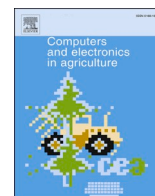




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Applicability evaluation of a demand-controlled ventilation system in livestock

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ABSTRACT

The distribution of agricultural and livestock products has been limited owing to the recent rapid population growth and the COVID-19 pandemic; this has led to an increase in the demand for food security. The livestock industry is interested in increasing the growth performance of livestock that has resulted in the need for a mechanical ventilation system that can create a comfortable indoor environment. In this study, the applicability of demand-controlled ventilation (DCV) to energy-efficient mechanical ventilation control in a pigsty was analyzed. To this end, an indoor temperature and CO₂ concentration prediction model was developed, and the indoor environment and energy consumption behavior based on the application of DCV control were analyzed. As a result, when DCV control was applied, the energy consumption was smaller than that of the existing control method; however, when it was controlled in an hourly time step, the increase in indoor temperature was large, and several sections exceeded the maximum temperature. In addition, when it was controlled in 15-min time steps, the increase in indoor temperature and energy consumption decreased; however, it was not energy efficient on days with high-outdoor temperature and pig heat.

1. Introduction

The global population is forecasted to reach 8 billion by 2023 and 10 billion by 2056 because of the high birth rates in developing countries and the extended average life span owing to medical advancements (United Nations, 2019). Given this expected population increase, it is expected that the food demand in 2050 will increase by approximately 59–98% compared with that in 2016 (Elferink and Schierhorn, 2016). In addition, restrictions on the export of agricultural and livestock products and distribution networks in some countries due to the coronavirus 2019 (COVID-19) pandemic has led to an increase in the demand for food security (de Paulo Farias and dos Santos Gomes, 2020). Consequently, people in related industries have become highly interested in increasing

the productivity of agricultural and livestock products (Baldos and Hertel, 2014).

Most fundamental measures used to enhance livestock productivity have included the improvement of the growth performance of livestock. It is critical to maintain a comfortable thermal environment to achieve high growth performance because livestock are sensitive to the indoor thermal environment (Quiniou et al., 2000; Collin et al., 2001; Aarmink and Versteegen, 2007; Hessel et al., 2010; Hu et al., 2017). Moreover, many pollutants are generated in the pigsty because of livestock manure (Banhazi et al., 2011), and this can have a significant effect on the productivity of the pigsty (Banhazi and Cargill, 1998; Lee et al., 2005). In conjunction with these factors, there has been a steady increase in the demand for animal welfare (Velarde et al., 2015; Cecchin et al., 2018;

Abbreviations and Variables: ACH, Air changes per hour; ANFIS, Adaptive neuro fuzzy inference system; ASHRAE, American Society of Heating, Refrigerating and Air-Conditioning Engineers; BES, Building Energy Simulation; CFD, Computational fluid dynamics; CVRMSE, Coefficient of variance of the root mean square error; DCV, Demand controlled ventilation; EBE, Energy balance equation; SSE, Sum-of-squared error; MBE, Mean bias error; PLF, Part-load-factor; VFD, Variable frequency drive; HVAC, Heating, ventilation, and air conditioning; f_{flow} , flow fraction [0–1]; f_{pl} , part-load-factor [0–1]; m , mass flow [m³/s]; m_{design} , design mass flow [m³/s]; M , measured value [kWh]; \bar{M} , mean measured value [kWh]; n , number of data; Q_{tot} , fan power [W]; Q_{design} , design fan power [W]; S , simulated value [kWh].

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O'Malley et al., 2019). Thus, there is a trend of increasing interest in the application and operation of ventilation systems to ensure a comfortable environment in the pigsty.

Ventilation systems applied to a pigsty can be largely classified as natural and mechanical. Natural ventilation systems can maintain an indoor environment by introducing fresh and cool air from the outer environment without using any energy. However, its effect varies based on weather conditions and building design elements. A mechanical ventilation system can attain a more comfortable indoor environment using a uniform volume of outside air. Hence, many studies have recently reported the application of mechanical ventilation systems to pigsties; these studies have focused on airflow distribution analysis using computational fluid dynamics (CFD). For example, Du et al. (2019) assessed the simulation accuracy based on the boundary settings for the inlet and outlet in the CFD model for a henhouse to which a tunnel ventilation system was applied; further, they analyzed the homogeneity of the indoor air movement according to the air inlet configuration and the existence or absence of a side-wall window using a model. Rong et al. (2015) conducted CFD modeling for a pigsty building into which natural and mechanical ventilation systems were applied together (hybrid ventilation); they analyzed the indoor ventilation performance based on the outside air wind direction, wind speed, and the existence or absence of surrounding topographic modeling. The wind direction and wind velocity were found to have a significant effect on the air-change rate; when the wind velocity was high, the existence or absence of surrounding topography modeling had a significant effect on the air-change rate.

Further, Topisirovic and Radivojevic (2005) experimentally analyzed the airflow speed, dust concentration, and energy consumption of the mechanical ventilation system in the pigsty based on its installation position, i.e., either on the floor, roof, or both. The results suggested that the ventilation performance was the best when fans were installed on both the floor and the roof. However, in summer nights during which the maximum ventilation rate was not necessary, the ventilation performance could be attained economically using only the floor mechanical ventilation system. Ecim-Djuric and Topisirovic (2010) suggested a natural ventilation system optimization method via the analysis of the indoor airflow speed based on wind velocity and incident angle at the opening in a pigsty through CFD analysis. The energy consumption was reduced by approximately 60% by appropriately replacing the mechanical ventilation system when an optimized natural ventilation system was applied.

In addition to the analysis of air flow distribution using CFD, the thermal behavior and energy consumption in the pigsty were analyzed based on the applied mechanical ventilation system. Teitel et al. (2008) experimentally analyzed the indoor thermal environment and energy consumption based on the on/off system and the variable frequency drive (VFD) system of the ventilation fan in a pigsty. The energy consumption required to maintain the same indoor thermal environment using the VFD system was approximately 25% smaller than that required with the on/off system. Xie et al. (2019) developed a model to predict the indoor temperature through the energy balance equation (EBE) and an adaptive neurofuzzy inferring system (ANFIS) with the weather condition and indoor environment data in a pigsty as input variables. As a result, the EBE model exhibited a higher prediction performance than that of the ANFIS model, and derived the minimum air-change rate based on the EBE model, which shows the possibility of reducing the energy consumption of the ventilation fan. Constantino et al. (2020) monitored data, such as indoor temperature and gas concentration in an actual chicken farm and developed an energy consumption prediction model based on the increase in the air-change rate for gas concentration control.

Mechanical ventilation system requires an effective ventilation performance and energy efficiency. A ventilation control strategy that considers the indoor air quality and thermal environment integrally is required because the role of outside air introduced through ventilation

not only improves indoor air quality but also induces cooling effects. Occasionally, outer (environment) air is introduced to ensure indoor air quality can lead to an excessive cooling effect and increased energy consumption. Therefore, fan control schemes need to satisfy both the indoor air quality and thermal environment requirements, and simultaneously serve as an energy-efficient operation method. However, studies on the energy-efficient operation of mechanical ventilation systems that consider indoor air quality and thermal environment in a pigsty in an integrated manner are lacking. Accordingly, this study analyzed the applicability of a demand-controlled ventilation (DCV) system based on CO₂ and indoor temperature control for livestock buildings. For this purpose, a model that can predict indoor temperature, CO₂ concentration, and fan electric energy according to the operation of a ventilation fan was developed, and the performance of maintaining the indoor environment and energy reduction potential using DCV control compared with the conventional control method were analyzed.

Fig. 1 shows a flowchart of all the processes involved in this study. First, data of the target livestock building, such as piglet conditions, information on ventilation fan operation, and indoor and outdoor environment information, are monitored. Subsequently, an energy model that can simulate thermal dynamic characteristics according to the operation of the ventilation fan is developed based on the collected data. Finally, based on a simulation analysis using the developed model, the DCV control method and conventional control method are compared and analyzed.

2. Materials and methods

2.1. Building description

2.1.1. Outline of the target pigsty

The target pigsty was a piglet house for raising piglets among pigsties located in Suncheon, South Korea. As shown in Fig. 2(a), the piglet house comprises two piglet rooms and one sick pig room. The floor is slatted and is designed to allow piglet manures to be treated in the basement (Fig. 2(b)). In each piglet room, up to 900 piglets were raised at intervals of approximately 50 days. Further, each room has four ceiling fans and six exhaust fans on the southern wall. In addition to these ventilation facilities, the indoor environment was controlled through radiant panels for heating and cooling pads. One of the two piglet rooms was used in this study.

Fig. 3 shows the exterior and interior views of the piglet house. The data on the indoor environment, weather conditions, piglet conditions, and facility system control state monitored at 5 min intervals for the target piglet room (Table 1). Temperature and humidity sensors were installed all over the piglet room for indoor thermal environment control. CO₂ and ammonia concentrations were monitored in the corridor and in the piglet room to assess indoor air quality. Further, outdoor air-condition data, such as outdoor temperature and humidity, wind direction, wind velocity, solar radiation, and precipitation, were collected through the weather station installed at the inlet of the piglet house. In addition to indoor and outdoor environment information, the conditions of the pigs were monitored in real time by collecting the average weight and feed intake data. The operating ratio of the ventilation fan, on/off state of the boiler, and cooling pad were used to control the facility system. This study conducted model development and DCV control simulation analysis using data collected from July 1 to July 28, 2020. Among the factors which affect the indoor air quality, ammonia was not considered in this study owing to the occurrence of many outliers and missing values for ammonia during the corresponding period. The specifications and installation locations of the sensors used in this study are shown in Table 2 and Fig. 4, respectively.

2.1.2. Ventilation system

In the target piglet house, the ventilation system is always in

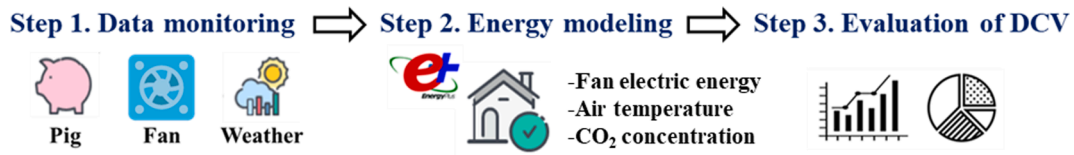


Fig. 1. Flowchart of the study.

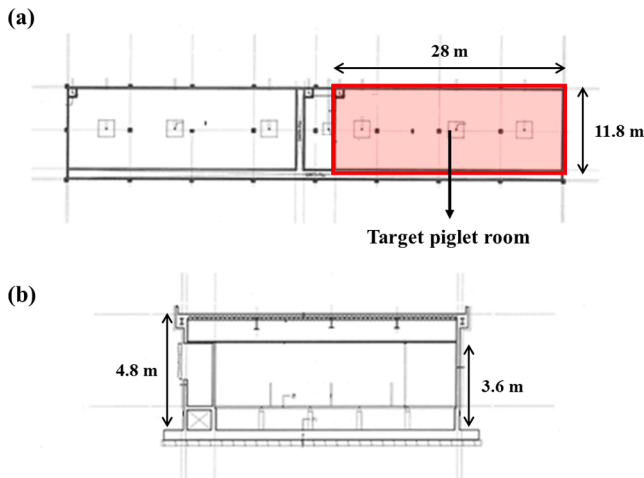


Fig. 2. Schematic of the target building. (a) First-floor plan and (b) longitudinal section.

operation because of pollutants generated inside the piglet house. The indoor environment is maintained using only the ventilation fan during the cooling and intermediary periods (excluding the heating period) because the cooling pad is operated for only one or two days in the year during the severe hot season. This study used data collected only during the intermediary and cooling periods to focus on the operation of the mechanical ventilation system. Fig. 5 shows the ceiling fan and side-wall exhaust fan installed in the piglet room; the specifications of the ventilation fans are summarized in Table 3. Data related to the exhaust fan were not collected because only the ceiling fan was operated during the study period.

2.2. Development of air temperature and CO₂ prediction model

2.2.1. Baseline modeling

For the energy modeling of the pigsty, EnergyPlus 9.0, a physics-based model, was used. EnergyPlus 9.0 is a building energy simulation (BES) program developed by the United States Department of Energy (DOE). This model has been used for modeling, and it combines the advantages of the existing Building Loads Analysis and System (BLAST)

and DOE-2. EnergyPlus has high reliability because it can calculate the load through the heat balance method and perform the dynamic analysis of conduction, radiation, and convective heat transfer in buildings.

Table 4 presents an overview of the baseline model. For the building envelope, materials listed on the design drawings were used; values provided by the Passive House Institute in Korea were applied as the thermal performance of the materials. The lights load was calculated based on an illumination of 350 lx to consider the heat inside the pigsty (Gadd, 2011). The pig heat was set such that heat changes would be reflected based on pig weights according to the equation derived in an existing study (Brown-Brandt et al., 2013).

EnergyPlus is a simulation tool used for the evaluation of the thermal behavior of buildings. CFD analysis or the CONTAM tool is used to simulate the behaviors of pollutants. In this study, EnergyPlus was used to analyze changes in the indoor environment and energy consumption based on the application of ventilation system control, while it simultaneously predicted the indoor temperature and CO₂ concentration. EnergyPlus shows the CO₂ concentration behavior based on the air exchange rate of the room considering the CO₂ concentration in outdoor air and CO₂ generation rate per pig heat through the “ZoneAirContaminantBalance” model. As mentioned above, the CO₂ concentration in outdoor air was assumed to be the same as the value measured in the corridor. In the case of the CO₂ generation rate per pig heat, the total CO₂ generation rate from the breathing and manures of pigs in the pigsty

Table 1
Measured data (5 min intervals).

Term	July 1–July 28, 2020 (2–5 weeks of growth)	
Data	Indoor environment	Air temperature Relative humidity CO ₂ and NH ₃ concentration
	Weather	Air temperature Relative humidity Wind direction and speed Radiation Rainfall
	Occupancy	Water and feed intake Average weight
	Operation	Fan operating ratio Boiler on/off Cooling pad on/off
	Energy Consumption	Fan electric energy Boiler electric energy

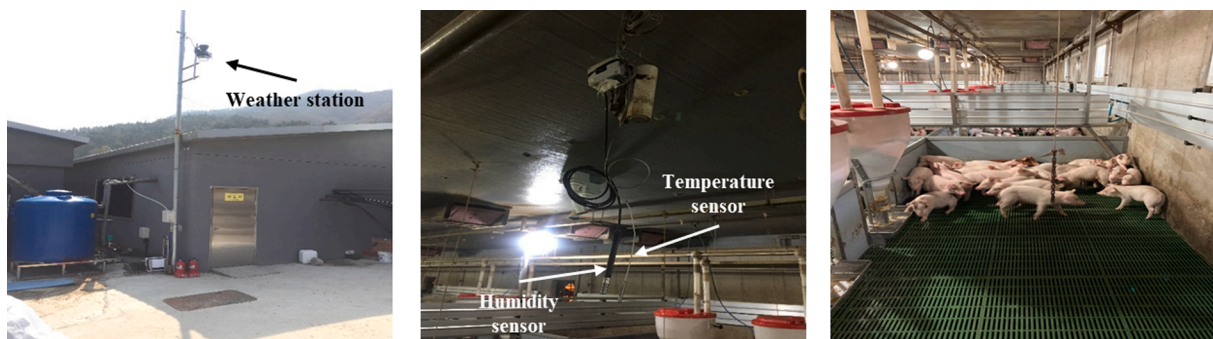


Fig. 3. Exterior and interior views of the pigsty.

Table 2
Sensor specifications.

	Model	Manufacturer	Scope	Accuracy
Fan operating ratio	SL-300	SUNG-IL	0–100%	.
Fan electric energy	mEMD	Green ENS	0–4,294,967 kW/kVar	±0.5%
Air temperature	PR-20	OMEGA	–73–260 °C	Class A per IEC60751
CO ₂ concentration	SH-VT260	SOHATECH	0–10000 parts per million (ppm)	±2%

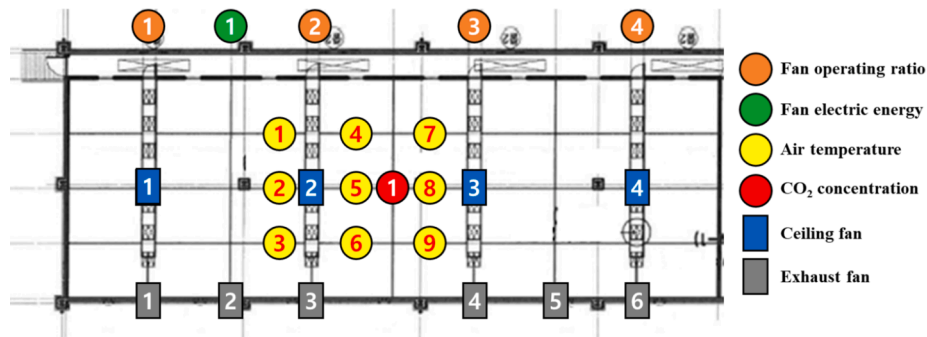
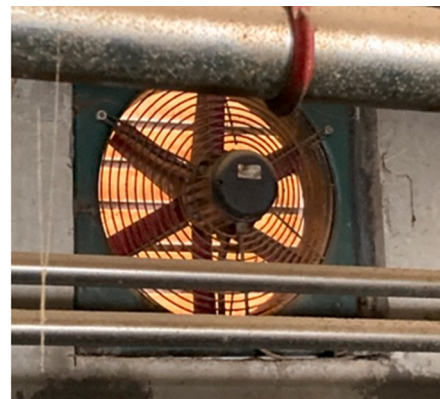


Fig. 4. Installation of sensors and fans.



(a)



(b)

Fig. 5. Ventilation system of pigsty. (a) Ceiling fan and (b) exhaust fan.

Table 3
Specification of ventilation fan.

Category	Model	Power (W)	Air flow (CMH)	Designed flow rate (m ³ /s)	Fan pressure (Pa)
Ceiling fan	SLF-500D4-6(4 EA)	418	8500	2.36	177
Exhaust fan	SLF-500A4-6(6 EA)	535	8500	2.36	227

with a slatted floor was set based on existing research (Pedersen et al., 2008).

The “ZoneVentilation:DesignFlowRate” class that can install multiple fans in one zone was utilized to implement 10 fans installed in the piglet room on EnergyPlus. This class calculates the fan flow rate and power consumption based on three inputs of the fan: design flow rate, fan pressure rise, and fan total efficiency. For the fan modeling of the piglet house, the design flow rate and fan pressure rise were applied based on performance items summarized in Table 3. The total efficiency

Table 4
Baseline model overview.

U-Value [W/m ² ·K]		Roof	0.114
		Ceiling	0.431
		Wall	0.311
		Floor	2.462
Internal loads	Pig	Heat production	4.71 W/kg
		CO ₂ production	5.139E-08 m ³ /s·W
		Equipment	15 W/ m ²
Heating, ventilation, and air-conditioning (HVAC)	Lights		9.46 W/m ²
	Ventilation fan		
	Radiant panel		
		Cooling pad	

of the fan was set to 0.7 after the manufacturer was consulted. The number of revolutions of the fan was adjusted by changing the voltage to the VFD method. It was assumed that the fan operating ratio (number of revolutions) exhibited a linear relationship with the fan flow rate based on the performance experiment data of the manufacturer because no experiment was conducted on the indoor air flow according to the fan operation in this study. Thus, when applying the fan schedule in the

energy model, the fan flow rate was set according to the fan operating ratio. The energy model predicts the indoor air temperature, CO₂ concentration, and fan electric energy every hour by reflecting the characteristics, such as weather conditions and fan schedules.

2.2.2. Sensitivity analysis

The sensitivity of the input variables was analyzed for each result of the indoor temperature and CO₂ concentration before the calibration of the prediction performance of the developed baseline model. Sensitivity analysis—used to sequence input variables affecting model results—is a statistical analysis method often used in studies on the prediction performance of building energy models (Heiselberg et al., 2009; Kong et al., 2015; Pang et al., 2020). Sensitivity analysis methods applied in the building energy field are largely classified into local, global, and screening approaches. The local approach calculates the sensitivity of each variable when a single variable is changed and the rest are fixed; thus, it does not consider relationships between variables. The global approach randomly samples the input variable baselines and then changes input variables by applying a statistical distribution. Thus, it considers the effects of input variables over the entire range unlike the local approach (Tian, 2013). Finally, the screening approach, which is also referred as the one-parameter-at-a-time method, calculates the sensitivity of one input variable in one performance; however, it prevents the sensitivity from converging to local conditions by changing the baseline model and repeating this several times (King and Perera, 2013). The screening approach has higher accuracy than that of the global approach in terms of the number of repetitions, and it is suitable for screening input variables with high impact. One of the most extensively used screening approaches is the Morris method.

The sensitivity analysis of the Morris method determines the impact of input variables based on the elementary effect (EE) (Morris, 1991). The EE is a variable that indicates the degree of change in the model results when a specific variable is changed. The importance of input variables is assessed by the sensitivity index (μ^*), absolute value average, and standard deviation (σ) of the EE. A larger EE indicates a more important variable. A combination of input variables that serve as the baseline must be sampled first to calculate the EE value of each variable. To this end, the minimum and maximum values of each input variable must be established, and the combination of input variables must be sampled randomly within the established range. After the combination of the baseline input variables is selected, the EE is derived by discretizing and dividing each input variable, and then changing it in a step-wise manner as.

$$EE_i = \frac{y(x_1, \dots, x_{i-1}, x_i + \Delta, x_{i+1}, x_k) - y(x_1, \dots, x_k)}{\Delta} \quad (1)$$

where $(x_1, \dots, x_{i-1}, x_i + \Delta, x_{i+1}, x_k) - y(x_1, \dots, x_k)$ denotes a set of input variables, y denotes the simulation result according to the input variables, and Δ denotes the change in the input variables. The finding of an existing study indicate that the best performance is obtained under conditions of 10 samplings ($r = 10$) and four changing stages of input variables ($p = 4$) (Franczyk, 2019).

Eight variables that can affect the results of indoor temperature and CO₂ concentration were selected to perform a sensitivity analysis; these are summarized in Table 5. It is crucial to select an appropriate value of the range of input variables because it influences the sensitivity analysis result (the larger the range is, the higher is the EE value). The fan flow rate is selected based on the rated air volume, and the design drawing is referenced for the U-value. Other variables are set based on the values estimated in existing studies (Pedersen et al., 2008; Gadd, 2011; Brown-Brandl et al., 2013).

Fig. 6 shows the sensitivity analysis results of each input variable that is part for the results of indoor temperature and CO₂ concentration. Both results were the most sensitive to the infiltration rate, followed by pig heat, activity level, and fan flow rate. The equipment load was

Table 5
Input variables for sensitivity analysis.

Label	Minimum	Maximum
Activity level	0.6	1.2
CO ₂ generation rate (m ³ /s-W)	0.00000005	0.000000055
Pig heat (W)	34	74
Fan flow rate (m ³ /s)	1.89	2.36
Lights load (W/m ²)	8	12
Equipment load (W/m ²)	10	20
U-value (W/m ² -K)		
Concrete	1.4	1.8
Insulation	0.2	0.4
Infiltration rate (ACH, Air changes per hour)	0	10

influenced only the indoor temperature, whereas the CO₂ generation rate was influenced only the CO₂ concentration. In this study, the prediction performance of the model was calibrated by adjusting the sensitive input variables, whereas the initial settings were maintained for the light load and U-value, which did not significantly affect the two results. Fig. 7 shows the input variables used in the calibration and the method used for setting each input variable.

2.2.3. Change of pig weights

Among the input variables, pig heat increases with pig weights (Brown-Brandl et al., 2013), and hence, a pigsty shows an internal heat production behavior different from that of general buildings. Further, it is important to reflect the changes in pig weights according to the day of growth for the prediction model developed in this study because the total amount of CO₂ generated increases with heat production. Thus, this study analyzed whether the change in pig weights reflected in the development of the prediction model had an impact on the prediction performance.

Pig weights were monitored in a pigsty using a weighing scale, as shown in Fig. 8. One weighing scale was installed in the piglet house, and the weights of pigs which passed through the internal passage were detected. Fig. 9 shows the daily average weights of pigs measured using the weight scale from May 1 to June 16 (1–7 weeks of growth). Given that the weight data were collected from many unspecified pigs, the pig weight may decrease even when the number of days of growth increases, as indicated in Fig. 9. This study considered the pig heat by reflecting the average weight per week of growth in the model based on the regression equation derived from past data, assuming that pig weights increase linearly as a function of time (growth days). Subsequently, the prediction performance was compared between the case of fixing the average weight during the analysis period and in the model.

2.2.4. Optimization

Input variables other than pig heat were set using the optimization technique. The input variable optimization method is one of the most commonly used energy model calibration methods. This method can find a combination of input variables that yield the smallest error rate using the difference between real and predicted values as the objective function (Coakley and Raftery, 2014). Before optimization, the prediction performance behavior of the model was analyzed through parametric work for each combination of input variables. Fig. 10 shows the indoor temperature and CO₂ concentration mean bias error (MBE) of the model based on the combination of input variables (see Eq. (2)). A trade-off between the two MBE values occurred because of input variables that affected both the indoor temperature and CO₂ concentration. Input variables in the third quadrant are sequenced in the descending direction of the absolute values of the two MBEs. However, those in the second quadrant are not sequenced because the absolute MBE value of the CO₂ concentration increased as the MBE absolute value of the indoor temperature decreased.

In this study, weights were not applied to the prediction performance for the indoor temperature and CO₂ concentration. Hence, as shown in Fig. 10, points where the MBE coordinates of the indoor temperature

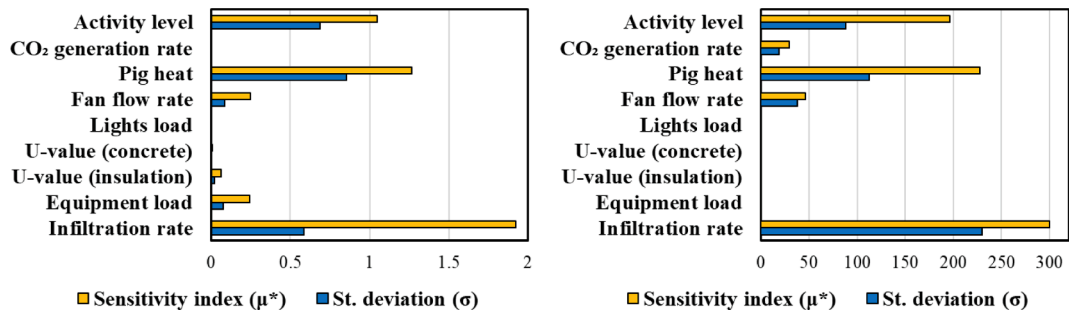


Fig. 6. Results of sensitivity analysis. (a) Air temperature and (b) CO₂ concentration.

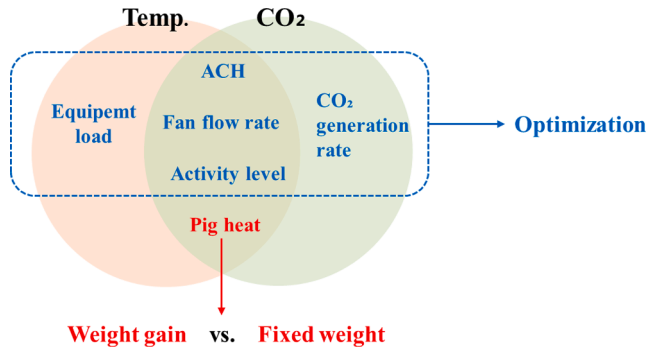


Fig. 7. Input variables used for calibration.

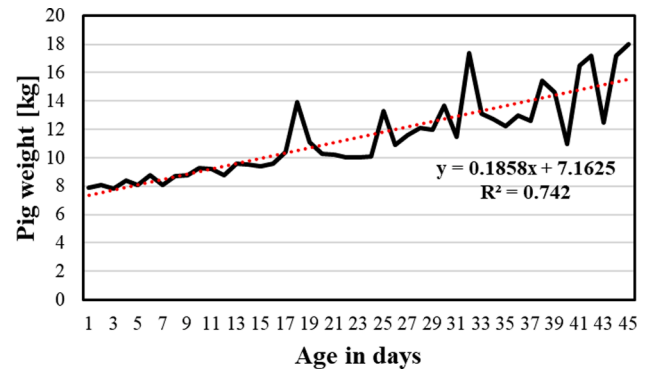


Fig. 9. Pig weight variation as a function of the day of growth (May 1–June 16).



Fig. 8. Weighing scale.

and CO₂ concentration are the closest to the origin are considered as the optimal solution. To this end, the optimization was performed with the objective function set to $MBE_{Temperature}^2 + MBE_{CO_2}^2$. The constraints for each input variable are the same as those applied to the sensitivity analysis, as summarized in Table 5. GenOpt—an optimization simulation tool—was used, and the GPSPOCCHJ algorithm—a hybrid global positioning system algorithm reset based on particle swarm optimization—was applied. The optimization was performed based on data collected from July 1 to July 7 (second week of growth). The

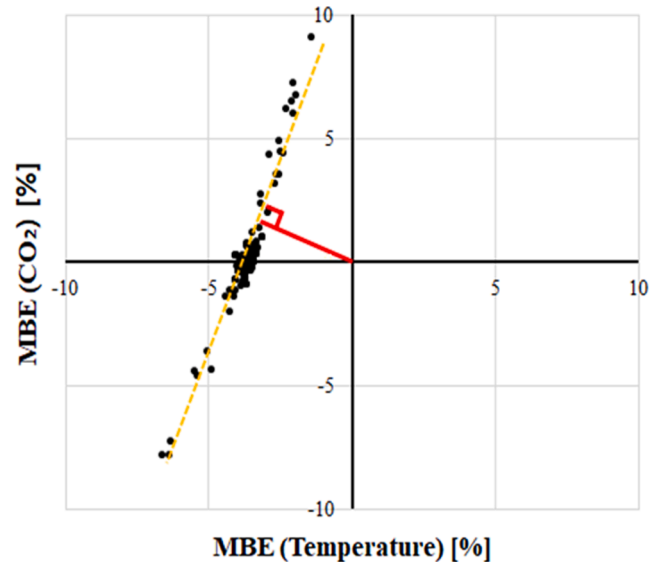
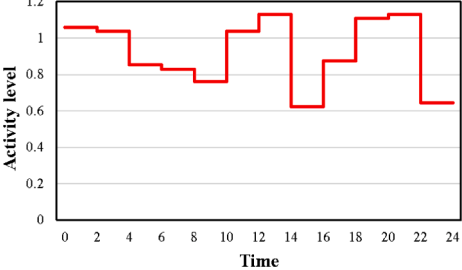


Fig. 10. MBE behavior of the model.

weather data and fan operating ratio data on the corresponding dates were input to EnergyPlus; a separate output was generated and applied to the objective function to calculate the differences between the actual temperature and CO₂ concentration. Table 6 lists the input variables derived from the optimization results. The activity level was set such that 2 h unit schedules could be input to reflect the differences in the activity of pigs over time. Based on the optimization input variables derived from the second week of growth data, a prediction model simulating the indoor temperature and CO₂ concentration behavior from July 8 to July 28 (3–5 weeks of growth) was developed by reflecting the weekly pig weights.

Table 6
Optimization results.

Infiltration rate	6 ACH
Fan flow rate	2.03 m ³ /s
Equipment load	11.5 W
CO ₂ generation rate	0.000000514 m ³ /s-W
Activity level	

2.2.5. Performance metrics

To evaluate the performance of the developed model for predicting indoor temperature and CO₂ concentration, MBE, coefficient of variance of the root mean square error (CVRMSE), and mean absolute percentage error (MAPE) indicators were used, as shown in Equations (2) to (4). MBE and CV (RMSE) are the most commonly used error indicators for assessing the performance of BES models (Chong et al., 2021). American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Guideline 14 (2014) presents the error limits standards for the two statistical indicators. MAPE values less than 10% represent an extremely precise forecast, while MAPE values from 11% to 20% indicate a decent forecast (Ahmadi et al., 2021). Table 7 shows the selected standards for each error indicator, based on which the prediction performance of the developed model was evaluated.

$$MBE = \frac{\sum_{i=1}^n (M_i - S_i)}{\sum_{i=1}^n M_i} \times 100 \tag{2}$$

$$CVRMSE = \frac{\sqrt{\frac{\sum_{i=1}^n (M_i - S_i)^2}{n}}}{\bar{M}} \times 100 \tag{3}$$

$$MAPE = \frac{\sum_{i=1}^n \frac{|M_i - S_i|}{M_i}}{n} \times 100 \tag{4}$$

2.3. Development of part-load factor (PLF) model for fan electric energy

EnergyPlus represents the relationship between the fan operating ratio and power consumption using the simple polynomial-based curve-fit model without considering the fan pressure rise model for the fan performance curve as.

$$f_{flow} = m/m_{design} \tag{5}$$

$$f_{pl} = c_1 + c_2 \cdot f_{flow} + c_3 \cdot f_{flow}^2 + c_4 \cdot f_{flow}^3 + c_5 \cdot f_{flow}^4 \tag{6}$$

$$Q_{tot} = f_{pl} \cdot Q_{design} \tag{7}$$

In view of this, a quaternary polynomial equation was developed in the present study to predict the PLF according to the fan operating ratio using past data for the fan operating ratio and power consumption data collected from the piglet house.

Table 7
Acceptable error rate.

Label	Acceptable error (%)
MBE	± 10
CV (RMSE)	30
MAPE	20

Fig. 11 shows instantaneous power data based on the fan operating ratio collected from May 25 to June 30, 2020. The average value of the four ceiling fans was used as the fan operating ratio. The PLF model for operating ratios with values between 0% and 45% was developed because the maximum fan operating ratio did not exceed 45% during the data collection period. For operating ratio values from 0 to 5%, the average instantaneous power was 0.54 kW; the power did not vary considerably as a function of the operating ratio. For operating ratio values from 35 to 37.125%, the instantaneous power sharply decreased and then increased as a function of the operating ratio. Owing to this irregular behavior, the instantaneous power for operating ratio values in the 35–40% range was difficult to represent, as indicated in Fig. 11, for a quartic polynomial model developed using the data set. This section accounts for a considerable part (approximately 16%) of the data collection period. Therefore, there is a need for a model that can reflect the characteristics of this section. We developed two PLF models by separating the data around the fan operating ratio of 37.125% as shown in Fig. 11 based on the changing trend characteristics of instantaneous power. Table 8 summarizes the curve fitting results of the developed PLF model. For curve fitting, the least absolute residual method was used among robust regressions.

To validate the electric energy prediction performance of the fan according to the PLF model application, MBE and the CV (RMSE) were used. Table 9 lists the recommended error values per data interval and the error indicators of the predicted values of energy consumption according to the application of the PLF model from July 1 to 28. A high prediction performance that satisfied the recommended error values of monthly data to which strict criteria were applied was obtained with MBE = 3.41% and CV (RMSE) = 12.25% by applying the PLF model.

2.4. DCV system

The target pigsty controls the indoor environment such that the fan operating ratio is changed by the indoor temperature, as indicated in Fig. 12. Fan control sections are divided into three categories—maximum, variable, and minimum operating ratios—using the four control variables of maximum/minimum temperatures and maximum/minimum operating ratios. In the maximum operating ratio section, the indoor temperature is higher than the maximum temperature, and the input maximum operating ratio is applied to lower the indoor temperature. When the indoor temperature is between the minimum and maximum temperatures, the operating ratio increases linearly according to the indoor temperature between the maximum and minimum operating ratios. In the minimum operating ratio section, the indoor temperature is lower than the minimum temperature, and the minimum operating ratio is applied to maintain the indoor air quality.

In a real pigsty, the minimum operating ratio is set to 10%, and the operation of the ceiling fan is controlled. It is crucial to secure a sufficient operating ratio to maintain indoor air quality because numerous pollutants are generated from the breathing and manures of pigs in a pigsty. However, even if the indoor temperature is sufficiently low, the thermal comfort can be disrupted because of the excessive cooling caused by the application of the minimum operating ratio. Therefore, in the minimum operating ratio section, the comfort of the indoor thermal environment and energy reduction is achieved by applying DCV control considering indoor air quality. The DCV is a ventilation control method that adjusts the operating ratio in response to indoor air quality factors, such as occupancy schedule or CO₂ concentration. Many studies on DCV have been conducted for general buildings because DCV has drawn attention as an energy-efficient ventilation control method that allows the reduction of unnecessary ventilation load while maintaining indoor air quality (Ng et al., 2011; Lu et al., 2011; Belmonte et al., 2019). In this study, the DCV control method that applies on/off ventilation fans using the indoor CO₂ concentration as the criterion in a section where the minimum operating ratio is applied by using the developed indoor temperature and CO₂ concentration prediction model. To this end, the

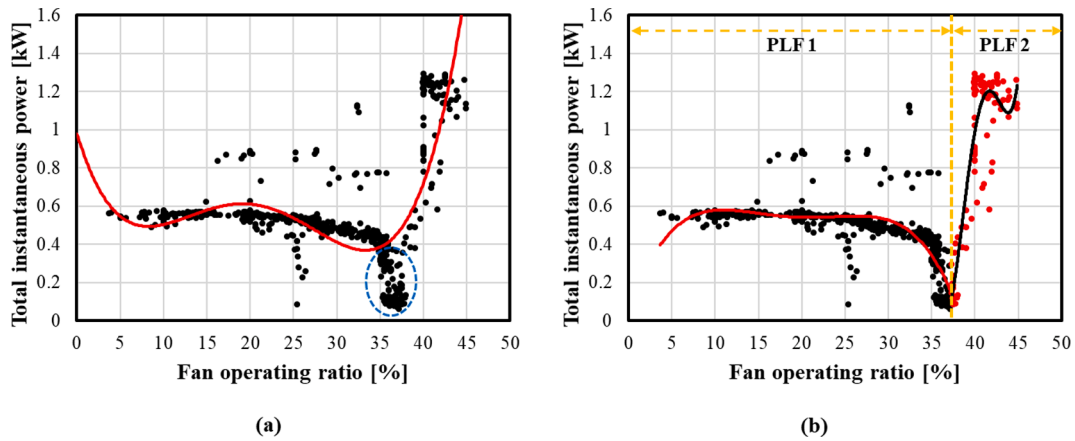


Fig. 11. Fan electric energy by operating ratio (four ceiling fans). (a) Single quartic and (b) multiquadric polynomials.

Table 8
Curve fitting results.

	Part-load factor (PLF 1)	PLF 2
c_1	-0.009936	0.05089
c_2	-0.02946	-0.02155
c_3	-0.02249	-0.2311
c_4	-0.01384	0.2399
c_5	0.3194	0.6408
SSE	0.05212	0.6627
R^2	0.9679	0.7618
RMSE	0.01539	0.1271

Table 9
CV (RMSE) and MBE of PLF model (July 1 to 28).

Label	Acceptable error (%)	PLF model error (%)
MBE (Hourly)	±10	
CV(RMSE) (Hourly)	30	
MBE (Daily)	.	3.41
CV (RMSE) (Daily)	.	12.25
MBE (Monthly)	±5	
CV (RMSE) (Monthly)	15	

indoor environment and fan energy consumption are compared between the existing control method and DCV method.

Fig. 13 shows the DCV control algorithm applied in this study. The maximum and variable operating ratio sections are the same as the existing control method. However, in the minimum operating ratio section, the on/off control is applied based on the CO₂ concentration.

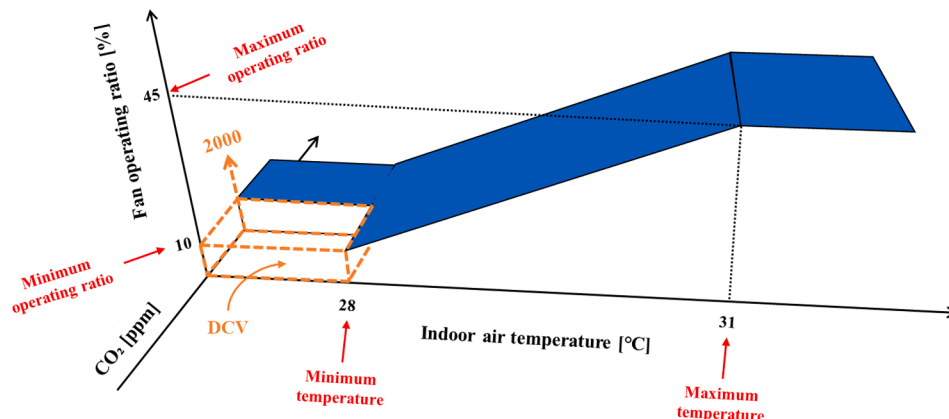


Fig. 12. Ventilation system control.

The control variables are set based on the measured data because the target pigsty randomly controls the ventilation system based on the experience of the manager without monitoring the fan control variable setting conditions. The minimum and maximum temperatures were set to 28 °C and 31 °C, respectively, based on the indoor temperature distribution (28.41–30.58 °C) after excluding outliers during the corresponding period (July 8 to July 28, 3–5 weeks of growth). The maximum and minimum operating ratios were set to 45% and 10%, respectively, as shown in Fig. 12. The control reference CO₂ concentration was applied by assuming that the allowable concentration in the piglet house was 2000 parts per million (ppm), according to the reported literature (Murphy, 2012).

3. Results and discussion

3.1. Model evaluation

MBE, CV (RMSE), and MAPE error indicators were used to evaluate the prediction performance of the developed model. In addition, the prediction performance was compared with a model that does not consider weight changes (fixed value for the optimization period, second week of growth) to assess the impact of the changes in pig weights on the prediction performance in the development of the pigsty indoor environment prediction model. The prediction performance of the model was analyzed by comparing the hourly data for the period from July 8 to July 28 (504 h).

Fig. 14 shows the measured values of the indoor temperature and predicted values of the model. The average indoor temperature of the measured values was 29.4 °C, and was maintained in the range of

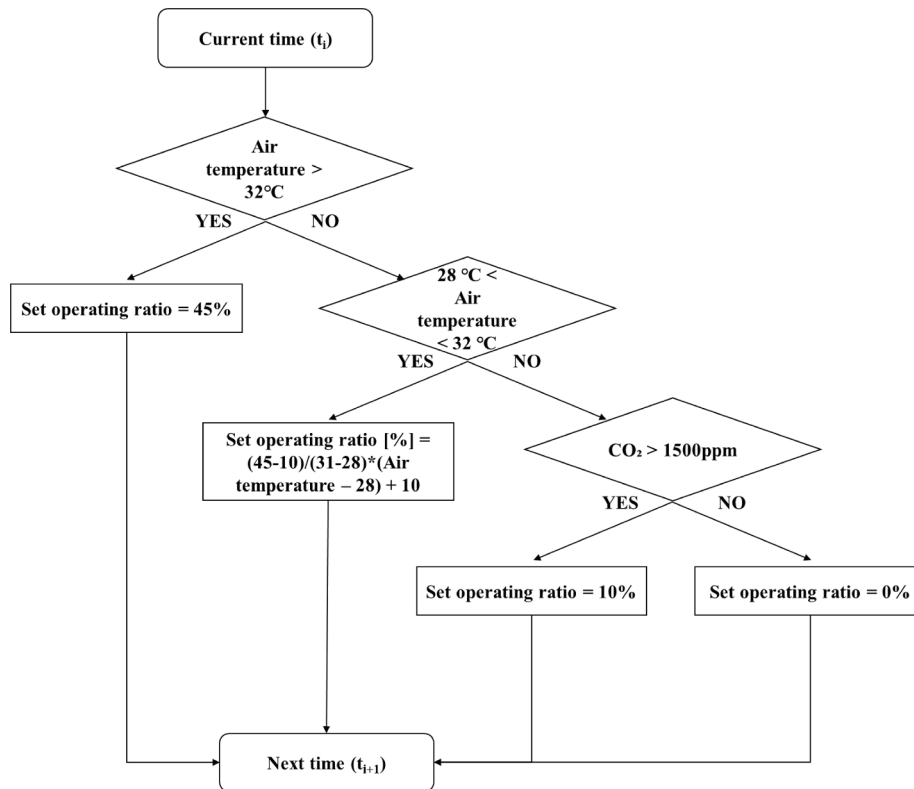


Fig. 13. Demand-controlled ventilation control algorithm.

28–31 °C. When the prediction value behavior of the model depended on whether the applied weight changes were applied was examined, the model reflecting weight changes shows values close to the actual values. The values of the model with fixed weights are found to be lower by approximately 0.73 °C on average. This is attributed to the low indoor heat production caused by the (fixed) relatively low weight (second week) corresponding to the optimization period. Table 10 shows that the weight gain model exhibits a higher prediction performance for this error rate. Both models satisfied the acceptable standards and yielded similar prediction performance to recent studies on calibrating the indoor temperature prediction performance of building energy system models (Donovan et al., 2019; Baba et al., 2022).

As indicated in Fig. 15, the CO₂ concentration prediction performance during this period was also compared. Similar to that for indoor temperature, the CO₂ concentration behavior of the weight gain model was also found to be closer to the actual values; it was highly similar if the 121–216 h section (wherein the actual CO₂ concentration was relatively high) was excluded. This is attributed to the decrease in the CO₂ concentration because of the low-heat production similar to that in the case of the fixed weight model that corresponds to the optimization

period where a relatively low weight was applied. Further, the error rate showed a significant difference between the two models. The fixed weight model showed MBE and MAPE values of −20.85 and 21.43%, respectively, which exceeded the acceptable error rates. In contrast, all error indicators of the weight gain model satisfied the acceptable error rates and were similar to those of recent studies on developing indoor CO₂ concentration prediction models (Pantazaras et al., 2016; Taheri et al., 2021). This suggests that it may be difficult to achieve adequate prediction performance if the change in pig weights is not considered when developing the CO₂ concentration prediction model. This implies it can be difficult to achieve the prediction performance unless the change in pig weights is considered when the CO₂ concentration prediction model is developed.

3.2. Application of DCV control

In this study, the applicability of DCV control in a pigsty was examined based on the developed model (weight gain). To this end, indoor environment and energy consumption were compared with those of an existing control method. The simulation period was set identical to

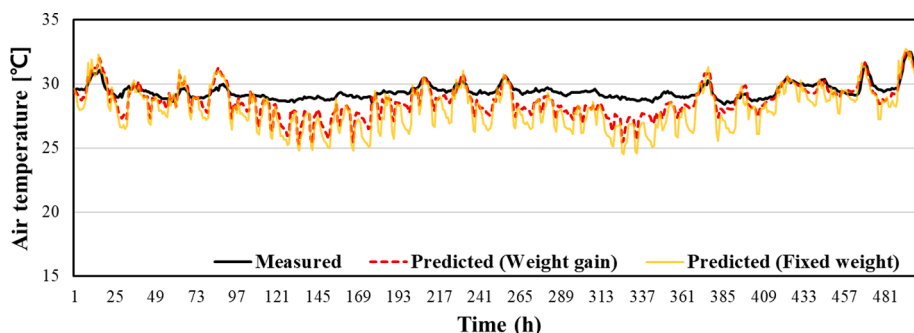


Fig. 14. Air temperature prediction performance comparison.

Table 10
Performance of the energy models (air temperature and CO₂ concentration).

		Weight gain (%)	Fixed weight (%)	Acceptable error (%)
Air temperature	MBE (Hourly)	-2.48	-4.37	± 10
	CV(RMSE) (Hourly)	3.87	6.02	30
	MAPE (Hourly)	3.03	4.87	20
CO ₂ concentration	MBE (Hourly)	-9.52	-20.85	± 10
	CV(RMSE) (Hourly)	20.24	26.54	30
	MAPE (Hourly)	14.15	21.43	20

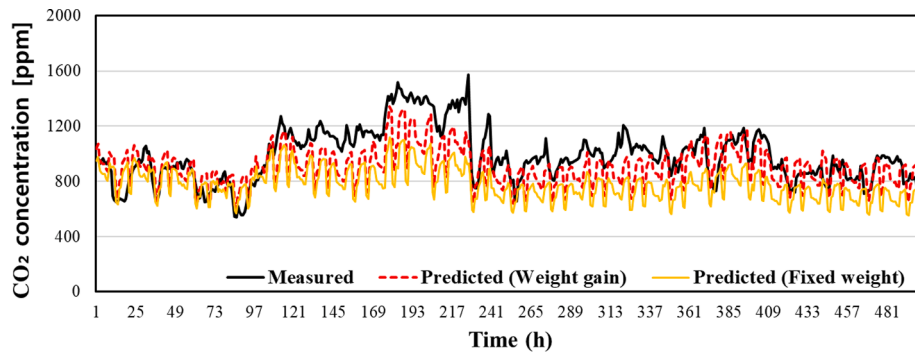


Fig. 15. CO₂ concentration prediction performance comparison.

the performance verification period for the prediction model. The control was applied based on hourly indoor temperature and CO₂ concentration values.

Fig. 16 shows the indoor temperature and outside air temperature behavior according to the control method. The DCV control method has a larger temperature change and a higher frequency of sections that exceed the maximum temperature of 31 °C compared with the conventional control method. This is because many sections with a 0% fan operating ratio occur during the application of the DCV control method, as shown in Fig. 18; the indoor temperature increased considerably during the time step when the fan was not operating. In contrast, the indoor temperature decreased during the time step when the maximum operating ratio was applied. In the conventional control method, the increase in the indoor temperature was relatively small because the minimum operating ratio was applied.

In the 97–192 h section, wherein the outside air temperature was relatively low, the conventional control method did not have many sections where the maximum temperature was exceeded. In the 408–504 h section wherein the outside air temperature was relatively high, both control methods yielded very high frequencies that exceeded the maximum temperature of 47.13%. This indicates that the control variable conditions applied to this simulation cannot satisfy the indoor temperature owing to the high outside air temperature and heat production by increasing pig weights.

Further, the CO₂ concentration showed large changes in the DCV

control method; however, the CO₂ concentration did not exceed the allowable value of 2000 ppm for both control methods, as indicated in Fig. 17. Because there was no section wherein the CO₂ concentration exceeded 2000 ppm, the fan control state was always off in the section where the temperature was below the set temperature (28 °C) during DCV control. For 3–5 week old piglets considered in this study, the CO₂ concentration was not high because of the relatively small weights. It is expected that in the growing pig and sow houses where pig weights are as high as 120 kg, the indoor CO₂ concentration behavior under DCV control is different from that observed in this study.

The differences in the indoor environment behavior based on the control method are attributed to the different fan operating ratios. These differences depended on application of the minimum operating ratio, as shown in Fig. 18. For the conventional control method, a minimum operating ratio of approximately 40.2% was applied to the corresponding period because there were many sections wherein the indoor temperature was lower than 28 °C; in the case of DCV control, approximately 41.89% of the entire period showed an off-state. The frequency of the maximum operating ratio of the entire period differed between the two control methods, and it was approximately 19.74% and 36.24% for the conventional and DCV control methods, respectively. This is because in the case of the DCV control the temperature increased significantly during the time step when the fan control state was off, and many cases occurred where the maximum operating ratio was applied above the maximum temperature. In contrast, the conventional control

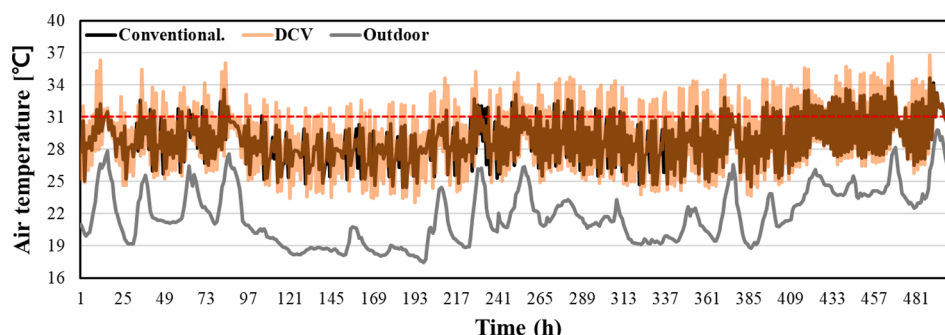


Fig. 16. Air temperature set by the ventilation system.

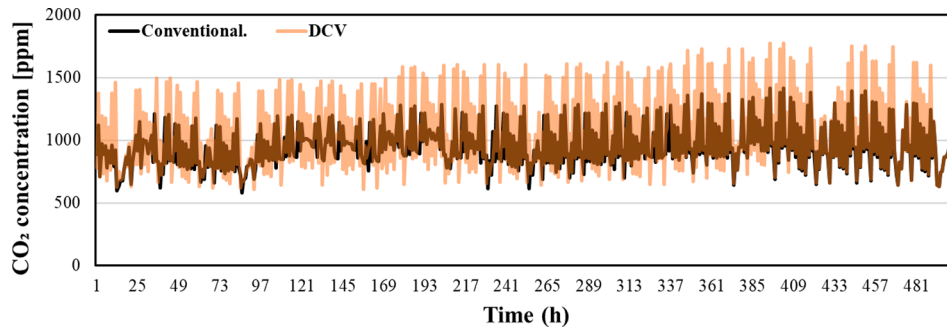


Fig. 17. CO₂ concentration set by the ventilation system.

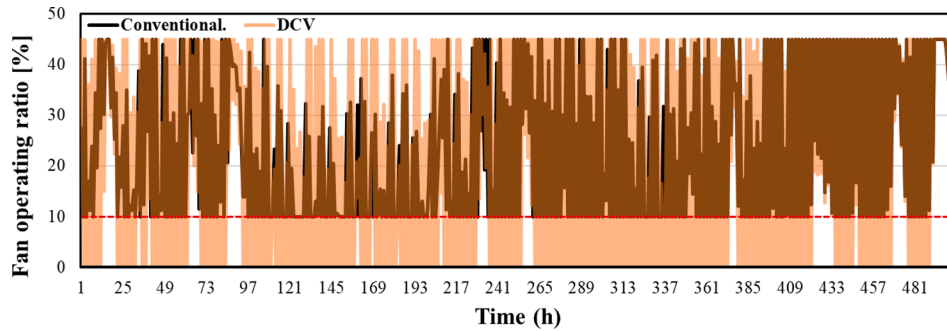


Fig. 18. Fan operating ratio set by the ventilation system.

method applied the minimum operating ratio, which resulted in a smaller increase in the indoor temperature compared with that in the DCV control method.

This difference in the fan operating ratio caused a difference in the energy consumption, as indicated in Fig. 19. The conventional control method consumed a fan power of 357.52 kWh during the corresponding period, whereas the DCV control method consumed approximately 18.2% lower power (292.44 kWh) during the same period. This difference can be attributed to the high frequency of the indoor temperature sections which required the minimum operating ratio during the period, and the significant effect of the on/off control of the DCV control method on energy reduction. Although the DCV control method showed smaller energy consumption, high-temperature sections occurred frequently during the time step at which the fan was switched off; this needs to be improved for the practical utilization of the DCV control method.

3.3. Consideration of DCV control interval

The DCV control method applied in this study frequently generated sections that greatly exceeded the maximum temperature because of the high-indoor temperature in the off time steps. This problem can be solved by applying a method to suppress the increase in indoor temperature through more frequent control changes can be applied. Thus, this study compared the 1 h time step control results with DCV control results when 15 min time steps were applied.

Fig. 20 shows the indoor temperature distributions with respect to the time step. The 15-min time step showed a narrower temperature distribution than the 1 h time step. The average temperatures were almost the same at 29.25 °C and 29 °C. The proportion of sections which exceeded the maximum temperature of 31 °C was 35.5% for the 1 h time

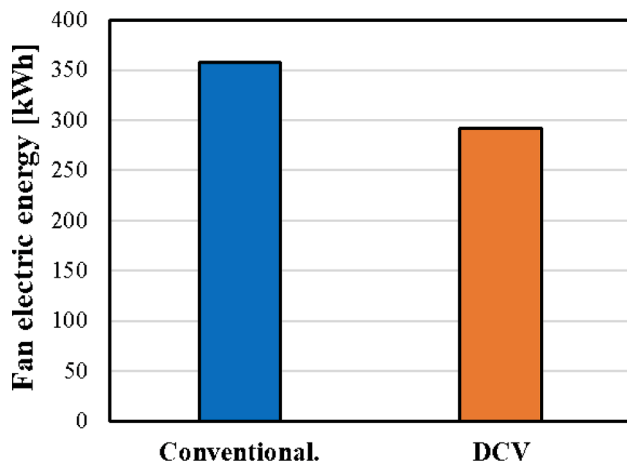


Fig. 19. Utilization of fan electric energy.

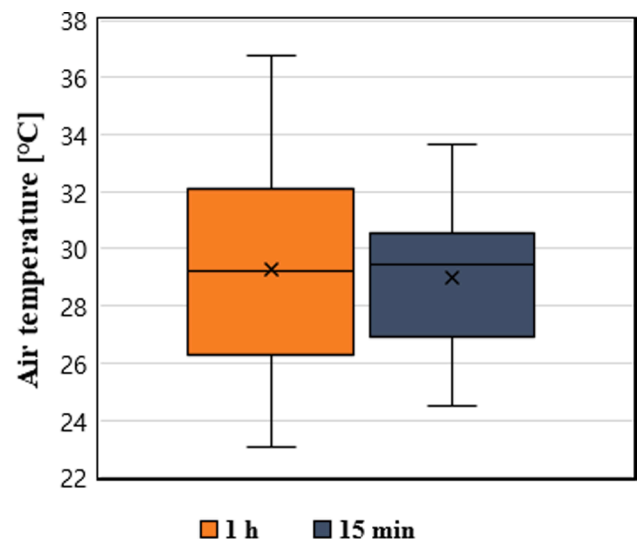


Fig. 20. Air temperature distribution at different time steps.

step, whereas the 15-min time step showed a proportion of 18.8%, which is approximately half of the 1 h time step. This occurs because the variation in the indoor temperature decreased with more frequent controls.

Fig. 21 shows the total energy consumption in terms of the time step at which the DCV control was applied. The 15 min time step control yields a smaller energy consumption of 7.65% compared with that of the 1-h time step control. This is attributed to the time step of the 15 min control wherein an excessive temperature rise is suppressed, which results in a smaller frequency of temperatures exceeding the maximum temperature, and a decrease in the frequency associated with the maximum operating ratio, which decreases the high energy consumption. However, as illustrated in Fig. 22, when compared with the daily energy consumption, the 15 min time step control method did not always yield low-energy consumptions. Until July 26, the 15 min time step control yielded low-energy consumptions compared with the 1 h time step control with the exception of July 11. However, after July 26, the 1 h time step control yielded smaller energy consumption.

Indoor and outdoor temperatures on July 13 and July 27, when the difference in energy consumption was the largest, were compared to analyze the different energy consumption behaviors at different time steps as a function of the date. On July 13, the 15 min time step control showed a 32.17% lower energy consumption compared with that of the 1 h time step. As shown in Fig. 23(a), the maximum operating ratio was not applied during the 15 min time step control because the time step exceeding the maximum temperature did not occur. On July 27, sections exceeding the maximum temperature occurred frequently, even during the 15 min time step control, as illustrated in Fig. 23(b). The sections to which the maximum operating ratio was applied occurred more frequently than the 1 h time step control. This was attributed to the increase in the indoor temperature which was not being sufficiently suppressed even by the 15 min time-step control because of the very high outer air temperatures and increase in the internal heat production which resulting from weight gain. This phenomenon worsened when a 1-h time step control was applied. On July 27, the daily maximum temperature rose to 37 °C in the 1 h time-step control case.

The differences in the daily energy consumption and indoor environment behavior caused by the application of DCV control originated from the increase in indoor temperature owing to the outer air-condition and internal heat production. If sections exist wherein the maximum temperature is exceeded frequently during the 15-min time step control (as on July 27), the existing fan control policy (maximum/minimum operating ratios and temperatures) needs to be changed to one that can suppress the increase in indoor temperature. For example, the increase in the indoor temperature could be suppressed if the overall operating ratio, including the variable operating ratio, is increased by increasing

the maximum/minimum operating ratios. Thus, for the application of effective DCV control to a pigsty, not only must the time step be considered, but the fan control policy must be established based on considerations of the outside air condition and changes in pig weights.

4. Conclusions

This study analyzed the applicability of a DCV system in a livestock building that considered both the indoor air quality and indoor temperature. For this purpose, an energy model based on actual measurements was developed, and the DCV control method and conventional control method were compared and analyzed based on a simulation analysis. The main results of this study are summarized as follows.

- 1) When the indoor temperature and CO₂ concentration prediction model for a pigsty was developed, changes in pig weight influenced the prediction performance of the model. The prediction performance of the CO₂ concentration prediction model exceeded the allowable error rate when the change in pig weights was not considered.
- 2) Upon the application of 1 h time step DCV control, the fan electric energy consumption was 18.2% lower than that of the conventional control. However, the change in the indoor temperature was larger than that of the conventional control method. Further, the frequency of sections exceeding the maximum temperature was high. In addition, the CO₂ concentration also showed a larger change when the DCV control was applied, but it did not exceed the allowable concentration.
- 3) Compared with the 1-h time step DCV control, the 15-min time step DCV control showed a smaller change in the indoor temperature than that of the 1-h time step control, and the frequency of sections exceeding the maximum temperature was also low. The energy consumption during the 15 min time step control was approximately 7.65% lower than that of the 1 h time step control. Although 15 min time step control exhibited higher energy consumption when the outdoor air temperature and pig heat were relatively high, it was judged to be a more suitable control interval than the 1 h time step based on considerations of the performance of maintaining the indoor environment.

These results confirmed that the DCV control method in a pigsty has high energy reduction potential, and that an appropriate control interval must be applied to maintain the indoor environment.

In this study, unlike previous studies that focused on the ventilation performance in a pigsty, energy-efficient control strategies were explored with a focus on the consumed power owing to the ventilation fan. To this end, the BES tool EnergyPlus was used. The research contents, ranging from the model development stage to simulation case analysis, are expected to be helpful to the use of the tool in the livestock industry. The analyzed results for the modeling method proposed in this study that reflect the characteristic elements of pigsty buildings, such as changes in pig weights and application of DCV control will be highly useful in the pigsty ventilation field. Further, for DCV control in an advanced pigsty, more detailed research on the control interval, control policy, outside air condition, and weight changes will be necessary.

CRediT authorship contribution statement

Hakjong Shin: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Visualization. **Younghoon Kwak:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision. **Seng-Kyoun Jo:** Conceptualization, Resources, Project administration. **Se-Han Kim:** Resources, Project administration, Funding acquisition. **Jung-Ho Huh:** Validation, Writing – review & editing, Supervision.

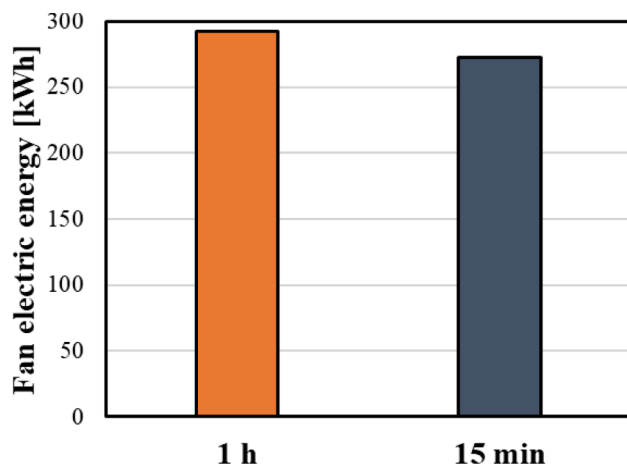


Fig. 21. Fan electric energy at different time steps (Total).

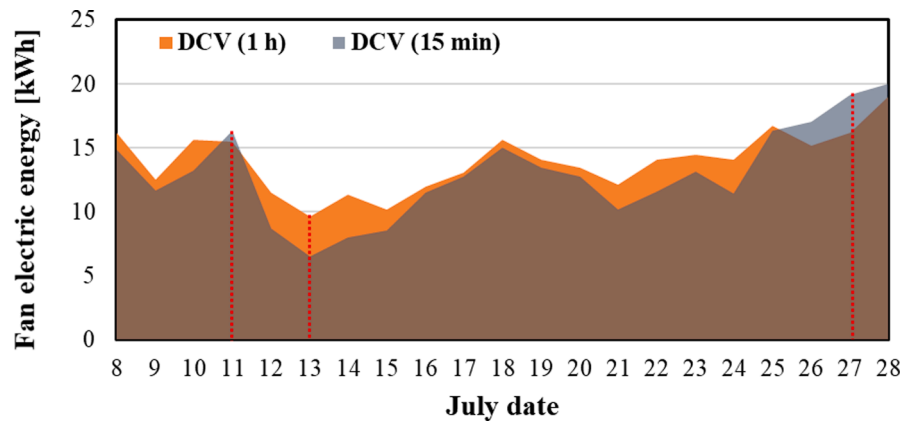


Fig. 22. Fan electric energy at different time steps (Daily).

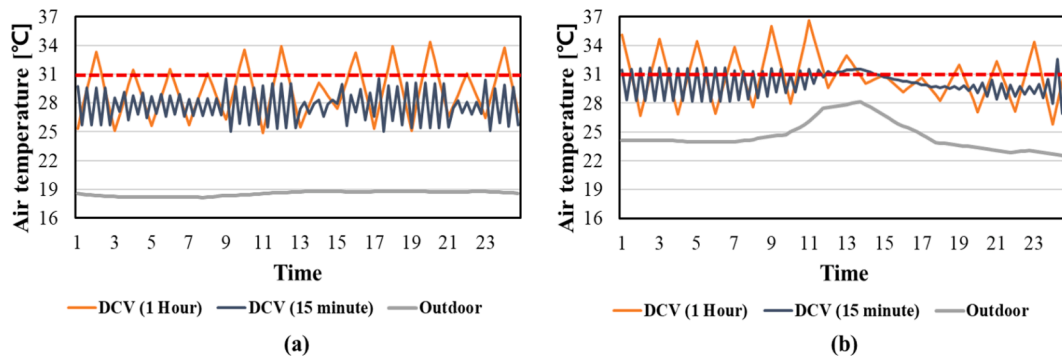


Fig. 23. Indoor and outdoor air temperatures at different timesteps on (a) days 13 and (b) 27.

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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