-1-3	Assess $PMV_i(t)$ in the room from $t_i^{pre}(t)$ and $rh_i^{pre}(t)$ when the air conditioner is operating.
2-1-4	Calculate $penalty_i(t)$ from Eq. (1).
2-1-5	Calculate $P_i(t)$ from $p_i^{avg}(t)$ and $penalty_i(t)$ from Eq. (2).
2-1-6	Find $Pbest_i(t)$ from Eq. (3).
	End For
2-2	Find $Gbest(t)$ from Eq. (4).
2-3	**For** $i = n$, work from the first particle to the n^{th} particle.
2-3-1	Adjust velocity $\vec{V}_i(t+1)$ from Eq. (5).
2-3-2	Adjust position $\vec{X}_i(t+1)$ from Eq. (6).
	End For
	End For

$\overrightarrow{X}_i(t)$= position of particle i at particle movement t
$\overrightarrow{V}_i(t)$ = velocity of particle i at particle movement t
$t_i^{tar}(t)$ = target temperature of particle i at particle movement t
$F_i(t)$ = air conditioner fan mode of particle i at particle movement t
$p_i^{pre}(t)$ = predicted power consumption of particle i at particle movement t
$t_i^{pre}(t)$ = predicted indoor temperature of particle i at particle movement t
$rh_i^{pre}(t)$ = predicted indoor humidity of particle i at particle movement t
$p_i^{avg}(t)$ = average predicted power consumption of particle i at particle movement t
$PMV_i(t)$ = predicted mean vote index of particle i at particle movement t
$penalty_i(t)$ = penalty term of particle i at particle movement t
$P_i(t)$ = fitness of particle i at particle movement t
$Pbest_i(t)$ = individual particle's best of particle i at particle movement t
$Gbest(t)$ = global particles' best at particle movement t
w, n_1, n_2 = weight parameters
r_1, r_2 = uniform random number between 0 and 1

4.5. Data acquisition and analytics processes

The overall architecture of the data analytics model used to determine the optimal air-conditioning adjustments is depicted in Fig. 7. At the core of this model lie the ANNs, which analyze the environmental conditions and power consumption associated with each air-conditioning adjustment case. The ANNs effectively process data from the five key variables, enabling them to make well-informed decisions regarding the optimal target temperature and the fan mode for the air conditioner. The sensors inside the home provide the ambient climate data for the three variables: indoor temperature, indoor humidity, and outdoor temperature. The PSO is specifically employed for its optimization capabilities, ensuring that the cooling energy management system attains the most suitable target temperature and fan mode to achieveoptimal energy efficiency and occupant comfort. The two output variables are determined by the PSO, namely the target temperature data, and the air conditioner fan mode. By combining the ANNs' pattern recognition and data processing abilities, coupled with the PSO's optimization ability, the data analytics model achieves a harmonious balance between energy conservation and occupant well-being.

Fig. 8 (a) shows the data acquisition process for training the ANNs. The data used to train the ANNs include power consumption, outside temperature, room temperature, room humidity, air conditoner fan mode, and target temperature. The data are normally collected for 30 days with a frequency of 1 min. The ANNs train the dataset and store the learning data in the format of.h5 files. Fig. 8 (b) presents the data analytics process to determine the optimal air conditioning adjustment in real time. The ANNs use the learning data stored in the.h5 file to predict the ambient temperature and the energy consumption of the air conditioner in the next 1 min ahead. The PSO will then select the most suitable air conditioner adjustment for a given input obtained from the ANNs. This predictive capability enables the system to anticipate changes in the indoor environment and the air conditioner's energy requirements, enabling proactive and responsive cooling management. Through this synergy between the trained ANNs and the PSO algorithm, the proposed cooling energy management system navigates dynamic environmental changes effectively, optimizing cooling operations and ensuring user comfort and energy efficiency.

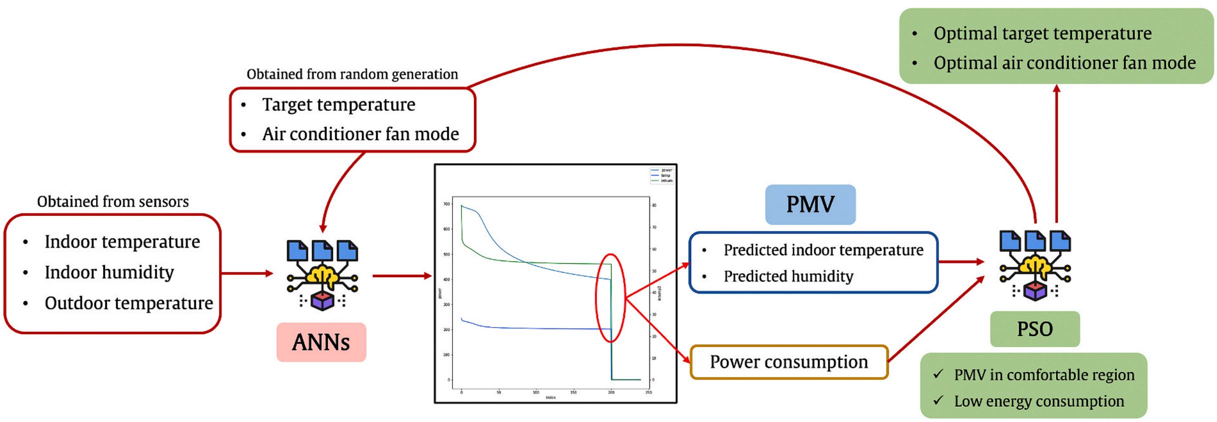


Fig. 7. Data analytics process for the optimal air conditioner adjustment.

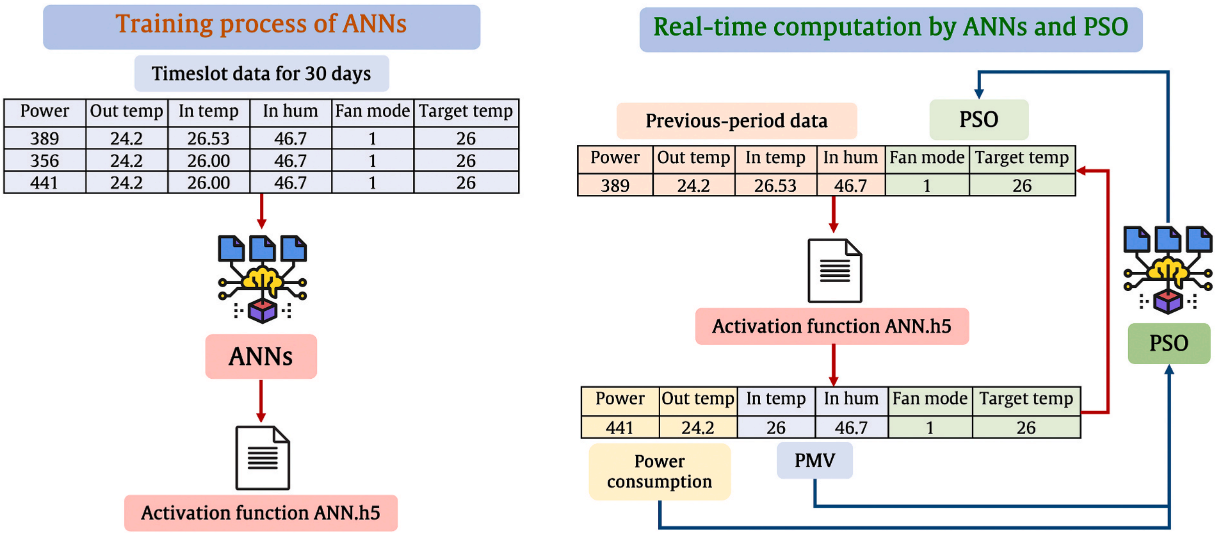


Fig. 8. Data acquisition and analytics processes. (a) training process of the ANNs, (b) real-time computation by the ANNs and the PSO.

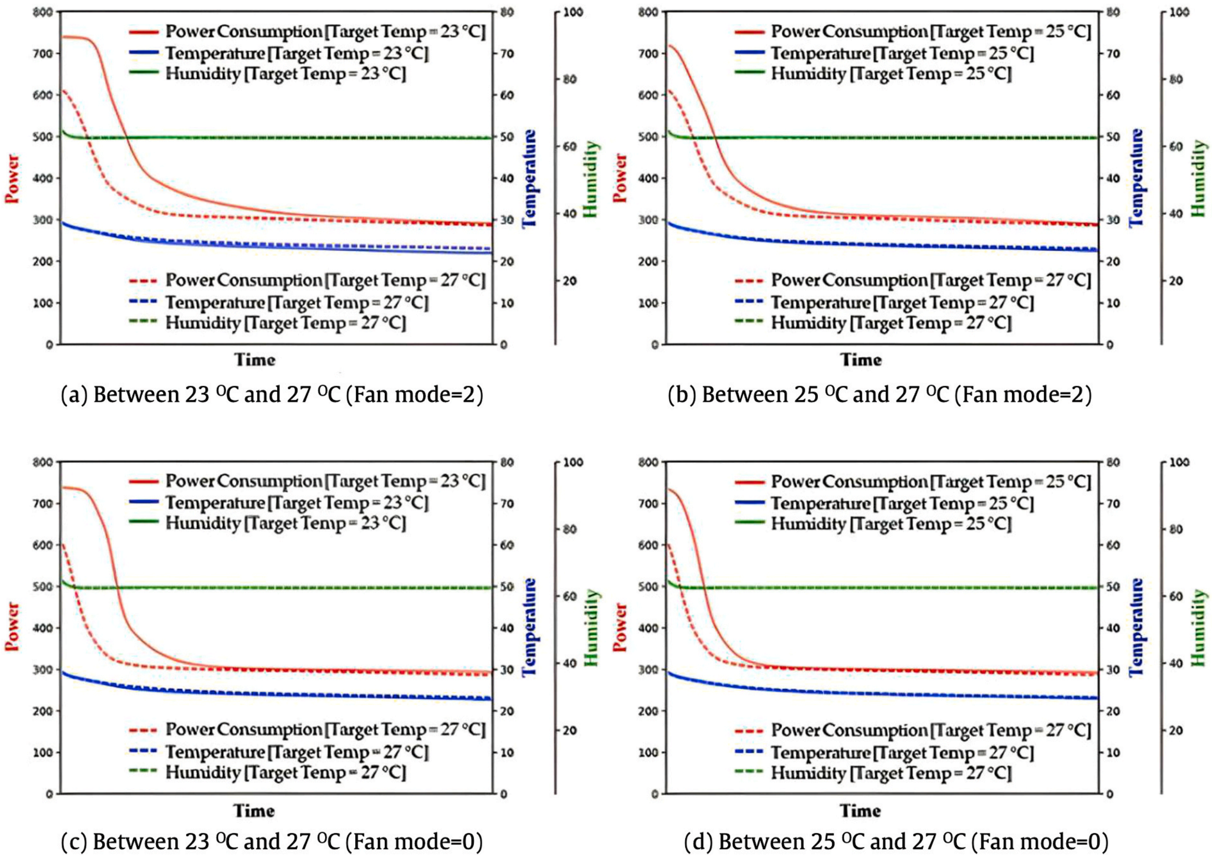


Fig. 9. Predicted results for different adjustments of target temperature.

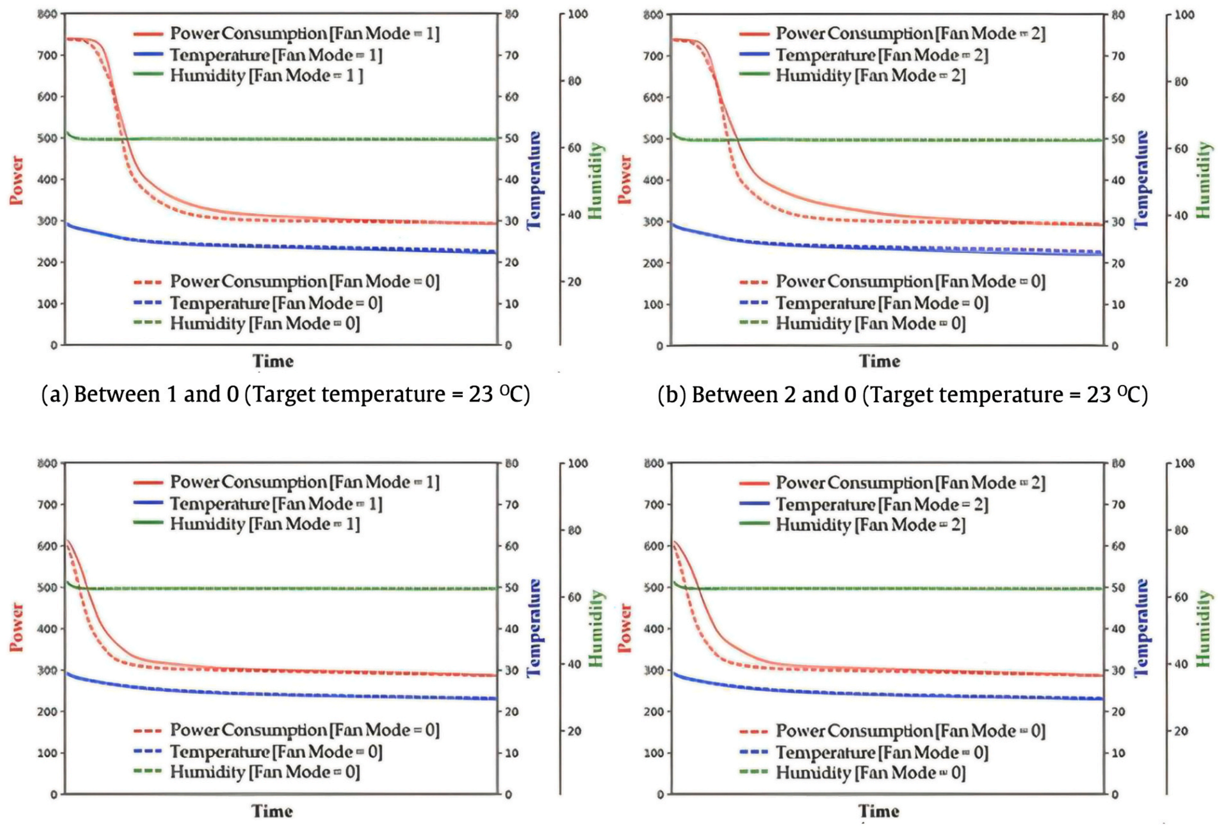
5. Implementation results

5.1. Testing environment

In the air conditioner control process, the data analytics model uses the developed ANNs to predict power consumption, indoor temperature, and indoor humidity. The collected data were stored and used for training and testing datasets. To validate the effectiveness of the cooling management system and the data analytics model, an empirical examination was conducted employing an 8,000 BTU air conditioner as the testbed. This evaluation was carried out within a real smart home environment, situated within a detached two-story house spanning an area of 8 × 5 m^2, accommodating four occupants. The devices and sensors used for data collection, such as smart meters, temperature and humidity sensors, and IR blasters, were installed in the test environment. The environmental weather data collected were representative of Thailand's hot and humid climate. The air conditioning settings data reflected the real usage patterns of the smart home occupants, with temperatures ranging from 23 °C to27 °C and fan modes from 0 (low) to 2 (high),which are typical usage patterns among the Thai population [45].

5.2. Evaluation of predicted parameters

Under ambient conditions with an outdoor temperature of 30.25 °C, an indoor temperature of 29.36 °C, and an indoor humidity of 64.66 rh, Fig. 9 presents a comparison of predicted outcomes resulting from different target temperature adjustments while maintaining the same air conditioner fan mode. Specifically, Fig. 9(a) demonstrates the variations in predicted outcomes following adjustments of the target temperatures to 23 °C and 27 °C, with a constant fan mode of 2 (high). In Fig. 9(b), the disparities in predictions are shown when altering the target temperatures to 25 °C and 27 °C, with the fan mode remaining set at 2 (high). Fig. 9(c) exhibits the variances in predictions resulting from changes in the target temperatures to 23 °C and 27 °C, while the fan mode remains at 0 (low). Finally, Fig. 9(d) illustrates the differences in projected outcomes with adjustments to the target temperatures at 25 °C and 27 °C, while the fan mode remains at 0 (low). Fig. 10 compares predicted outcomes with different air conditioner fan mode adjustments while keeping the target temperature constant: a fan mode change between 1 (medium) and 0 (low) at 23 °C in Fig. 10(a)–a fan mode change between 2 (high) and 0 (low) at 23 °C in Fig. 10(b)–a fan mode change between 1 (medium) and 0 (low) at 27 °C in Fig. 10(c)–and a fan mode change between 2 (high) and 0 (low) at 27 °C in Fig. 10(d).



(a) Between 1 and 0 (Target temperature = 23 °C)

(b) Between 2 and 0 (Target temperature = 23 °C)

(c) Between 1 and 0 (Target temperature = 27 °C)

(d) Between 2 and 0 (Target temperature = 27 °C)

Fig. 10. Predicted results for different adjustments of fan mode.

The various predicted outcomes indicate that the air conditioner's energy consumption initially peaked as it worked aggressively to reduce the room's temperature to the predetermined level while also rapidly reducing the humidity. Once the room reached the desired temperature, the air conditioner switched to a mode that maintains a constant temperature and humidity level while consuming less energy. Changes in the fan mode had a minor impact on power consumption, while adjustments to the target temperature significantly affected the air conditioner's power consumption, especially during the initial cooling phase when the air conditioner had to actively lower the room temperature to meet the set target.

5.3. Optimal selection of air conditioner adjustment

The developed PSO algorithm was utilized in the data analytics model to determine the most optimal air conditioner adjustment. For an ambient air condition where the ambient temperature outside the room was 30.25 °C, the room temperature was 29.36 °C, and the humidity inside the room was 64.66 rh, the PSO would select the most appropriate air conditioner setting at a target temperature of 27 °C and an air conditioner fan mode at 0 (low). Fig. 11 shows the convergence report of the PSO calculations. Fig. 11 (a) indicates the initial position of each randomized particle with two dimensions, where the horizontal axis represents the temperature target, and the vertical axis represents the air conditioner fan mode. The fitness of each particle would be evaluated by its PMV index and average predicted power consumption. A particle exhibiting a PMV index closer to zero and lower average predicted power consumption indicates superior fitness defined by Eq. (2). The optimal particle with the lowest fitness was set to the global best position defined by Eq. (4) to determine the position and speed of other particles in the next iteration. Fig. 11 (b) and (c) show the position of the particles that were converging more and more toward the optimum with each subsequent movement. The PSO eventually succeeded in identifying the optimal setting for the test environment at a temperature of 27 °C and fan mode 0 (low).

Table 2 presents the predicted indoor temperature, the indoor humidity, the average predicted power consumption, the PMV index, and the fitness value for each air conditioner adjustment case. These adjustments reflect the typical air conditioning usage patterns observed among the residents of the test group. Their settings typically fall within the range of 23 °C–27 °C for temperature and between 0 (low) and 2 (high) for the fan mode. The results demonstrate that each air conditioner adjustment case produces a unique average predicted power consumption. The PSO successfully identified the optimal solution illustrated in Case No. 5, with the remaining other cases evaluated and listed in the table for comparison. Increasing the target temperature can lower power consumption during the phase where the air conditioner lowers the indoor temperature to reach the target. Similarly, decreasing the air conditioner fan mode can reduce power consumption. When the indoor temperature is maintained equal to the target temperature, the air conditioner's power consumption is comparable across all cases with different air conditioner fan modes (as shown in Figs. 9 and 10).

Regarding the use of the air conditioner, humidity decreased to 62 rh across all test air conditioner cases. The indoor temperature would be reduced to an equal or lower level than the target temperature. However, it is important to note that changes in the indoor temperature and the indoor humidity vary from one air conditioner to another. It can be observed that the PMV index for the target temperature of 27 °C of the tested air conditioner exceeded the comfort range as the resulting indoor temperature dropped to 23 °C. Finally, the PSO-based data analytics model decided to select Case No.5, in which the target temperature was set to 27 °C and the air conditioner fan mode was set to 0 (low) as this case gave the best fitness. The response time from temperature adjustment until reaching a steady state condition took about 5 min.

In situations where exhaustive datasets capturing air conditioner usage patterns have been compiled and validated for training and testing purposes, the analysis can proceed as intended. Nonetheless, this study relied on the empirical data collected from actual smart home environments, where residents' air conditioner usage was recorded. The dataset primarily consisted of daily life usage within the test group, with most samples falling within the 23°C–27 °C temperature range. This range aligns with the typical comfort preferences of the majority of the population in Thailand, a region characterized by hot and humid weather. While the test air conditioner used in this study was able toadjust temperatures beyond this range, like 18°C–30 °C as per the device specifications, the focus was on the more commonly targeted comfort range.

In the context of air conditioning practices in Thailand, temperatures outside the range of 23 °C–27 °C are uncommon. Therefore, the test air conditioner's capability to operate below 23 °C or above 27 °C should be considered within the context of a research

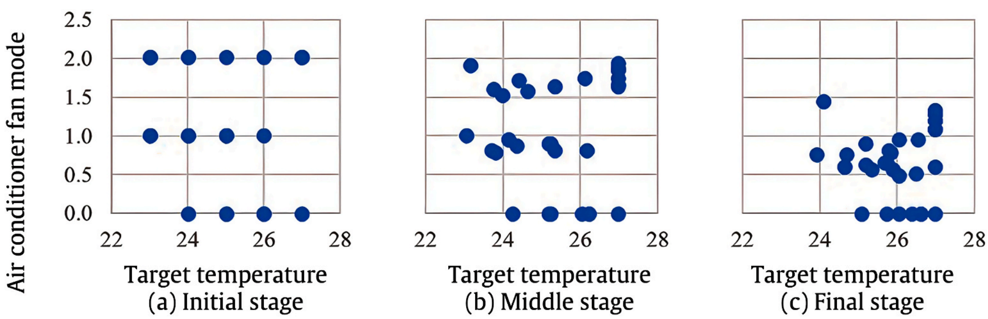


Fig. 11. Convergence results obtained from the PSO.

Table 2
Outcome of different air conditioner adjustments in 3 h of operation.

Case No.	Temperature target (°C)	Fan mode (mode)	Predicted indoor temperature by ANN (°C)	Predicted indoor humidity by ANN (rh)	Average predicted power consumption by ANN (W)	PMV index	Fitness value
1	23	0	22.69	62	361	−2.04	565
2	24	0	22.89	62	351	−1.96	547
3	25	0	23.00	62	340	−1.91	531
4	26	0	23.10	62	327	−1.86	513
5	**27**	**0**	**23.20**	**62**	**314**	**−1.82**	**496**
6	23	1	22.24	62	373	−2.25	598
7	24	1	22.49	62	363	−2.14	577
8	25	1	22.73	62	351	−2.02	553
9	26	1	22.91	62	337	−1.95	532
10	27	1	23.07	62	325	−1.88	513
11	23	2	22.06	62	380	−2.33	613
12	24	2	22.24	62	369	−2.25	594
13	25	2	22.51	62	356	−2.12	568
14	26	2	22.78	62	342	−2.00	542
15	27	2	23.01	62	329	−1.90	519

experiment, rather than as a reflection of typical regional usage patterns. In situations where the analytical model was deployed in areas with diverse climate profiles or differing air conditioner usage habits involving a broader range of temperatures, it would be necessary to collect localized data that capture both weather conditions and the population's air conditioner usage behaviors. The inclusion of such additional data sets would enhance prediction accuracy and facilitate more thorough data analysis, all without necessitating significant alterations to the proposed hardware and software model developed in this study.

For the users' setting of the air conditioner for a temperature at 23 °C and a fan mode at 2 (high), the average predicted power consumption over the 3 h of operation is 380 W, whereas the optimal setting for a temperature at 27 °C and a fan mode at 0 (low) consumed only 314 W. A saving of 66 W per hour can be obtained in this case. If the air conditioner was regularly used for 10 h a day, a total energy of 660 Wh a day, or equivalently about 240 kWh a year could be saved. The cost saving depends on the electric tariff of the users. For example, if the average cost of electricity is 4.72 Baht/kWh (about $0.137/kWh), the users would save 1,133 Baht (about $33) a year for each air conditioner unit. In a competitive electric market, a retailer can offer this smart home feature to its customers for energy-saving benefits. From the retailer's perspective, the microservices-based data analytics model presented in this paper offers scalability in expansion and flexibility in customization and cost management. This is facilitated through the shared, upgradable hardware and software infrastructure among a large number of households. Consequently, the retailer can retain customers with improved satisfaction while realizing substantial cost savings related to the number of air conditioners in households and their operational hours.

5.4. Discussion

The data analytics model employs the two sets of ANNs and the PSO to analyze and determine the optimal target temperature and fan mode for the air conditioner. The joint utilization provides an efficient and effective method for optimizing the operation of the air conditioner, which contributes to energy conservation and enhanced indoor comfort. The ANNs are responsible for forecasting the surrounding weather conditions and the energy consumption caused by air conditioner settings. These settings include the desired temperature, the mode of the air conditioner's fan, and the ambient weather data including indoor temperature, indoor humidity, and outdoor temperature. The predicted energy consumption results from the first ANN for each case can be used to validate the energy-saving capability of each setting. The comfort of the occupants can also be evaluated based on the predicted ambient weather conditions derived from the second ANN. These predicted weather conditions are converted into the PMV index that is used to evaluate the occupants' level of comfort. This implies that errors in the ANNs' prediction stage could be a significant source of analysis errors.

The recognition of errors arising during the prediction phase by the ANNs holds a significant impact on the overall analysis. Overfitting, where ANNs perform well on training data but poorly on unseen data, is a common prediction error problem. Regularization, dropout, and early stopping can reduce overfitting. These methods help the model generalize to unseen data, improving its robustness and accuracy. Training data inadequacy is another common prediction error cause. Thus, comprehensive data collection, including ambient weather conditions and air conditioner usage patterns among the target population, is essential. For instance, in a country like Thailand, characterized by a hot and humid climate with similar weather conditions and air conditioner usage patterns across different seasons, data collection becomes relatively straightforward. However, in areas with distinct geographical characteristics and extreme variations in weather conditions across seasons, more detailed and extensive data collection efforts are required.

The process of collecting detailed and numerous amounts of data improves the prediction accuracy of the ANNs, which can be determined by comparing the predicted results based on the test data inputs with the actual results. In addition, the quantity of training data is essential for assessing the occupants' comfort, as the PMV index serves as a benchmark. However, the PMV calculation is determined by six primary variables: air temperature, mean radiant temperature, air velocity, relative humidity, metabolic rate, and thermal resistance of clothing. Due to the limitations of available measuring devices, air velocity, metabolic rate, and thermal resistance of clothing are normally set as constants for bedroom environments. If these constants were replaced with other measurement devices, it would increase the accuracy of evaluating the comfort level of occupants, impacting the accuracy of selecting the most suitable air conditioning settings.

PSO is an algorithm inspired by natural social behaviors. Its strengths are simplicity, rapid convergence, and a balanced exploration and exploitation strategy. Its ease of implementation and efficiency make it an appealing choice for optimization tasks. Nevertheless, PSO algorithm performance can be sensitive to parameter selection, such as the number of particles and the weights assigned to personal and social influences, necessitating careful tuning and experimentation.

In summary, the proposed model in this study, which combines the ANNs and the PSO algorithm, offers a robust method for determining optimal air conditioner settings that maximize energy efficiency while ensuring occupants' comfort. The research highlights the importance of comprehensive data collection in improving prediction accuracy and the potential for enhancing evaluations of occupant comfort. By utilizing the PMV as a metric for comfort evaluation, the model can be effectively applied in various smart home applications to achieve energy savings and enhance the overall user experience.

6. Conclusion

This research has introduced an intelligent cooling management system that efficiently determines the target temperature and air conditioner fan mode to ensure economical energy usage. The system development holds significant potential for energy conservation, particularly in buildings where cooling systems account for a substantial portion of energy consumption. The foundation of the intelligent cooling management system rests upon a range of ambient data, air conditioner operation records, and specific performance data. The ambient data include indoor temperature, indoor humidity, and outdoor temperature, while operation records cover usage patterns, target temperatures, and fan modes. The performance data delves into the power consumption in relation to the air conditioner's temperature. The hardware and software development of the intelligent cooling system was designed based on the microservice-based architecture that enhances flexibility and scalability, allowing for easy customization and expansion to accommodate growing user bases. It is highly compatible with automated demand response programs particularly relevant to air conditioning systems and offers cost-effective implementation and maintenance, making it suitable for large-scale deployment.

Two sets of ANNs were utilized in our data analytics model to forecast power consumption, indoor temperature, and indoor humidity with adjustments in target temperature and fan mode. Our PSO algorithm searched for optimal adjustments to maximize energy savings while ensuring minimal disruption to user comfort. User comfort was quantified using the PMV index. The results have demonstrated that the data analytics model adapts well to real-time data collection and fast responses to changing ambient conditions. This adaptability facilitates energy consumption reduction, leading to cost savings for users in terms of electricity expenses.

The challenges and limitations encountered during this research primarily originated from data collection. In the process of gathering data for training and testing, devices, including a smart meter, temperature and humidity sensors, and an IR blaster, were installed in a real-life smart home environment. However, a situation where users regularly operated the air conditioner'sremote control instead of the IR blaster could lead to disparities in the recorded data. Such discrepancies could compromise the accuracy of power consumption, indoor temperature, and humidity predictions. Therefore, for enhanced prediction accuracy, it is crucial to gather comprehensive data that encompass a wide range of ambient conditions and diverse air conditioner adjustments.

Future research can expand on this study in several ways. For instance, upgrading the algorithms for predicting air conditioner energy consumption and forecasting indoor temperature and humidity can be achieved by using recurrent neural networks (RNNs) [46] or long short-term memory (LSTM) [47] instead of ANNs. Given their suitability for time-series data, RNNs or LSTM would match well with the sequential data used in our data analytics model, leading to improved prediction accuracy. Additionally, further development could focus on analyzing an individual user's comfort index instead of the standard PMV. This individual-specific model can enhance comfort level evaluation accuracy.

The developed methodology can be seamlessly extended to other smart systems, opening new avenues for energy efficiency and environmental sustainability, such as heating and lighting. By enabling intelligent control over these aspects of a building or facility, energy consumption can be optimized. For instance, the heating system can be automatically adjusted based on occupancy and weather patterns, while lighting can be controlled to provide the required illumination with minimal energy use. Integrating the data analytics model with domestic or building demand response programs can optimize energy usage and contribute to more efficient energy use. Future exploration could also encompass the incorporation of green energy technologies such as renewable energy resources, electric vehicles (EVs), and energy storage systems into cooling management systems for smart homes and buildings. This strategic integration could drive sustainability and meet the commitment to carbon neutrality and zero-emission targets.

CRediT authorship contribution statement

Somporn Sirisumrannukul: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Tosapon Intaraumnauy:** Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation. **Nattavit Piamvilai:** Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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