

Article

Air Conditioning Energy Saving from Cloud-Based Artificial Intelligence: Case Study of a Split-Type Air Conditioner

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Abstract: This study developed cloud-based artificial intelligence (AI) that could run AI programs in the cloud and control air conditioners remotely from home. AI programs in the cloud can be altered any time to provide good control performances without altering the control hardware. The air conditioner costs and prices can thus be reduced by the increasing energy efficiency. Cloud control increased energy efficiency through AI control based on two conditions: (1) a constant indoor cooling rate and (2) a fixed stable range of indoor temperature control. However, if the two conditions cannot be guaranteed or the cloud signals are lost, the original proportional-integral-differential (PID) control equipped in the air conditioner can be used to ensure that the air conditioner works stably. The split-type air conditioner tested in this study is ranked eighth among 1177 air conditioners sold in Taiwan according to public data. It has extremely high energy efficiency, and using AI to increase its energy efficiency was challenging. Thus, this study analyzed the literature of AI-assisted controls since 1995 and applied it to heating, ventilation, and air conditioning equipment. Two technologies with the highest energy saving efficiency, a fuzzy + PID and model-based predictive control (MPC), were chosen to be developed into two control methodologies of cloud-based AI. They were tested for whether they could improve air conditioning energy efficiency. Energy efficiency measurement involved an enthalpy differential test chamber. The two indices, namely the energy efficiency ratio (EER) and cooling season power factor (CSPF), were tested. The EER measurement is the total efficiency value obtained when testing the required electric power at the maximum cooling capacity under constantly controlled temperature and humidity. CSPF is the tested efficiency value under dynamic conditions from changing indoor and outdoor temperatures and humidity according to the climate conditions in Taiwan. By using the static energy efficiency index EER for evaluation, the fuzzy + PID control could not save energy, but MPC increased the EER value by 9.12%. By using the dynamic energy efficiency index CSPF for evaluation, the fuzzy + PID control could increase CSPF by 3.46%, and MPC could increase energy efficiency by 7.37%.

Keywords: cloud-based artificial intelligence; cooling season power factor (CSPF); energy efficiency ratio (EER); fuzzy + proportional-integral-differential (PID); model-based predictive control (MPC); split-type air conditioner

1. Introduction

According to the International Energy Agency (IEA) report titled “The Future of Cooling” published in 2018 [1], the global amount of air conditioners in buildings will grow to 5.6 billion by 2050, up from 1.6 billion today, which amounts to 10 new air conditioners sold every second for the next 30 years. Global energy demand from air conditioners is expected to triple by 2050. Supplying power to

air conditioners results in large costs and environmental implications. Energy efficiency improvements can cut the energy growth from air conditioning (AC) demand. The IEA report indicated that increased cooling demands will be particularly crucial in hot regions of the world. This problem is particularly sensitive in fast-growing nations, such as India, where the share of AC in peak electricity load may reach 45% in 2050, if no actions are taken. This will require large investments in new power plants to meet peak power demand.

This study aims to develop a methodology for improving AC energy efficiency. Artificial intelligence (AI) is considered as the solution since it has had a boom in development since 1997, and that was the year when Deep Blue from IBM defeated the world chess champion, which indicated major progress in AI technologies. The review of AI developments will be illustrated in Section 3.2. Among different AI techniques, cloud-based AI that can run AI programs in the cloud is proposed as the main methodology. It has the advantage that control algorithms can be changed without altering the control hardware of air conditioners. That contributes to reducing the cost of AC energy efficiency improvement. In this study, AC energy efficiency was measured using the energy efficiency ratio (EER) and cooling season power factor (CSPF). Whether AI techniques can save energy was discussed. Except energy efficiency, the costs and benefits are other research focuses.

Research on the cost and benefit analysis of energy efficiency improvements for room air conditioners in China was reported in 2020 [2]. The study analyzed several combinations of technologies that can be used to improve the efficiency of room air conditioners. A total of 359 design combinations of efficient technologies were investigated, and the efficiency levels of low-cost combinations were estimated. These technologies, both in the market and in development, tend to fall into one of four categories, namely (1) compressors, (2) heat exchangers, (3) variable speed drives (VSDs), and (4) expansion valves. This research analyzed incremental retail prices and energy saving performance for Chinese 3.5 kW 1.0 Refrigeration Ton (RT) split-type air conditioners. The baseline of this air conditioner is a 2.9 energy efficiency ratio (EER) rating. When the expansion valve is changed from a thermostatic valve to an electronic expansion valve, energy saving performance increases by 5–8%. The retail price can increase by up to RMB 180. Compressor improvement can increase the EER rating from 3.0 to 3.6. Energy saving can be by up to 20%. The increment retail price increases to RMB 400 when a high-efficiency compressor is equipped. Modified heat exchange design can improve energy efficiency by 7–23%. However, the material cost of a heat exchanger is higher than that of other technologies. The incremental retail price ranges from RMB 180–1000. VSDs used for compressors and fans can save energy by 23–28%. The energy saving effect of VSDs is higher than that of compressors, heat exchangers, and expansion valves. Due to the large-scale modification for controlling hardware, the incremental retail price is also relatively high and reaches RMB 510–930. The study investigated the cost by USD. The conversion rate of 1:7.0501 was used to convert the monetary value of data denominated in RMB.

In short, air conditioners that use VSDs have the greatest energy efficiency improvements. However, these costs are higher than those of other energy saving improvement methods. In particular, the selling price of air conditioners with basic improvements is higher by up to RMB 510. Higher selling prices affect the sales of highly efficient air conditioners. This study collected air conditioner sales statistics from 2010 to 2018 according to commercial data in China. Earlier fixed-speed units that did not adopt VSDs constituted 60–80% of sales. Until 2014, the sales of variable speed units adopting VSDs surpassed those of fixed-speed units. In 2015, fixed-speed units took the lead again. In 2016–2018, the sales numbers of these two unit types continued to fluctuate because the cost of hardware modifications to adopt VSDs is high. Consumers considered differences between economic benefits from saving energy and increased air conditioner prices and chose the economic technology. They did not necessarily adopt technology with high energy efficiency.

Based on the above surveyed results, this study proposes and develops cloud-based artificial intelligence (AI), and its energy saving effect is expected to increase on the basis of VSDs given the

stable minimum hardware costs. In addition, it is hoped that the economic incentives will increase so that technologies that improve AC energy efficiency can be widely adopted by consumers.

2. VSD Applied to Split-Type Air Conditioners

Before explaining the technologies developed, the conditions for applying VSDs to the study case are explained as the baseline before energy efficiency improvement.

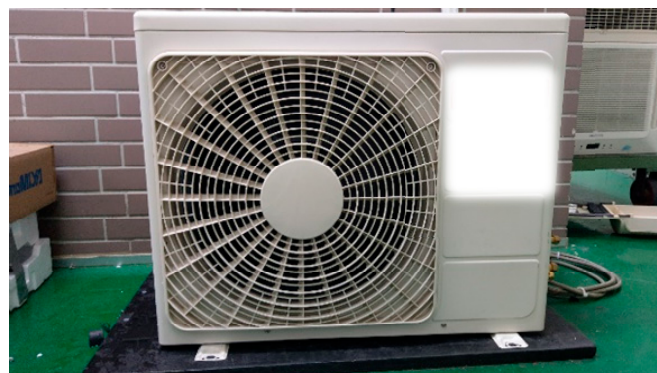
2.1. Energy Efficiency Study Case and Baseline

For the study case, the chosen range that split-type air conditioners with cooling capacity can provide to cool a space is 13–20 m². The reason for choosing air conditioners in this range is that compared with the investigated subject, Chinese 3.5 kW mini-split room air conditioners, the literature [2] states that air conditioner models of this range have extremely close mechanical specifications, cost structures, and market prices. Data obtained in this study can be used to compare with data from the literature, including energy saving performance and incremental retail prices.

The experiment involved a single unit in a range of air conditioners for real modification and tests. The choice was based on the energy efficiency of ductless air conditioners [3] published by the Taiwan Bureau of Energy. This report included 1177 air conditioner models from 49 air conditioner manufacturers. Manufacturers willing to cooperate and provide test models for dismantlement were also considered. Finally, a split-type air conditioner with a cooling capacity of 2.2 kW and dehumidifier capacity reaching 1.4 L/h, which ranked eighth in energy efficiency, was chosen as the model for technology development and tests in this study. The study case is displayed in Figure 1.



(a)



(b)

Figure 1. The split-type air conditioner consists of an (a) indoor unit and (b) outdoor unit. It has a 2.2 kW cooling capacity and a 1.4 L/h dehumidifying capability.

The model presented in Figure 1 was sent to the Enthalpy Analytical laboratory to test its EER value and cooling season power factor (CSPF) before modifications were designed. The energy efficiency baseline was established, and test methods are explained in the Experimental Setup Section in Section 4. Test data were used to compare standard values for cloud-based AI improvement.

2.2. Proportional-Integral-Differential Control

A proportional-integral-differential (PID) controller was employed for VSDs as the core of the control algorithm [3]. Figure 2 illustrates the VSD of a split-type air conditioner.

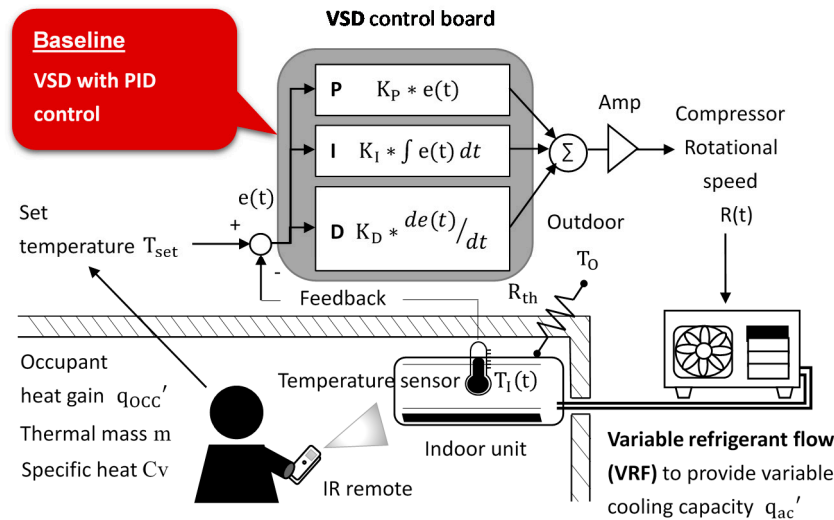


Figure 2. The variable speed drive (VSD) of a split-type air conditioner uses the proportional-integral-differential (PID) control algorithm to provide variable refrigerant flow for air conditioning. This control architecture builds the energy consumption baseline for the discussion of energy efficiency improvement.

As presented in Figure 2, a PID control involves three arithmetic operations. All calculations are based on the control error determined by $e(t) = T_I(t) - T_{set}$, where T_{set} is the desired temperature set by the occupant using an infrared (IR) remote control and $T_I(t)$ is the indoor temperature. The operations are added up to determine how to adjust compressor rotational speed $R(t)$ by the following equation:

$$R(t) = K_P * e(t) + K_I * \int_0^t e(t) dt + K_D * \frac{de(t)}{dt} \quad (1)$$

where K_P , K_I , and K_D are the proportional, integral, and differential coefficients.

A PID control works with an electronic expansion valve that can balance the high and low pressure of the whole AC system automatically. Therefore, the pressure and enthalpy values of the whole cooling cycle can remain constant to ensure that the cooling capacity only depends on the refrigerant volume flow rate. However, the constant cycle pressure drop makes the compressor operate in a constant torque mode, and the compressor power output only depends on rotational speed. Because cooling capacity is proportional to the refrigerant volume flow rate and equal to the compressor power multiplied by a constant efficiency value, we derived variable refrigerant flow (VRF)-induced variable cooling capacity q'_{ac} to be proportional to $R(t)$. Such a control architecture builds an energy efficiency baseline.

2.3. Control Model

The relationship between cooling capacity q'_{ac} and indoor temperature $T_I(t)$ can be simulated in the following model:

$$q'_{ac} = mC_v \frac{dT_I(t)}{dt} + \frac{T_I(t) - T_O}{R_{th}} + q_{occ}' \quad (2)$$

where q_{occ}' is the occupant's heat gain, m is the thermal mass in an indoor environment, and C_v is the heat coefficient. T_O is the outdoor temperature, and R_{th} is the thermal resistance between the indoor and outdoor environments, as displayed in Figure 2. By adjusting $R(t)$ to provide variable q_{ac}' , $T_I(t)$ can be controlled and approach T_{set} . This is the basic working principal of VSD based on a PID control.

According to Equation (2), a PID control achieves the following control goals:

1. Rapidly decrease the indoor temperature, and this control goal decreases $T_I(t)$ to equal T_{set} in 25 min.
2. Stably control the indoor temperature, with the control goal stabilizing to $T_I(t)$ in the range of $T_{set} \pm 0.5$ °C for an unlimited amount of time.

Air conditioner manufacturers give an estimated personnel load of q_{occ}' considering the environmental space size in which split-type air conditioners are installed. In addition, the PID controller is designed, and three fixed K_P , K_I , and K_D parameters are given and incorporated into the manufacturing of products on the market.

3. Cloud-Based AI Development

The customers to whom air conditioner products are sold can considerably differ, and the fixed K_P , K_I , and K_D parameters cannot satisfy the demands for temperature controls in space and energy saving for all customers. Therefore, this study developed a cloud-based AI, and AI techniques were introduced to improve performance with no or limited changes in the inner control structure of air conditioners. The expected improvement goals were as follows:

1. After the introduction of AI, the time required to reduce indoor temperature and maintain a stable temperature range unchanged.
2. After the introduction of AI, the energy consumption reduced from the aforementioned PID control.

Apart from these aforementioned improvement goals, the cloud-based AI developed in this study may change the costs and benefits of AC efficiency improvement. The goals expected to be accomplished were as follows:

AI was introduced for energy efficiency based on software improvements. Higher benefits can be achieved with lower costs than those achieved from previous hardware modifications.

The chosen study case is ranked as the top 5% high efficiency air conditioner sold in Taiwan and has extremely high energy efficiency. Thus, using AI to increase its energy efficiency is a considerable challenge. Therefore, the AI-assisted control literature since 1995 was reviewed to be applied to heating, ventilation, and AC (HVAC) equipment. Techniques with high energy saving efficiency were chosen for implementation in the cloud end to achieve the improvement goals.

3.1. Review of AI Techniques

Keywords such as "AI technique" and "HVAC control" were searched on the Science Direct Online and Institution of Engineering and Technology Electronic Library databases, and 832 studies were found. Studies after 1997 were searched, and that was the year when Deep Blue of IBM defeated the world chess champion, which indicated major progress in AI technologies. The studies with the following conditions were chosen:

1. AI applied to HVAC control and not to diagnosis, prediction, or forecasting.
2. Containing actual quantization data and energy saving percentages reported after AI technique implementation.
3. Fully reported implementation control structure.

A total of 44 studies conformed to these conditions, and they are listed in Table 1.

Table 1. Artificial intelligence (AI) techniques for improving energy efficiency in heating, ventilation, and air conditioning (HVAC) systems.

AI Techniques	References	Effects
Genetic algorithm and model-based predictive control for the air conditioning system	[4–12]	Max energy saving up to 39.8%
Fuzzy + proportional-integral-differential controller for the air conditioning system	[12–16]	Max 36.8%
Neural networks (NNs) including artificial, spiking, and recurrent NNs for thermal comfort control and energy saving in the air conditioning system	[17–24]	Max 36.5%
Distributed AI for understanding users' behavior in working spaces	[25–31]	Max 34.9%
Cloud-based AI for intelligent control	[32–36]	Max 22.5%
Improved energy consumption by the Internet of Things and machine learning/reinforcement learning/deep learning	[37,38]	Max 20%
Knowledge-based system for HVAC control	[39,40]	Max 20%
Decision-making system for household energy saving and HVAC control	[41,42]	Max 10%
Rule-based reasoning for the optimized scheduling control of a chiller	[43]	Max 4%
Multi-agent system in the end control device	[44–47]	Max 1.1%

Table 1 lists AI techniques applied to HVAC systems. This study investigates 9 items: artificial neural network (ANN); decision-making system (DMS); fuzzy, generic algorithm (GA); multi-agent system (MAS); machine learning (ML); model-based predictive control (MPC); rule-based reasoning (RBR); recurrent neural network (RNN); and spiking neural network (SNN). Despite diverse developments, 44 studies consistently reported AC energy savings by AI-assisted control. AC energy saving effects can be compared with each other. Which AI techniques were related to this study was proposed according to the energy saving effects.

One additional item is cloud-based AI for intelligent control, which is the cloud system structure mainly referenced in this study. The AI calculation service was provided by a cloud service and operated with the PID controller equipped on a remote air conditioner to increase energy efficiency.

The operation of the cloud-based AI service was mainly in coordination with machine-to-machine communication. A previous study designed and implemented an intelligent cloud-based energy management system. In the test bed, the proposed system reduced the power consumption of the test bed by up to 22.5%. This study referred to the cloud service structure reported in [32–36] and tried to introduce AI techniques with an energy saving ratio higher than 22.5%. This indicated the fuzzy, GA, MPC, and NN techniques, which were integrated and reassembled to develop cloud-base AI for split-type air conditioners. The details are illustrated in the following two sections.

3.2. Energy Efficiency Improvement Methodology #1: Fuzzy + PID Control

The first methodology optimized the PID controller by a fuzzy algorithm [13–17] or a so-called fuzzy + PID control. The cloud-based AI used system models to optimize the PID controller. The model is described in Equation (2).

The cloud-based AI controls had the same model as PID controls. However, in contrast to the IR remote control for the current air conditioner, a mobile phone was employed as the control interface. Mobile phones have two types of communication. The first is Bluetooth, which was used to control the indoor unit of split-type air conditioners and receive feedback signals. The two signals included indoor temperature, $T_1(t)$, and compressor rotational speed, $R(t)$. The second was WiFi, which delivered the temperature settings, T_{set} , and feedback signals to the cloud. From these three data points, the cost function is as follows:

$$J_E = \int_0^t (q'_{ac})^2 dt \quad (3)$$

where $q'_{ac} \propto R(t)$.

The penalty for deviating from a set temperature is computed based on the cost function of the temperature control, shown as follows:

$$J_C = \int_0^t (T_{\text{set}} - T_I(t))^2 dt \quad (4)$$

Evaluation of the control system is the inverse of the sum of the two cost functions:

$$\text{Evaluation function} = \frac{1}{J_E + J_C} \quad (5)$$

The optimized control status determines the minimum value of the evaluation function. To achieve this target, the original control status of the air conditioner was collected by WiFi and sent to the cloud. Then, the GA used the $T(t)$ and $R(t)$ records as parents to generate new chromosomes (i.e., new children from the $T(t)$ and $R(t)$ records). The new records generated new error inputs that were compared with the original $e(t)$ and $de(t)/dt$. From the membership functions of the fuzzy technique, the optimized K_P , K_I , and K_D parameters were determined to improve the performance of the air conditioner by the cloud-based AI. The implementation framework is displayed in Figure 3.

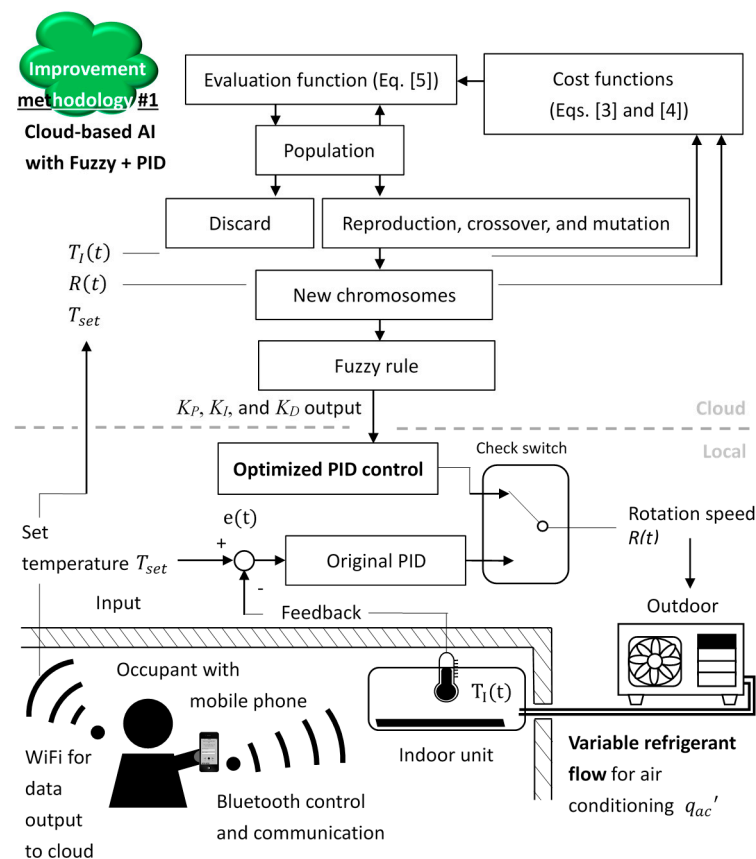


Figure 3. The methodology for improving the energy efficiency of a split-type air conditioner by optimizing the proportional-integral-differential (PID) settings by the generic algorithm–fuzzy algorithm.

3.3. Energy Efficiency Improvement Methodology #2: MPC

The second methodology was MPC. This methodology used prediction instead of feedback control. With the model function described in Equation (2), the cloud-based AI could determine optimized set point SP_{opm} according to the sensor output in the next stage, $S(t + 1)$. The optimized setting function used knowledge-based system tools [39,40] from the database, which stored control cases collected

beforehand to determine the set point (SP). The similarity index (SI) between a retrieved and test case as employed during the calculation, as indicated in the following equation:

$$SI_i = f\left(\left|\frac{y_{ic} - y_{ip}}{MV_i}\right|\right) \quad (6)$$

where y_{ic} and y_{ip} are the neural outputs of variable i for control and past cases, respectively. MV_i is the mean difference of variable i stored in the database. Function f maps the test case to the whole case difference. Based on SI, global similarity (GS) is calculated according to the following equation:

$$GS = \frac{\sum_i (SI_i \cdot \omega_i)}{\sum_i \omega_i}, \quad i = 1, 2, \dots, n \quad (7)$$

where n is the number of controlled cases and ω_i is the weighting coefficient.

GS is the sum of global similarities between selected n cases. Then, the optimized set point SP_{opm} can be determined by the following equation:

$$SP_{opm} = \sum_j (P_j \times SP_j) / N(j) \quad (8)$$

where SP_j is the SP of past case j . The optimized SP is determined as the solved case, including previous controllable and uncontrollable parameters and the desired SP value. After completing the predictive control, this case is retained as a learned case and stored in a database.

Predictive controls determine probability. After the calculation methods of several articles were compared, the following equation is suggested:

$$Prob_i(t+1) = \frac{U_{k \in \theta} [\tau_{i,k}]^\alpha \cdot [S_{i,k}(t)]^\beta}{\frac{\sum_k [\tau_{i,k}]^\alpha \cdot [S_{i,k}(t)]^\beta}{N(k)}} \quad (9)$$

where i indicates the i th sensor to detect controllable or uncontrollable parameters. $S_{i,k}(t)$ is the i th sensor value. $\tau_{i,k}$ is the pheromone intensity, and α and β are experience parameters. In addition to the probability value, a guess value was necessary for predictive control and was calculated by the ANN ML. This ML tool was constructed by the commercial software Azure Machine Learning SDK 1.0.62.

Guess is determined by the following equation:

$$Guess_i(t+1) = g\left(\sum_{k \in \theta} \omega_k S_{i,k}(t)\right) \quad (10)$$

where $\omega_0, \omega, \dots, \omega_n$ are weighting coefficients and g is the nonlinear activation function. The following equation can predict the sensor output of the next stage.

$$S(t+1) = a \cdot S(t) + b \cdot R_1 \cdot \sum_{i=0}^n MAX[Prob_i(t+1)] + c \cdot R_2 \cdot \sum_{i=0}^n Guess_i(t+1) \quad (11)$$

where a is the momentum parameter, b is the self-influence parameter, and c is the measure insight. R_1 and R_2 are random numbers within $[0, 1]$ for predictive control. The implementation framework is displayed in the following figure.

In this study, a web crawler program was developed to get weather conditions from the Central Weather Bureau open weather data platform. A total of 26,280 data points were collected. Seventy percent of them were used to train the ANN and the other 30% for testing. Indoor conditions were collected in an environmental control chamber with respect to different AC conditions. The specifications of the chamber will be illustrated later in Section 4.2. A total of 26,512 data points

were collected. Similar to the weather conditions, 70% of the data points were for training and 30% for testing. A total of 21,715 data points related to occupancy status were collected. The status included different numbers of occupants, different indoor illumination, and other appliances operating in the test chamber. The same ratio was employed for learning and testing. The above three datasets were employed to train the ANN to output correct SI and GS, as illustrated in Equations (6) and (7). These output data were stored in a database as shown in Figure 4. With respect to different occupant status feedback by a mobile phone, MPC could be executed on a split-type air conditioner.

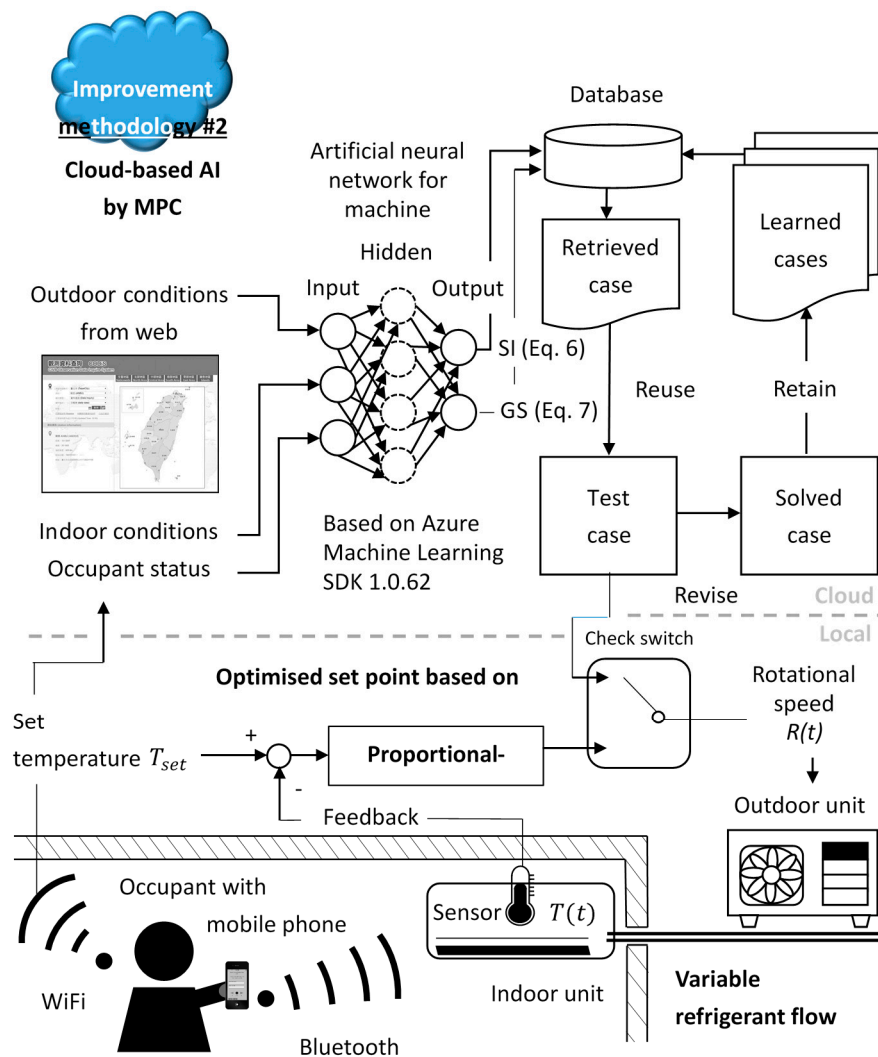


Figure 4. The methodology uses a model-based predictive control (MPC).

3.4. Additional hardware

In order to operate with a cloud-based AI as shown in Figures 3 and 4, two necessary hardware modifications for the AC control system are illustrated in Figure 5.

As shown in Figure 5a, an electric pressure gauge must be installed on the outdoor unit to measure high pressure in the AC system. The energy efficiency improvement methodologies displayed in Figures 3 and 4 all used check switches to converge the original PID control output and cloud-based AI output. During conversion, the compressor rotational speeds calculated from the two outputs could have large differences that cause instantaneous high pressure. An additional electronic digital meter must be installed for the connection with the VSD control board. When confirming cloud commands, if high pressure increases to over 5% of the set refrigerant pressure, the original PID control can be switched back to ensure stable work in the AC system.

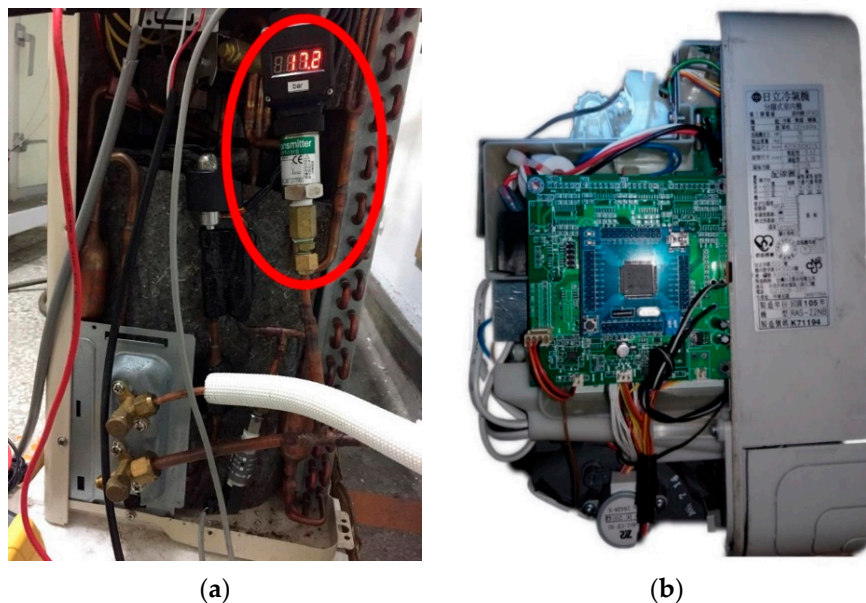


Figure 5. To implement the cloud-based artificial intelligence, two hardware modifications were necessary for split-type air conditioners. **(a)** Digital pressure meter. One is a digital pressure meter installed on the outdoor unit to maintain stable refrigerant pressure. **(b)** Communication board. The other is a board installed on the indoor unit for communication with mobile phones.

Figure 5b indicates that dual communication with a mobile phone is necessary to implement the cloud-based AI for the occupant's commands to be accepted when setting the AC temperature. In addition, the VSD board control parameters were set. For the first methodology, the main control parameters were setting temperature T_{set} , air temperature detected by a sensor equipped in the indoor unit $T_I(t)$, and compressor rotational speed $R(t)$. For the second methodology, setting temperature T_{set} was required. In addition, geographic locations for collecting outdoor weather status online were delivered manually or automatically. This information could be uploaded to the cloud through WiFi on a control basis.

After hardware conversion, two improvement methodologies of the cloud-based AI, fuzzy + PID and MPC, were implemented. The energy efficiency of these methods and with the original PID control was tested by the following experimental setup.

4. Experimental Setup

The experimental design mainly targeted the cloud-based AI control methodologies introduced in Sections 3.2 and 3.3 and measured energy efficiency. The obtained data were compared with the original energy efficiency obtained from the PID control as the baseline. Thus, energy efficiency index differences were quantized to verify the effectiveness of the AI techniques.

The quantization indexes included EER and CSPF. EER is energy efficiency when measuring the rated cooling capacity with fixed temperature and humidity in both indoor and outdoor air conditioners. CSPF is energy efficiency when testing cooling capacity created from changing temperature and humidity in indoor and outdoor air conditioners according to Taiwan's climate conditions. The two indexes were used to test energy efficiency in this study. AI techniques were evaluated for their effects with varying AC statuses. The mathematical definitions and test methods of the two types of energy efficiency are explained in Section 4.1.

The energy efficiency tests were commissioned to an external laboratory, and the research team could not capture machine parameters in the test environment. Thus, the control effects of the AI technique could not be analyzed. Therefore, four conditions (late spring, early summer, hot summer, and early autumn) were additionally set with the environmental control chamber to reference Taiwan's

climate conditions in CSPF tests. The split-type air conditioner was installed for these tests, and the compressor rotational speed and indoor temperature changes were collected. The control effects of AI techniques were analyzed with the control model in Equation (2). The test methods in this part are explained in Section 4.2.

4.1. Energy Efficiency Measurement

Energy efficiency measurement was commissioned to an external standard laboratory. Specifications for the enthalpy of the differential test chamber in that laboratory are listed in Table 2.

Table 2. Specifications for the enthalpy of the analytical laboratory for energy efficiency measurement.

Parameter	Range
Cooling capacity	2.5–12 kW
Heating capacity	3–13.5 kW
Air volume flow rate	300–2500 m ³ /h
Static pressure	−50 to 450 Pa
Differential pressure	0–1000 Pa
Pressure measurement accuracy	±0.5 Pa
Pressure control accuracy	±2 Pa
Indoor dry-bulb temperature	5–45 °C
Indoor humidity	35–93%
Outdoor dry-bulb temperature	−20 to 60 °C
Outdoor humidity	25–90%
Indoor/outdoor temperature measurement accuracy	±0.1 °C
Indoor/outdoor temperature control accuracy	±0.2 °C
Indoor/outdoor humidity measurement accuracy	±0.2 °C (WB)
Indoor/outdoor humidity control accuracy	±0.5 °C (WB)
Standard uncertainty of energy efficiency measurement	±0.15%

4.1.1. EER

EER tests static efficiency. The test chamber with specifications listed in Table 1 was used. The controlled outdoor dry-bulb temperature was 35 °C ± 0.2 °C, and the outdoor wet-bulb temperature was 24 °C ± 0.4 °C. The indoor dry-bulb temperature was 27 °C ± 0.2 °C, and the indoor wet-bulb temperature was 19 °C ± 0.4 °C. The tests were conducted under the aforementioned conditions.

For ISO 5151 standards, the EER value tests used a separate outdoor and indoor environment. After the temperature and humidity reached the control requirements, the cooling capacity q'_{ac} and the power consumption P were separately tested. The coefficient of performance (COP) was calculated using the following formula:

$$COP = \frac{q'_{ac}}{P} \text{ (kW/kW)} \quad (12)$$

Then, the EER value was obtained by unit conversion as indicated in the following formula:

$$EER = COP \cdot 0.86 \text{ (kcal/W} \cdot \text{h)} \quad (13)$$

4.1.2. CSPF

EER is the energy efficiency test value obtained under a single condition. However, air conditioners are not always operated at the high temperature of 35 °C. To understand efficiency with low outdoor temperatures and test whether AI techniques can also save energy under changing conditions, this study tested CSPF values simultaneously. This value specifically used statistical data from the outdoor temperatures of air conditioner usage in Taiwan. The indoor temperature was set at 24 °C, and the humidity was maintained between a comfortable 40–60%. When the outdoor temperature was at 23 °C, the air conditioner was not required, and the required indoor cooling capacity was 0 W. At 24 °C, the air conditioner was turned on, and the required indoor cooling capacity was 220 W. According

to statistical data from Taiwan, air conditioners are turned on under this condition for 228 h in a year. At 25 °C, 26 °C, 27 °C, 28 °C, 29 °C, 30 °C, 31 °C, 32 °C, 33 °C, 34 °C, 35 °C, and 36 °C, the air conditioner was turned on, and the cooling capacity was 440, 660, 880, 1100, 1320, 1540, 1760, 1980, 2200, 2420, 2640, and 2860 W, respectively. The air conditioner was on for 290, 332, 343, 346, 311, 245, 196, 123, 49, 16, 5, and 1 h, respectively, for the year. According to these data, the test conditions of outdoor temperatures were adjusted, and the turned-on hours of air conditioners were multiplied. Thus, the CSPF value can be obtained in the following formula:

$$\text{CSPF} = \frac{\text{Total load of cooling season (kW}\cdot\text{h)}}{\text{Total power consumption of cooling season (kW}\cdot\text{h)}} \quad (14)$$

4.2. Environmental Control Chamber Test

This study used EER and CSPF as indexes to quantize and evaluate the energy efficiency improving effects of the cloud-based AI. However, when testing these two indexes, the operational parameters of the split-type air conditioner, such as compressor rotational speed, refrigerant pressure, and indoor temperature variation, could not be obtained. To solve this problem, second-stage tests were arranged in an environmental control chamber. The chamber specifications are listed in Table 3.

Table 3. Specifications of the environmental control chamber for investigating the operations of the split-type air conditioner.

Parameter	Range
Cooling capacity	1.05–10.47 kW
Heating capacity	1.05–10.47 kW
Indoor dry-bulb temperature	5–45 °C
Indoor humidity	40–80%
Outdoor dry-bulb temperature	5–60 °C
Outdoor humidity	25–90%
Indoor/outdoor temperature measurement accuracy	±1 °C
Indoor/outdoor temperature control accuracy	±2 °C
Dimensions	5 × 3 × 2.6 m ³

The split-type air conditioner was installed in the environmental control chamber. A pressure sensor was equipped in the outdoor unit to measure the refrigerant pressure. The measurement range of the sensor was −1 to 16 bar, and the pressure sensor precision was ± 0.25% at full scale. The sampling time of the sensor was ms. In addition, the compressor rotational speed was read by the VSD control board of the outdoor unit directly. The indoor unit was additionally equipped with a Bluetooth communication chip as displayed in Figures 3 and 4. A mobile phone was used by the occupant to replace the IR remote control and give instructions to the air conditioner. The indoor unit captured data required for cloud-based AI to control the air conditioner. The temperature of the indoor side of the environmental control chamber was recorded and compared with the compressor rotational speed captured from the outdoor unit. Thus, whether AI-assisted control could truly effectively increase the energy efficiency was analyzed. The conditions of the environmental control chamber where the indoor and outdoor units of the split-type air conditioner were installed are displayed in Figure 6.

The installation conditions illustrated in Figure 6 compensated for the inability to install sensors in the enthalpy of the differential test chamber to collect signals related to control status. Thus, signals in the environmental control chamber could be collected to analyze the control performances of cloud-based AI. Four climate conditions were chosen for performance analysis: late spring, early summer, hot summer, and early autumn. The simulation time of late spring was approximately May to June in Taiwan, which is known as the plum rain season. Daytime temperatures are not considerably high, and humidity is high. Temperatures do not differ much between daytime and nighttime. The outside temperature was initially set at 28 °C and gradually reduced to 25 °C in 4 h. The initial outside

humidity was set at 78%, and the humidity was simulated to increase gradually to 80% in 4 h, such as in the late spring rainy season. An early summer climate occurs in Taiwan approximately in July. Daytime temperatures are approximately over 30 °C, and relative humidity is approximately 70%. The outside temperature was initially set at 30 °C and gradually decreased to 28 °C in 4 h. Initial outside humidity was 70% and increased to 72% in 4 h. A hot summer climate occurs in Taiwan in August, the hottest month of the year in Taiwan. Temperatures before nighttime can be over 32 °C. Due to high temperatures, humidity is lower than that in other months. Thus, the outside temperature was initially set at 35 °C and decreased to 30 °C in 4 h. Initial outside humidity was 60% and increased to 66% in 4 h. An early autumn climate occurs in Taiwan from September to October. The most distinct characteristic of this climate is the apparent temperature drop in the nighttime. Due to decreasing temperature, relative humidity increases considerably. Thus, the outside temperature was initially set at 28 °C and decreased gradually to 25 °C in 4 h. Initial outside humidity was 73% and increased gradually to 80% in 4 h. These conditions covered the temperature and humidity settings for EER and CSPF measurements. Compressor rotational speeds and indoor temperature drops were recorded with continual outdoor temperature changes dynamically to obtain control dynamic responses.



(a)



(b)

Figure 6. Case installed in an environmental control chamber to analyze the control status of cloud-based AI. (a) Outdoor and (b) indoor unit installation.

5. Results and Discussions

Two improvement methodologies of cloud-based AI, fuzzy + PID and MPC, were implemented in this study. The energy efficiency of these methods was compared with the original PID control used by the split-type air conditioner. The evaluation was performed with EER values and CSPF separately, and the results are illustrated in Figures 7 and 8.

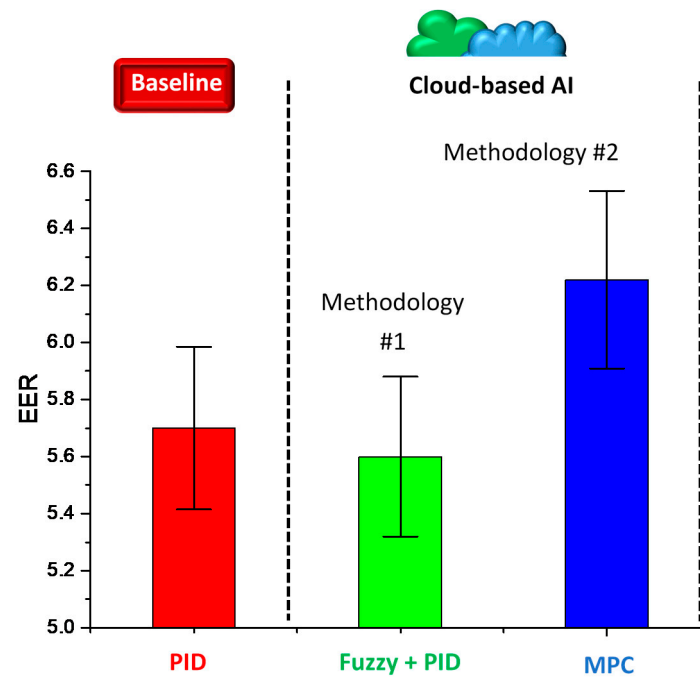


Figure 7. Efficiency ratio (EER) values of the baseline with a proportional-integral-differential (PID) control and two improvement methodologies using cloud-based artificial intelligence (AI) to implement a fuzzy + PID and model-based predictive control (MPC) on a split-type air conditioner.

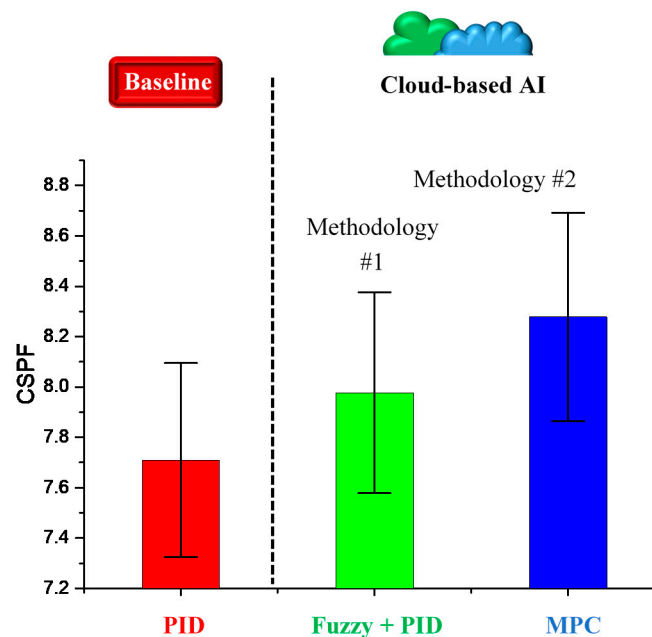


Figure 8. Cooling season power factor (CSPF) of the baseline with a proportional-integral-differential (PID) control and two improvement methodologies using cloud-based artificial intelligence (AI) to implement a fuzzy + PID and model-based predictive control (MPC) on a split-type air conditioner.

Based on the literature discussion, the conclusion was that fuzzy + PID and MPC had the highest energy saving effects, with details shown in the data collation in Section 3.1 and Table 1. This study implemented control algorithms in the cloud and tested the static energy efficiency index EER. The results are displayed in Figure 7. The fuzzy + PID control was unable to save energy, whereas MPC increased the EER value to 9.12%.

The results of the evaluation with the dynamic energy efficiency index CSPF are presented in Figure 8. The fuzzy + PID control could increase CSPF to 3.46%, and MPC could increase energy efficiency to 7.37%.

A comparison of the energy saving effect presented in Figures 7 and 8 with the data shown in Table 1 revealed that the highest energy saving effect of MPC in the literature was 39.8%. In the static and dynamic energy efficiency index evaluation in this study, the energy saving effect only reached 7.37–9.12% because the study with the highest energy saving effect [5] was conducted in the sunny summer, cloudy summer, sunny spring, and sunny winter. However, the climate conditions in the dynamic energy efficiency tests in this study were late spring, early summer, hot summer, and early autumn. The seasonal spans of the two studies differed, and the reference study spanned the winter and summer. During winter, the demand for cooling is considerably decreased from that during summer. When only the energy saving effect of a single season in [5] was compared, the maximum effect was 8.1%. The energy saving effect achieved with MPC in this study was 7.37–9.12%; thus, the two were comparable.

The maximum energy saved in [13] was 36.8% when a fuzzy + PID control was used. However, the comparison baseline was an on-off control, which is an AC system with extremely low efficiency. The comparison baseline in this study was VSD, and split-type air conditioners adopt PID controls. According to [2], VSDs applied to air conditioners can save energy by 28%. In addition to the fuzzy + PID control tested in this study, which can increase the dynamic energy efficiency index CSPF by another 3.46%, overall energy efficiency should increase by 31.46%. This was comparable to the highest energy saving effect in [13].

To sum up these test results and literature references, the cloud-based AI developed in this study could save a similar amount of energy as in the literature. Furthermore, as illustrated in Section 4.2, the environmental control chamber was used to test the control responses. The relationship between compressor rotational speed and indoor temperature variation was analyzed, which identified the key to the energy saving effect of AI. First, under the simulated climate conditions for late spring, the control responses of the PID control and the two methodologies of the cloud-based AI are displayed in Figure 9.

In the late spring climate conditions, the outdoor temperature decreased gradually from 28 °C to 25 °C in a 4 h period. The indoor AC temperature setting was fixed at 24 °C. The control responses shown in Figure 9a indicated that the compressor rotational speeds given by the AI-controlled methodologies decreased by 13.79% and 24.14% compared with the PID control. However, the stably controlled temperatures were high, particularly for MPC. The final stably controlled temperature was 24.3 °C, which was 3.08% higher than that of the PID control. For late spring, which is less hot, AI-controlled methodologies satisfied the demands for increasing energy efficiency with low compressor speeds to satisfy the three control goals indicated in Section 2.3.

For the early summer simulation, which had high temperatures, the control responses are displayed in Figure 10.

For the early summer simulation, which features hot weather, the outdoor temperature decreased from 30 °C to 28 °C. In that period, AI-controlled methodologies adopted a compressor speed 16.19% lower than that of the PID control to restrain the indoor temperature within the control goals. A comparison between Figures 9 and 10 revealed that the main control characteristic of AI controls, particularly the one implemented by MPC, was the indoor air temperature slope $\frac{dT_i(t)}{dt} \rightarrow 0$.

For the simulation showing an even hotter summer, the control responses are presented in Figure 11.

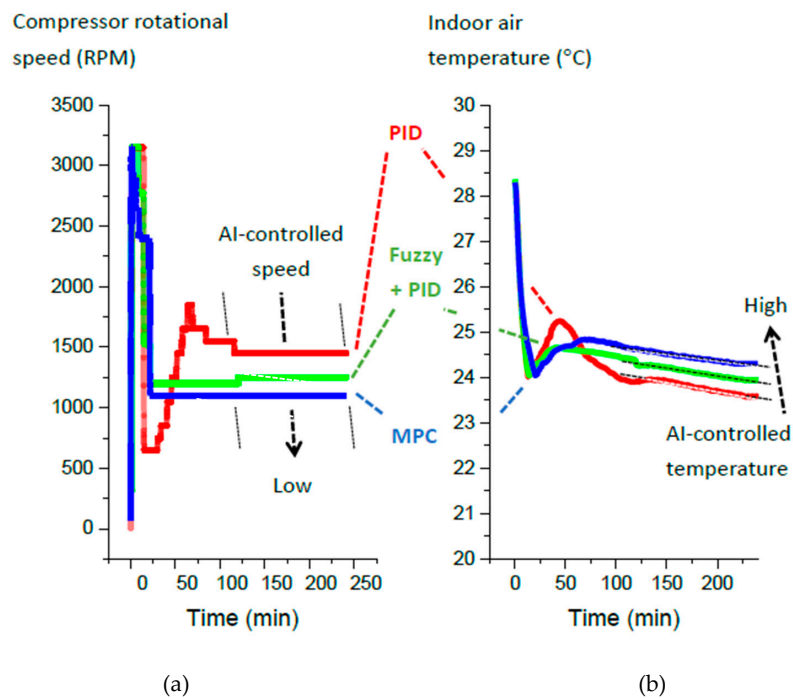


Figure 9. The simulated weather conditions of late spring; the control responses of a proportional-integral-differential (PID) control and two improvement methodologies used cloud-based artificial intelligence (AI) to implement fuzzy + PID and a model-based predictive control on a split-type air conditioner. (a) Compressor rotational speed during a 4 h test period; (b) indoor temperature of the environmental control chamber.

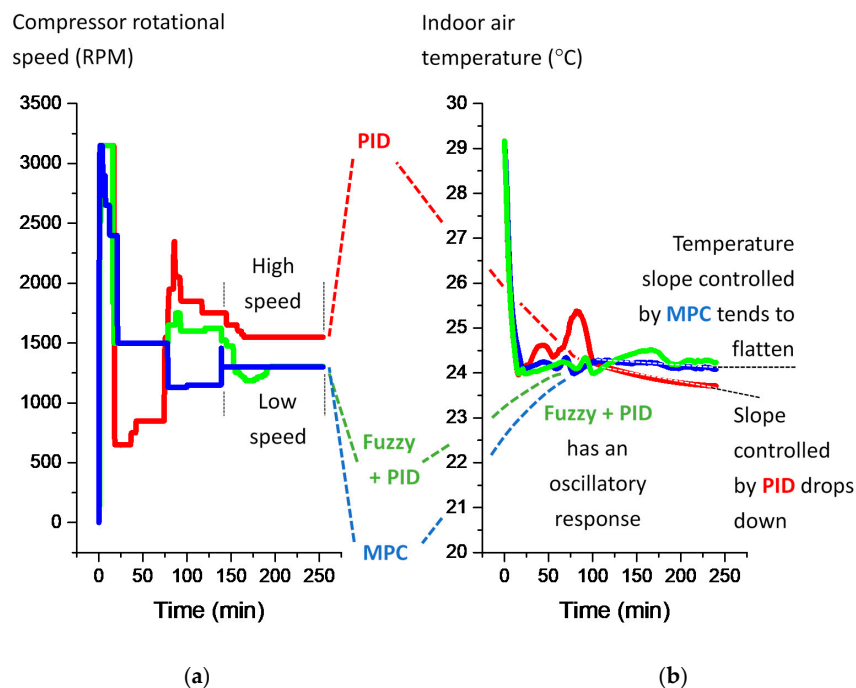


Figure 10. Early summer simulated weather conditions; the control responses of a proportional-integral-differential (PID) control and two improvement methodologies used cloud-based artificial intelligence to implement fuzzy + PID and a model-based predictive control (MPC) on a split-type air conditioner. (a) Compressor rotational speed during a 4-h test period; (b) indoor temperature of the environmental control chamber.

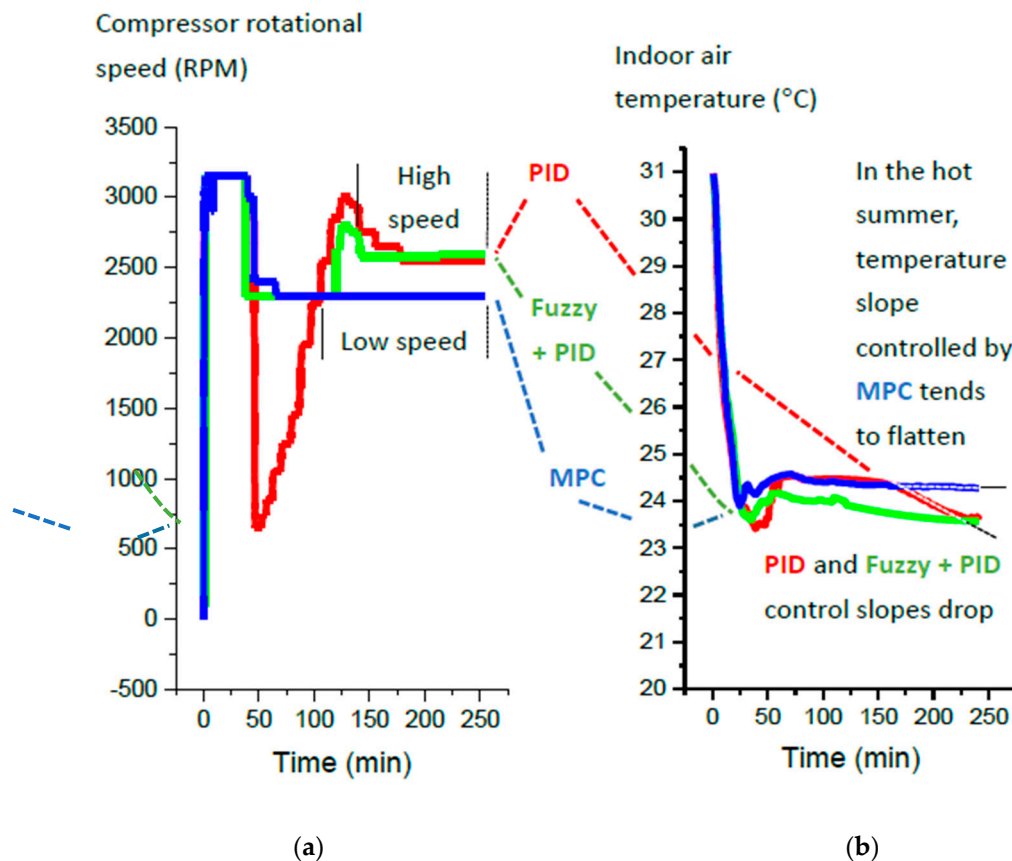


Figure 11. The hot summer simulation; the control responses of a proportion-integral-differential (PID) control and two improvement methodologies used cloud-based artificial intelligence to implement fuzzy + PID and a model-based predictive control (MPC) on a split-type air conditioner. (a) Compressor rotational speed during 4-h test period; (b) indoor temperature of the environmental control chamber.

In the hot summer simulation, the outdoor temperature decreased from 35 °C to 30 °C. In the environment with an even higher temperature, the final controlled compressor speed was, by contrast, 1.57% higher than the PID control for the AI-controlled fuzzy + PID methodology from Figure 10. However, MPC still adopted a rotational speed 9.8% lower than that of the PID control and controlled the indoor temperature within the goal. Nevertheless, the temperature remained higher. Instead of the set 24 °C, MPC maintained a temperature of 24.27 °C.

Another observed result was that the initial control point of the hot summer simulated conditions had comparable temperature conditions with the static energy efficiency index EER. Under such conditions, the final stably controlled rotational speed of the AI control methodology of fuzzy + PID was almost identical to the results of the VSD with PID control of the baseline. This also explains why the fuzzy + PID control used by cloud-based AI could not effectively increase the EER value in Figure 7.

Figures 10 and 11 were integrated for observation, and the outdoor temperature and operational time of the air conditioner of the CSPF listed in Section 4.1.2 were compared. The simulated climate conditions of Figures 10 and 11 covered 90% of the tested CSPF interval. The tests under these two conditions revealed that the fuzzy + PID control could not improve energy efficiency during the hot summer, whereas MPC could increase energy efficiency by reducing the compressor speed by 9.8%. Under early summer conditions, both fuzzy + PID and MPC could improve energy efficiency. The final conclusion was that the two AI-controlled methodologies could increase dynamic energy efficiency, but the fuzzy + PID control produced poorer effects. By comparison, MPC was a more effective control methodology in this study. Figure 8 indicates that CSPF could be improved by 7.37%.

Finally, a cool early autumn climate was simulated, and the control responses are illustrated in Figure 12.

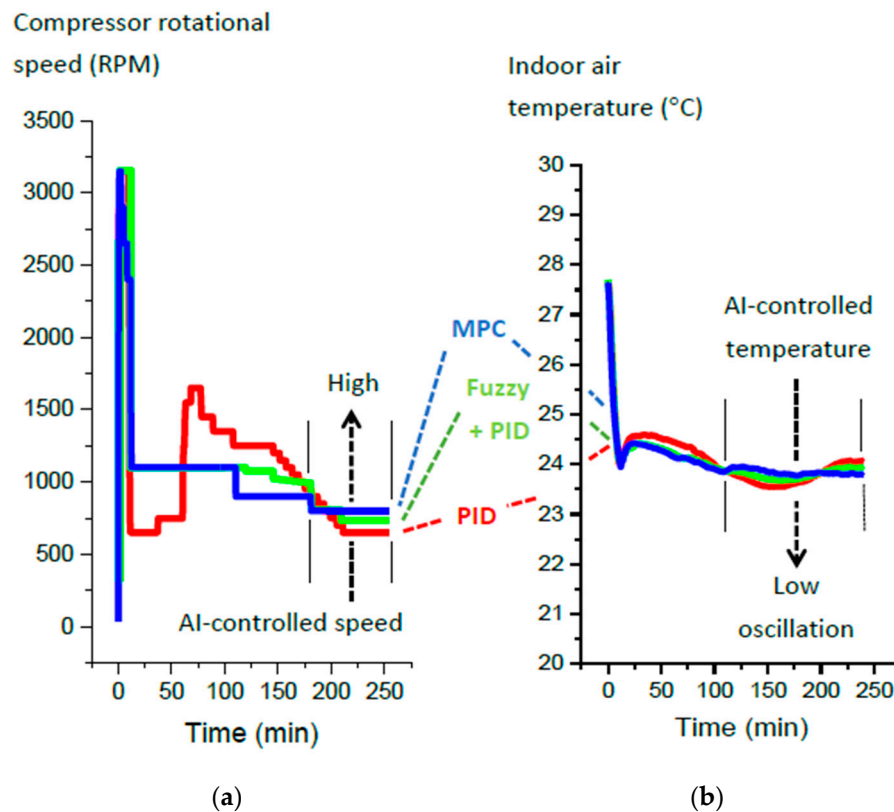


Figure 12. The early autumn simulated weather conditions; the control responses of the proportional-integral-differential (PID) control and two improvement methodologies used cloud-based artificial intelligence (AI) to implement the fuzzy + PID and MPC on a split-type air conditioner. (a) Compressor rotational speed during 4-h test period; (b) indoor temperature of the environmental control chamber.

Figure 12 shows that the cloud-based AI could decrease temperature response oscillations. The control goal settings in Sections 2.3 and 3 can be referenced, and the two AI-controlled methodologies finally controlled higher rotational speeds than those of the traditional PID control, likely from the 73–80% humidity in the early autumn simulated climate conditions. These simulated conditions resulted in the highest humidity of the four climate conditions. The different cooling performance of the outdoor unit was caused by highly humid air. Deviation from original control conditions reduced AI-controlled performance. Thus, energy usage could not be reduced effectively. However, the evaluation function used by the fuzzy + PID control and retrieved cases used by the MPC still controlled the temperature to reach a stable range. Consequently, the cloud-based AI still restrained the temperature oscillations.

The results from Figures 7–12 revealed that the cloud-based AI could effectively use an MPC to save energy. Apart from increasing EER and CSPF, when outdoor temperatures change, the final stable control can reduce the indoor air temperature drop-down slope to zero. Aside from the early autumn conditions that continued to oscillate, the indoor temperature drop-down slope obtained by a PID control ranged from -0.0009 °C/min to -0.00365 °C/min. For the indoor temperature control with an MPC, the slope ranged from 0.001792 °C/min to -0.00295 °C/min. A high slope indicated little energy used by the air conditioner. Observation using control models, as in the formula below, expresses the critical reason that AI saved energy.

$$\text{Minimum } q_{ac}' = mC_v \frac{dT_I(t)}{dt} + \frac{T_I(t) - T_O(t)}{R_{th}} + q_{occ}'$$

Tends to zero
Linear relationship to $R(t) \propto q_{ac}'$
Uncontrollable parameter that can be estimated by cloud-based AI

A model-based control, such as the equation model above, can make $\frac{dT_I(t)}{dt} \rightarrow 0$. In addition, the linear output related to ΔT between indoor and outdoor environments can be provided with the coefficient of the inverse of thermal resistance, R_{th} . This was a key characteristic of the cloud-based AI control. As presented in Figure 4, outdoor conditions can be collected online, and compressor speed $R(t) \propto q_{ac}'$ can be regulated. Thus, $\frac{T_I(t) - T_O(t)}{R_{th}}$ is displayed with linear changes, and the heat transmitted outdoors to indoors is minimized. In addition, occupants' heat gain is an uncontrollable parameter. The control response tests adopted a fixed heat flux of 100 w. In the actual application field, mobile phones can be used to collect indoor conditions and estimate heat gain, as illustrated in Figure 4. When the indoor temperature was stably controlled to $\frac{dT_I(t)}{dt} \rightarrow 0$, the linear compressor speed of ΔT between the indoor and outdoor environment was achieved. The cooling capacity q_{ac}' was minimized, which was the main reason that the cloud-based AI could increase energy efficiency.

Given the four climate conditions, 44 tests were repeated in the environmental control chamber. Compressor speeds under different circumstances of ΔT between the indoor and outdoor environment were verified. The results are displayed in Figure 13.

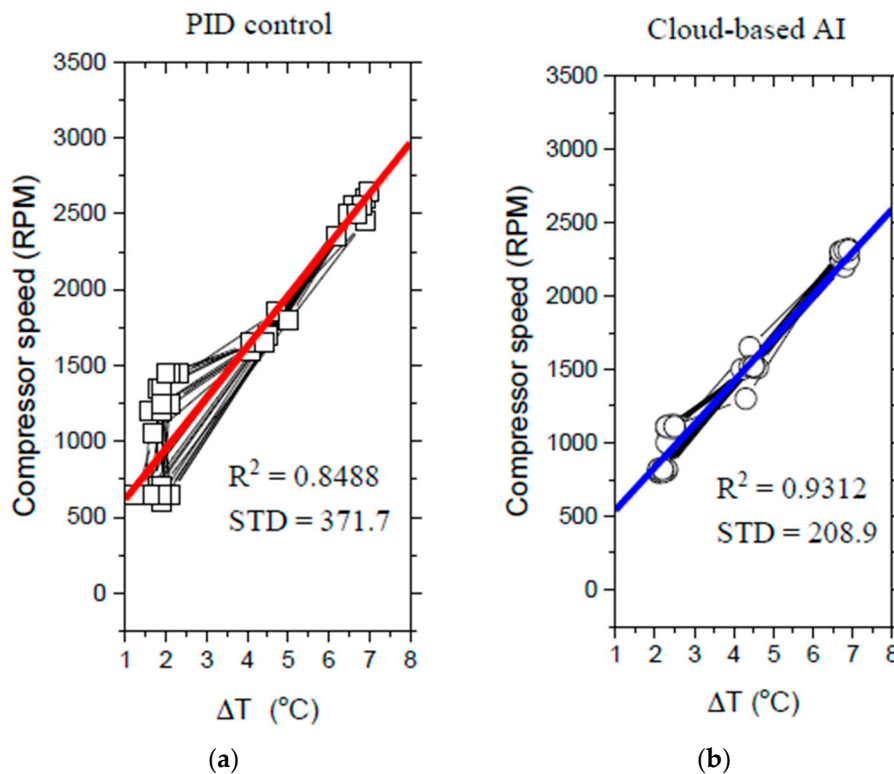


Figure 13. Speed versus ΔT between indoor and outdoor environments by using a proportional-integral-differential (PID) control and cloud-based artificial intelligence (AI). (a) PID control. (b) Cloud-based AI

As in Section 2.2, the PID control used errors between indoor temperature $T_I(t)$ and set temperature T_{set} to control rationing, integrating, and differentiating. Under the four simulated climate conditions, compressor speeds were finally controlled with ΔT between the indoor and outdoor environment. As presented in Figure 13a, the linear relations were poor, and the R^2 value was 0.8488. The standard

deviation of compressor speed was up to 371.1 RPM. The cloud-based AI had superior linear relations, as shown in Figure 13b, and the R^2 value was 0.9312. The standard deviation of the compressor speed was 208.9 RPM because the MPC collected indoor and outdoor information and used SI to contrast with the control case in the database. The retrieved case was selected to output rotational speed directly to the compressor. Relative to variable weather conditions, linear output could be achieved. According to Equation (14), the linear output conditions and $\frac{dT_1(t)}{dt} \rightarrow 0$ can be collocated to minimize the cooling capacity q_{ac}' .

Finally, data from [2] were added for the cost-benefit analysis, and the results are shown in Figure 14.

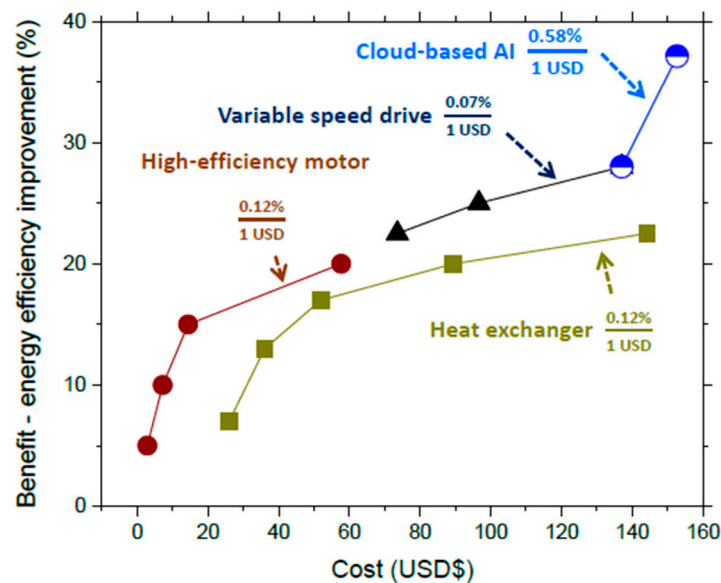


Figure 14. Analysis of cloud-based artificial intelligence (AI) and comparison with other air conditioner improvements.

The two necessary hardware modifications for the cloud-based AI are displayed in Figure 6. In addition to a software communication fee for MPC implementation, the total cost was 152.74 USD. Energy efficiency improved by 9.12% with the EER value as the standard. In [2], the EER value was also used for efficiency evaluation to allow data to be compared directly. That study investigated air conditioners sold in the Chinese market from 2010 to 2018. Energy efficiency improvement involved a high-efficiency motor, novel heat exchanger design, and VSDs used for cost-benefit evaluation. In this study, the results of cloud-based AI were integrated, and energy improvement percentages per US\$1 were compared. The improvement of the cloud-based AI was 5–8 times that of the other three improvement methods. More importantly, the curves in Figure 14 indicated that when energy improvement methodologies were applied to air conditioners, the benefit–cost ratios had gentle curves. This implied that more cost was required to improve energy efficiency. Only the introduction of AI techniques could change the original slopes and considerably improve energy efficiency with low costs after VSD development.

6. Conclusions

Cloud-based AI was developed to improve the energy efficiency of a split-type air conditioner in cooperation with an original VSD based on a PID control to receive commands from the cloud to perform advanced control algorithms. In this study, AI techniques, including ANN, DMS, fuzzy, GA, MAS, ML, MPC, RBR, RNN, and SNN, were evaluated for their energy saving effects. Fuzzy + PID and MPCs were selected as the methodologies because their energy saving ratios were higher than those of other techniques. The cloud-based AI with two improvement methodologies was tested by

enthalpy differential measurements and an environmental control chamber. EER, CSPF, and dynamic control responses were obtained. Based on the experimental data, the following can be concluded.

1. MPC was the most effective methodology for improving the energy efficiency of air conditioners. In the study case, a split-type air conditioner equipped with a VSD and PID control had an EER value of 5.7. By using MPC, the cloud-based AI could increase the EER value to 6.22. Up to 9.12% energy efficiency improvement was achieved.
2. Dynamic control responses were tested under four weather conditions, including late spring, early summer, hot summer, and early autumn. In the late spring with low outside temperatures, the cloud-based AI maintained a compressor speed 24.12% lower than that of the original PID control in the air conditioner. In the hot summer, the cloud-based AI maintained a speed 9.8% lower than originally and achieved high energy efficiency.
3. Compared with a high-efficiency motor, heat exchanger, and VSD applications on air conditioners, the cloud-based AI was the most cost effective way to improve energy efficiency. It only cost 1 USD to achieve a 0.58% improvement in energy efficiency. This was 5–8 times less expensive than the other three methods. For other energy improving methodologies applied to air conditioners, the cost–benefit ratios all had gentle curves; thus, more cost must be invested to improve energy efficiency. Only AI introduction could increase cost–benefit ratios and considerably improve energy efficiency without considerable cost.

The main reasons that AI could control room temperatures with low compressor rotational speeds are as follows:

1. The cloud-based AI used the MPC to extract the control case in the database with SI. The demanded rotational speed was directly inputted to the compressor, and the error feedback control of the PID control was replaced. Thus, indoor temperature control could achieve $\frac{dT_I(t)}{dt} \rightarrow 0$ in stable periods.
2. According to climate conditions, cloud-based AI could provide linear outputs related to ΔT between indoor and outdoor environments, and $\frac{T_I(t) - T_O(t)}{R_{th}}$ had linear changes. Thus, heat transmitted from outdoor to indoor environments was minimized.
3. The cloud-based AI could allow mobile phones to collect indoor statuses to estimate heat gain. In addition, the control model could be controlled precisely, such as the parameters shown in Equation (3).

All experiments in this study were conducted in an environmental control chamber, and the effective evaluation of indoor heat gain through mobile phones was not verified. In the future, a mobile phone application must be developed to estimate heat gain. This will only be conducted to commercialize the outcomes of this study. In addition, in parts of the environmental control tests, high outdoor humidity resulted in AI control deviation, and the energy used by the air conditioner could not be reduced effectively. Further experiments are recommended to analyze the reasons for control deviation.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

AC	air conditioning
AI	artificial intelligence
ANN	artificial neural network
COP	coefficient of performance
CSPF	cooling season power factor
C_v	heat coefficient
DMS	decision making system
$e(t)$	control error
EER	energy efficiency ratio
GA	genetic algorithm
GS	global similarity
h	hour
HVAC	heating, ventilation and air conditioning
IEA	international energy agency
IR	infra-red
J_c	cost function of temperature control
J_e	evaluation function of the control system
kW	kilo-watt
K_p	proportional coefficient
K_i	integral coefficient
K_d	differential coefficient
m	thermal mass in an indoor environment
MAS	multi-agent system
min	minute
ML	machine learning
MPC	model-based predictive control
PID	proportional-integral-differential
q_{ac}'	air conditioning cooling capacity
q_{ac}''	occupants' heat gain
$R(t)$	compressor rotational speed
R_{th}	thermal resistance between indoor and outdoor environments
RMB	Chinese Yuan
RNN	recurrent neural network
RBR	rule-based reasoning
RT	refrigeration ton
SDK	software developing kits
SI	similarity index
SNN	spiking neural network
SP	set point
SP_{opm}	optimized set point
$S(t + 1)$	sensor output prediction of the next stage
$T_i(t)$	indoor air temperature varied with time
T_o	constant outdoor air temperature
T_{set}	desired temperature set
USD	united states dollar
VSD	variable speed drive
VRF	variable refrigerant flow
α and β	experience parameters for sensor value prediction
$\tau_{i,k}$	pheromone intensity
ω_k	weighting coefficients

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