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Research Paper

Variations of multiple environmental factors and multi-objective optimisation control in a pig house

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ABSTRACT

With the increasing scale and intensification of pig farming, the environmental quality of pig houses has become crucial for pigs' health and reproductive ability. Numerous environmental factors in the pig house have formed a complex nonlinear microclimate environment that is dynamic, time-varying, and coupled, making it difficult to achieve precise control of the environment. In this study, sixty days of indoor environmental data were collected by an Internet of Things platform to analyse the diurnal changes in indoor temperature, humidity, and concentrations of CO_2 and NH_3, as well as the seasonal changes in winter and summer. A multi-objective control strategy for optimising the pig house environment using Double Deep Q-Network (DDQN) was established. The results showed that 1) there were significantly higher correlations between multiple environmental factors in summer than in winter; 2) the determination coefficients R^2 of the multiple linear regression models constructed with indoor temperature and CO_2 concentration as dependent variables reached 0.915 and 0.778, respectively; 3) the DDQN control strategy kept the indoor temperature variation within ± 1.7 °C, compared to ± 2.1 °C with the traditional temperature threshold control strategy (TTCS); 4) the total running time of the three fans in a day under the DDQN control strategy was 28.01 h, with the total power consumption of 11.4 kWh, and an energy-saving rate of 7.39 % and the indoor various environmental factors are closer to the setting values. This research offers feasible reference for the intelligent and energy-saving environmental regulation in large-scale pig production for precise environmental control.

1. Introduction

The environment in the confined pig house is a relatively independent microclimate system with nonlinear variations formed by the coupling effect of multiple environment factors. The air quality in a pig house is primarily determined by factors such as temperature, humidity, and concentrations of carbon dioxide (CO_2) and ammonia (NH_3), and other gases. These factors directly influence the health of pigs and their reproduction. Due to their relatively small lungs and lack of functional sweat glands, the pigs' ability to dissipate heat through panting is weak compared to other animals (Niu et al., 2024), making them more susceptible to indoor climate conditions. Excessively high thermal environments can induce adverse reactions, such as heat stress, resulting in considerable reductions in activity and feed intake, thereby decreasing growth and reproductive performance. Meanwhile, low temperatures can induce cold responses in pigs (Mayorga et al., 2019) and negatively impact production. Humidity affects the thermoregulation of pigs; high humidity not only promotes bacterial growth and the spread of infectious diseases but also increases the risk of respiratory diseases. Conversely, low humidity can lead to dry skin and dehydration of pigs (Hu et al., 2023).

Harmful gases are the primary cause of poor environmental conditions and foul odours in pig house. High concentrations of NH_3 may lead to respiratory damage, reduced weight gain, and a decreased feeding conversion efficiency (Kim et al., 2023). The concentration of CO_2 also affects the health and growth of pigs, as high concentrations can cause chronic hypoxia, mental instability, slow weight gain, and reduced production performance.

Therefore, improving the environmental quality of pig houses is

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Nomenclature

Adam	Adaptive moment estimation
ANN	Artificial Neural Networks
CO_2	carbon dioxide
DDQN	Double Deep Q-Network
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
ISSA	Invasive Weed Optimisation
MSE	Mean Squared Error
NH_3	ammonia
Out RH	Outdoor relative humidity, %
Out T	Outdoor temperature, °C
PID	Proportional-Integral-Differential
PLF	Precision livestock farming
PSO-DNN	Particle Swarm Optimisation combined with Deep Neural Networks
QPSO	Quantum-behaved Particle Swarm Optimisation
ReLU	Rectified Linear Unit
RH	Relative humidity, %
RL	Reinforcement Learning
TTCS	Traditional temperature threshold control strategy
WNN	Wavelet Neural Networks
a	Control action
$\underset{a'}{argmax} Q_\theta(s_{t+1}, a')$	Action a' with the largest Q-value in state s_{t+1} is selected
a_t	Fans' action at time t
C	Specific heat capacity, J kg^{-1} °C^{-1}
C_t	The carbon dioxide concentration at time t, ppm
C_{target}	The target value of carbon dioxide concentration in the pig house, ppm
D	Experience buffer
f_1	States of Fan1
f_2	States of Fan2
f_3	States of Fan3
H_t	Indoor relative humidity at time t, %
H_{target}	Target humidity values, %
IC_{Fanx}	Intercept, m^3 min^{-1}
M	Mass of air in the pig house, kg
N	Total number of test instances
N_t	The indoor ammonia concentration at time t, ppm
N_{target}	The target value of ammonia concentration in the pig house, ppm
P	Static pressure, Pa
Q	Heat loss, kJ
$Q_\theta(s_t, a_t)$	Q value of the action a_t taken in the state s_t
Q_{Fanx}	Ventilation rate of the wall fan, m^3 min^{-1}
r	Reward
R_{avg}	Average reward
R_i	Return obtained at the ith test moment
R_{max}	Maximum reward
s	State
s'	Next state
SL_{Fanx}	Slope, m^3 min^{-1} Pa^{-1}
S_t	Current state
S_{t+1}	Next state
T	Indoor temperature, °C
T_t	Values of indoor air temperature at time t, °C
T_{target}	Target temperature values, °C
V	Volume of the pig house, m^3
x	Ventilation time, min
y_{Fan0}	Indoor temperature under ventilation modes of Fan 0, °C
y_{Fan2}	Indoor temperatures under ventilation modes of Fan 2, °C
$y_{Fan1+Fan2}$	Indoor temperatures under ventilation modes of Fan 1+Fan 2, °C
$y_{Fan1+Fan2+Fan3}$	Indoor temperatures under ventilation modes of Fan 1+Fan 2+Fan 3, °C
α	Learning rate
γ	Discount factor to assess the instant and subsequent impact on reward
ΔT	Temperature variation rate, °C
θ	Q network parameter
θ′	Parameter of the target Q-network
λ_1, λ_2, λ_3, λ_4	Weights for the four environmental factors to reward function
λ_5,λ_6	Penalty coefficients for fans' states switching and energy consumption
σ_c, σ_g	State and gate activation function, respectively
ρ	Density of air, kg m^{-3}

essential to enhancing pig health and productivity in large-scale farms. However, due to the coupling characteristics of multiple environmental factors, variations in each environmental factor are influenced by numerous factors, and their interactions complicate precise control of indoor environmental quality. Therefore, achieving a multi-objective joint precise control of thermal-humidity conditions and gas environments in closed pig house with lower energy consumptions is a particular challenge for the industry (Guo et al., 2024).

Over the past decades, researchers have explored different methods to achieve automatic environmental control in farm animal houses (Li et al., 2023). Several control methods have been discussed and implemented for achieving precision environmental control in livestock and pig house, ranging from Proportional-Integral-Differential (PID) control (de Souza Granja Barros et al., 2017), robust nonlinear feedback control (Yang, 2019), adaptive control (Phan et al., 2024), and model predictive control (MPC) (Oldewurtel et al., 2012). These strategies have primarily focussed on the control systems of temperature and ventilation. For example, Ma (2008) described an environmental control strategy based on different ventilation and heating equipment and operating times, which significantly improved farming environments. However, most of these discussed control methods are either too simple, e.g. PID control (de Souza Granja Barros et al., 2017), to optimise complex coupled dynamic models, or rely too heavily on an accurate indoor climate model, e.g. MPC (Oldewurtel et al., 2012), which is not always available. With the continuous increase in the scale and intensification of animal farming, traditional control systems can no longer meet the demand for the joint environment control of temperature, humidity, and air quality in livestock and pig housing.

Due to the recent development of sensing and communication techniques, vast amounts of data are available, which has led to advances in both system identification and automatic control. Currently, intelligent control technology, which includes sensors (Herlin et al., 2021), cameras, and microphones, has been widely used for continuous, real-time data monitoring and environmental control in livestock and pig houses, promoting an integrated management system for animal husbandry (Fournel et al., 2017). Notably, algorithms from artificial intelligence (AI) and machine learning (ML) have demonstrated unique advantages in data analysis and prediction (Bao & Xie, 2022). More and more researchers have started using statistical methods to predict gas concentration changes in indoor facilities (Yan et al., 2024). For example, some prediction models based on Artificial Neural Networks (ANN) (Cho, 2022), Wavelet Neural Networks (WNN) (Wang & Wang,

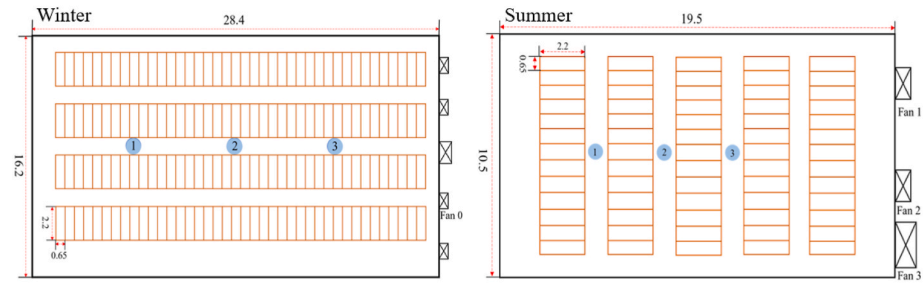

Fig. 1. Top view of organisation of the two pig buildings used in the study. Unit: m, represents the positions where the sensors are installed.

2024), Particle Swarm Optimisation combined with Deep Neural Networks (PSO-DNN) (Abdolrasol et al., 2021) have been used to forecast environmental factors, including temperature, humidity, CO_2, NH_3 concentrations, and particle concentrations in animal houses. In addition, some optimisation algorithms, such as Quantum-behaved Particle Swarm Optimisation (QPSO) (Song et al., 2021), Invasive Weed Optimisation (ISSA), and the Dung Beetle Algorithm (Guo et al., 2024) were employed to improve neural network models. These improved models aimed to enhance the prediction accuracy of environmental factors in livestock and pig houses (Zhang et al., 2023). Also, fuzzy control strategies have been established to achieve the fuzzification and logical reasoning of various environmental factors in the pig house (Küçüktopcu, 2021; Xie, 2014).

However, most of these ML methods still rely on an accurate model (Kenge, 2020). Currently, the variations of multiple environmental factors within pig houses remain unclear, making it difficult to establish a scientific basis for precise environmental regulation. Additionally, these ML methods are typically only developed for a fixed environmental setting, with limited adaptability, and fail to account for dynamic changes, especially in the presence of uncertainties (Sturm et al., 2023). Most existing environmental control technologies and methods based on ML also face challenges in solving multi-objective optimisation problems and struggle to simultaneously achieve energy efficiency and the precise control of heat, humidity, and gas concentrations, which presents a significant barrier to meeting the green, energy-saving production requirements of Precision livestock farming (PLF).

Reinforcement Learning (RL) is a learning-based control method in the ML field (Li et al., 2024), being widely used in areas such as natural language processing, computer vision, intelligent agriculture and industrial Internet of Things (IoT). Deep Reinforcement Learning (DRL) uses deep learning methods, to extract high-level features by nonlinearly transforming raw data through multilayer neural networks, coupled with RL, to learn optimal strategies through the interaction of intelligences with their environment. The Deep-Q-Network (DQN) method is a model-free DRL algorithm that relies on a value function, which does not need to build a complex model, and can often learn the optimal strategy through the continuous trial-and-error of the agent with the real environment (Sun & Si, 2025). Additionally, the DQN method, which is grounded in state-action value functions, is well-suited for scenarios involving a discrete action space. It can process high-dimensional state space by using deep neural networks, and improve stability and convergence by using experiential playback mechanisms and a target network. More importantly, RL methods, including DQN, have the capacity to handle complex systems with uncertainties and adaptability through continuous learning, improving its control strategies using trial and error (Morcego et al., 2023). Therefore, the application of DQN algorithm in the actual environmental control of pig houses is hypothesised to be more reliable, efficient, stable and adaptable compared with other traditional control methods with single environmental variables, such as temperature threshold, and has certain generalisation ability.

Therefore, the objective of this paper is to further explore the multi-environmental factor variations in pig houses and develop a multi-objective optimisation and control method for the pig house environment based on DRL that is superior to current control methods. This research aims to contribute to optimal thermal environment and air quality control in pig houses, with improved precision in environmental control, considering the joint control objectives of temperature, humidity, air quality, and reduced energy consumption to enhance both animal welfare and the economic benefits for stakeholders.

2. Materials and methods

2.1. Building description

To explore the environmental control methods suitable for the pig house in the cold northern regions, this study carries out winter experiments and summer experiments respectively. The summer experiments are conducted at Jingzhe Breeding Base in Yabuli, Heilongjiang Province. During the summer, more attention is paid to the changes in temperature and humidity inside the pig house. On the basis of reducing energy consumption, ventilation fan operation is adjusted to keep various environmental parameters of the pig house within a more suitable range. The winter experiment is conducted in a pig house in Jiangbei, Heilongjiang Province. Due to the relatively cold environment outside in the northern winter, in order to maintain the indoor temperature, only one fan (Fan 0) is used. The focus of the winter experiment shifts to keeping the interior warm, and it is necessary to reduce both the duration and the volume of ventilation.

Jiangbei pig house is designed with a flat sloping roof, the thickness of insulating layer of external wall is 150 mm, and with an above-floor (a slatted concrete floor) and a deep manure pit below the floor. The dimension is 28.4 m × 16.2 m × 2.4 m (L × W × H), with a capacity of housing 130 pregnant sows in four rows of crates (Fig. 1). There are two feeding periods each day at 8:00 a.m. to 9:00 a.m., and 3:30 p.m. to 4:00 p.m. Manure flushing occurs from 8:30 a.m. to 9:00 a.m. each day. Five wall ventilation fans (four of 1.1 m and one of 1.4 m diameter) are equipped. In winter, to keep the indoor air temperature, there is only one wall ventilation fan (Fan 0, ventilation rate 34000 m^3 h^{-1}) turned on for the indoor environment control.

Jingzhe Breeding Base in Yabuli Town is also designed with a flat sloping roof, with a thickness of 100 mm insulation for the external wall. The concrete floor has two side manure gutters. Jingzhe Breeding Base has a dimension of 19.5 m × 10.5 m × 2.4 m (L × W × H) with five rows of crates (Fig. 1) housing 35 pregnant sows. There are two feeding periods per day from 8:00 a.m. to 8:30 a.m., and 2:00 p.m. to 2:30 p.m. Manure is flushed twice at 8:30 a.m. to 9:00 a.m., and 2:30 p.m. to 3:00

Table 1
Relevant parameters of environmental sensors.

Sensor detection index	Sensor type	Response time	range	precision
Temperature	VMS-3002-WS-N01	≤25 s	−40 °C–60 °C	±0.5 °C
Humidity		≤8 s	0∼100 %	±3 %
NH_3	VMS-3002-NH_3-N01-50P-2	≤90 s	0∼100 ppm	±5 % F·S
CO_2	VMS-3002-CO_2-N01	≤90 s	0∼10000 ppm	± (40 ppm + 3 % F·S)

p.m., each day. Three wall fans (two of 0.8 m and one of 1 m diameter) with ventilation rates of 22000 m^3 h^{-1} (Fan 1), 22000 m^3 h^{-1} (Fan 2), and 30000 m^3 h^{-1} (Fan 3) are equipped for indoor air temperature control in summer.

2.2. Building environment monitoring

The buildings are equipped with a continuous environmental monitoring system to measure gas concentrations, temperatures, relative humidity, and ventilation rates. Data from all on-line instruments and sensors are acquired at an average interval of 1 min. All sensors operated with the RS-485 bus and standard Modbus communication protocol.

There were three sampling locations: centre, left, and right, in each room, with sensors placed 1.6 m above the floor in the pig houses, both in winter and summer for better data collection and validation (Fig. 1). Indoor air temperature (T) and relative humidity (RH) are measured using temperature sensors (VMS-3002-WS-N01, Shandong Vemsee Technology, Jinan, China). Gas concentrations are measured using electrochemical sensors for CO_2 (VMS-3002-CO_2-N01, Shandong Vemsee Technology, Jinan, China) and NH_3 (VMS-3002-NH_3-N01-50P-2, Shandong Vemsee Technology, Jinan, China). The sensors are checked weekly with handheld transmitters. The specific parameters of the three environmental sensors are shown in Table 1.

Pig numbers and pig weight in each building are recorded manually. The numbers of pigs are recorded manually every week during the experiment. The weights of individual pigs are recorded every two weeks. The numbers and weights are interpolated to match the other continuously measured data. The energy consumption monitoring of the in-house ventilation system is achieved through the intelligent electronic Three-phase Four-wire Active Energy Meter (Model: DTSY6607, TuoQiang Electric, Heifei, China) installed in the pig house to monitor the power consumption of the fans.

Table 2
The learning process of DQN algorithm.

DQN algorithm design
Input:state *s*, action *a*, discount rate γ, learning rate α
Initialise:experience buffer D, Q Network parameter θ, Target Q network parameter θ'
Repeat
Initialise the starting state *s*
Repeat
Under state *s, the current action a* is selected by the ε-greedy strategy according to the Q value of the current state
The environment performs the action, obtaining the next state *s'* and the reward *r*
Store the experience (*s, a, r, s'*) in the experience buffer D
If the number of samples in experience buffer D is greater than batch size:
Sample a batch of experience data randomly from the experience buffer
Calculate Q values and target Q values
Calculating the loss function
Update Q network parameters
If reach target Q network update interval:
Update the target Q network parameters $s = s'$
Until *s* is terminated
Until Q (*s, a*) convergence

Ventilation fan control is vital for pig house environmental regulation. This study employs distinct strategies in winter and summer to meet the pigs' environmental needs. In winter, due to the cold climate, minimising heat loss while ensuring proper ventilation is a key concern. In winter, only one wall ventilation fan (Fan 0) is turned on for indoor environment control. This is done to maintain the indoor air temperature at a suitable level for the pigs. The operation of Fan 0 is carefully regulated to balance ventilation and heat conservation. In summer, three wall fans (Fan 1, Fan 2, and Fan 3) are used for indoor air temperature control. The control of these fans is more complex, as the focus is on reducing the high indoor temperature, while also managing humidity and gas concentrations.

Wall fan operational conditions are monitored, and ventilation rates are obtained indirectly through post-measurement calculation according to Eq. (1).

$$Q_{Fanx} = SL_{Fanx} \cdot P + IC_{Fanx} \tag{1}$$

where Q_{Fanx} is the ventilation rate of the wall fan, in m^3 min^{-1}; SL_{Fanx} is the slope, in m^3 min^{-1} Pa^{-1}; P is the static pressure, in Pa; and IC_{Fanx} is the intercept, in m^3 min^{-1}.

3. Model development of multi-objective control for pig building environment

Usually, pig house environmental control mainly considers indoor air temperature as the indicator for environmental control strategy. However, due to the coupling characteristics among the multiple environmental factors of air temperature, relative humidity, and gas concentrations, there are some contradictions between thermal environment and ventilation control. To optimise the joint control of multiple environmental factors, a control strategy is developed based on DQN and Double Deep Q-Network (DDQN).

3.1. A DQN-based algorithm

3.1.1. Steps of the DQN-based algorithm

By combining deep neural network with Q-learning algorithm, the DQN algorithm can improve the learning efficiency and performance. The learning process of the DQN algorithm is shown in Table 2.

Step 1: Initialisation. Initialise the parameters of θ in Q-network and θ′ in target Q-network, and experience replay buffer for values storage of state, action and reward;
Step 2: Action selection. Agent selects an action according to the current state using ε-greedy strategy in each time step;
Step 3: Environment feedback. Agent will receive the next state *s'* and reward ***r*** after the action be conducted;
Step 4: Update the experience replay buffer. Put the current state of environmental factors S_t, fans' action a_t, reward r_t and the next state S_{t+1} into the experience replay buffer;
Step 5: Update the Q values. Q values are calculated and updated according to Eq. (2) using the updated experience replay back buffer. When the updated interval step of the target Q value reaches 1000, copy the parameters in the current Q network to the target Q network. This can achieve an optimised environment control in pig building according to the continuous state-action updating.

$$\theta_{i+1} = \theta_i + \alpha\left(r + \gamma \max_{a'} Q_{\theta_i'}(s', a') \text{-} Q_{\theta_i}(s, a)\right)\nabla_{\theta_i} Q_{\theta_i}(s, a) \tag{2}$$

where θ and θ' are parameters of the current and target Q networks; α is learning rate; γ is discount factor to assess the instant and subsequent impact on reward; ***r*** is the instant reward value responding to

Table 3
Action combination for wall fans operation in summer.

Wall fan	A1	A2	A3	A4	A5	A6	A7	A8
Fan 1	0	1	0	0	1	1	0	1
Fan 2	0	0	1	0	1	0	1	1
Fan 3	0	0	0	1	0	1	1	1

the action of a_t under the current state of S_t;

$\max_{a'} Q_{\theta_i'}(s', a')$ is the value acquired from state-action function with the action a' that could acquire the maximum value among all the potential actions at next states.

Step 6: Iteration. Repeat Steps 2 to 5, until the preset number of training is reached or algorithm convergence.

Step 7: Test. Agent doesn't explore but only selection the actions according to the trained Q function.

3.1.2. Environment state and action design

The DQN is a DRL method based on state-action functions. To achieve multi-objective control in a pig building, the four environmental factors of indoor air temperature (T), relative humidity (RH), and concentrations of CO_2 and NH_3 are used to construct the environmental states. According to the actual growth requirements of pregnant sows and preliminary experimental data, combined with the environmental parameters and management standards of domestic large-scale pig farms in China (Standardization Administration of China. 2008) the optimal temperature range for the growth of pregnant sows is 15–20 °C, with critical high and low temperatures set at 27 °C and 13 °C, respectively. The optimal humidity range is 60 %–70 %, with critical high and low humidity levels at 85 % and 50 %, respectively. The maximum allowable concentration of NH_3 is 25 ppm, and for CO_2, it is 1500 ppm. Based on these parameters, four-dimensional state spaces and corresponding state intervals for the four environmental factors are designed. The state intervals are set as [10 °C, 35 °C], [40 %, 100 %], [0 ppm, 20 ppm], and [0 ppm, 2500 ppm], respectively, for T, RH, and the concentrations of NH_3 and CO_2.

Indoor air quality in the pig buildings could be improved through wall fan ventilation. The values of 0 and 1 are used for wall fan operation status of turning on and turning off, respectively. Therefore, the number of action combinations for wall fans operation status can be calculated as 2^n, where n is the number of wall fans. Taking wall fans in summer as an example, there are three wall fans: Fan 1, Fan 2, and Fan 3, and the possible operation combinations are expressed in Table 3. Fans are tested under the operation combination scheme in Table 3 for 20 min. According to indoor environment quality and control effect, operation combinations of A1, A3, A5, and A8 are selected as actions for the three fans and A1, A3, A5, and A8 are defined as actions a1, a2, a3, and a4 for the DQN to achieve an optimised ventilation control.

3.1.3. Reward function for the optimal ventilation control

The reward function in the DQN decides the values of current fans' actions, and it directly affects the learning effects and final decisions of the agent. Four environmental factors of T, RH and the concentrations of CO_2 and NH_3 are introduced as parameters for the reward function. The reward function is described in Eq. (3).

$$r_t = \frac{\lambda_1}{\sqrt{\left(\frac{T_t - T_{\text{target}}}{T}\right)^2 + 1.0}} + \frac{\lambda_2}{\sqrt{\left(\frac{H_t - H_{\text{target}}}{H}\right)^2 + 1.0}} + \frac{\lambda_3}{\sqrt{\left(\frac{C_t - C_{\text{target}}}{C}\right)^2 + 1.0}} + \frac{\lambda_4}{\sqrt{\left(\frac{N_t - N_{\text{target}}}{N}\right)^2 + 1.0}} - \lambda_5 \sum_{i=1}^{3} \left| f_i - f_{i,t-1} \right| - \lambda_6 \sum_{i=1}^{3} f_{i,t} \tag{3}$$

where T_t °C, H_t %, C_t ppm and N_t ppm are values of T, RH, and concentrations of CO_2 and NH_3 at time t; T_{target} °C, H_{target} %, C_{target} ppm, N_{target} ppm are target values; T_L, H_L, C_L, N_L are differences between the upper and lower boundaries of states intervals; λ_1, λ_2, λ_3, and λ_4 are weights for the four environmental factors to reward function; λ_5 and λ_6 are penalty coefficients for fans' states switching and energy consumption; f_1, f_2, and f_3 are states of Fan 1, Fan 2, and Fan 3.

In this study, according to the requirement of multiple environment control in pregnant sows building, $T_{\text{target}} = 19$ °C, $H_{\text{target}} = 75$ %, $C_{\text{target}} = 10$ ppm, $N_{\text{target}} = 800$ ppm; $\lambda_1 = 12$, $\lambda_2 = 10$, $\lambda_3 = 7$, $\lambda_4 = 7$, $\lambda_5 = 4$, and $\lambda_6 = 4$.

The reward function will achieve maximum values according to a Gaussian distribution deviations calculation on each environment factors, and at the same time, the impact degree of each environment factors is adjusted based on the relevant weights for better environmental control effects in pig building.

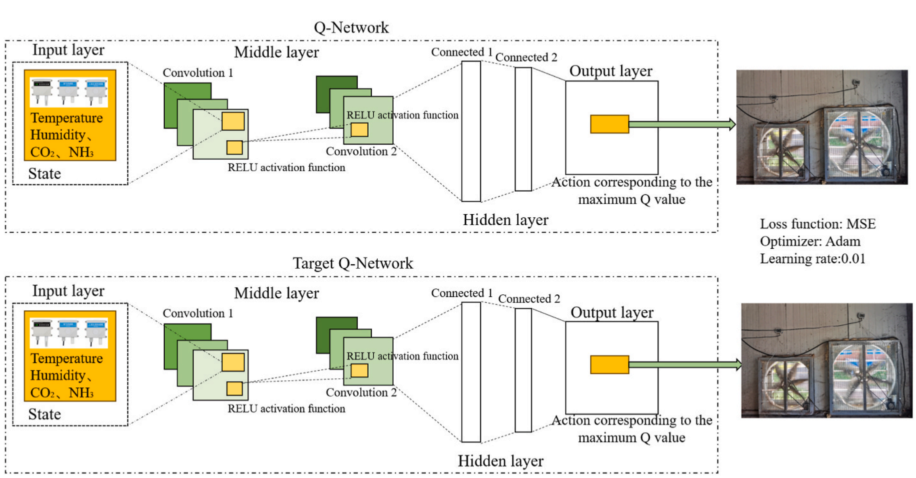

Fig. 2. Structure of DDQN for the fans' operation according to the environmental data.

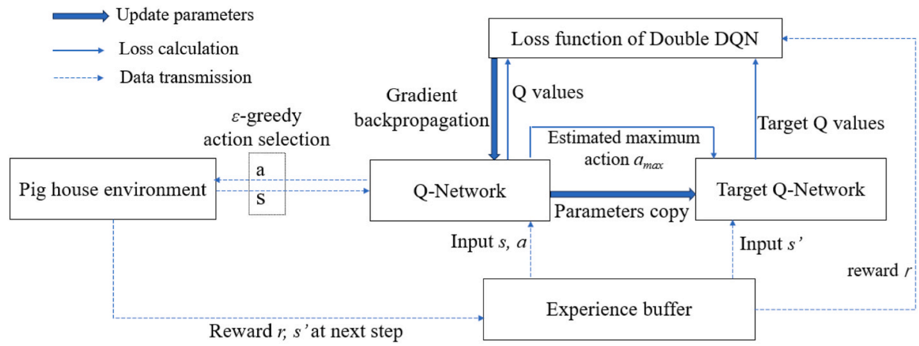

Fig. 3. The algorithm framework of DDQN for environmental control in the pig house.

3.2. An optimal environment control model based on DDQN in pig building

3.2.1. The structure of the double DQN

Although the DQN algorithm can mitigate the problem of overestimation to a certain extent, the estimation of the target Q-value still tends to exhibit excessive bias, leading to unstable training or convergence difficulties. Fortunately, the Double DQN algorithm can effectively reduce the overestimation of the Q-value and more accurately approximate the optimal value of a chosen action by utilising two independent neural networks to estimate the current state value and the optimal value of a chosen action separately (Yu et al., 2023). Therefore, a Double DQN-based self-adaptive optimisation control model for pig house environments is proposed and developed to realise the precise energy-saving control by regulating the start-stop actions of three fans in accordance with the temperature, humidity, CO_2 concentration, and NH_3 concentration in the pig house. The DDQN architecture is shown in Fig. 2. It comprises a Q-network layer and a target Q-network, where one of the Q-networks is utilised for evaluating and selecting actions, and the target Q-network is responsible for computing the Q-value of the selected action to mitigate potential overestimation issues. Both Q-network and target Q-network are integral neural network structures consisting of an input layer, an output layer, a middle layer and a hidden layer, which work together to accomplish the mapping and prediction from environment state to action value. The input layer receives measurements from the environment, including T, RH, and the concentrations of CO_2 and NH_3 in the pig house. These measurements are input into the model as feature vectors. The middle layer uses a multilayer perceptron (MLP) using the ReLU as the activation function for the nonlinear transformation. The hidden layer, the core part of the model, contains several sublayers, each with 64 neurons. Neurons in each sublayer receive the output from the previous sublayer as input. The output layer receives the output from the last hidden layer and produces an estimate of the Q-value for each possible action. It consists of three neurons representing the Q-values for each of the three fans' actions. These Q-values are used as a basis for control decisions, guiding the model to start and stop the three fans according to the environmental parameters of the pig house.

The algorithm framework of the DDQN is shown in Fig. 3. Firstly, the initial state of the pig house environment is provided. This initial state, denoted as (s), and an action, denoted as (a), are input to the Q-network. The network then outputs an estimation of the corresponding Q-value. Based on this Q-value estimation, an action for the fan is selected using the ε-greedy policy to regulate the pig house environment. Subsequently, the pig house environment provides the next state and reward, which are then stored, along with the previous state and action, in the experience buffer.

During the interaction with the environment, both the Q-network and the target Q-network are trained using data drawn from the experience buffer. Specifically, the Q-network accepts the current state (s) and action (a) as inputs and produces an estimated Q-value as output. The target Q-network receives the next state (s') as input and selects the maximum Q-value as the target Q-value. The mean squared error (MSE) is utilised as the loss function for the DDQN, and the parameters of the Q-network are updated through gradient backpropagation. Periodically, the parameters of the Q-network are copied to the target Q-network to ensure that the estimated Q does not deviate too far from the target value. Through continuous interaction with the environment and iterative training of the network, the accuracy of the control model is improved, and a faster identification of the optimal strategy for precise energy-saving regulation of the pig house environment is achieved.

3.2.2. Multi-objects optimisation

To achieve precise regulation of the pig house environment using the DDQN algorithm, two optimisation objectives are determined: (1) improve the accuracy of the pig house environment control, and (2) minimise the cycles of fan's start-stop to reduce power consumption. To achieve these objectives, an optimal control strategy is constructed based on the DDQN algorithm.

In the DDQN-based self-learning control model for the pig house environment, the establishment of the control objective can be expressed as Eq. (4).

$$\mathrm{L}(\theta) = \mathrm{E}_{s_t,a_t,r_t,s_{t+1}\sim \mathrm{D}}\left[(y_t\text{-}Q_\theta(s_t,a_t))^2\right] \tag{4}$$

where θ denotes the Q network parameter, D denotes the experience buffer, s_t denotes the current state, a_t denotes the current action, r_t denotes the current reward, and s_{t+1} denotes the next state, $Q_\theta(s_t,a_t)$ represents the Q value of the action a_t taken in the state s_t,while y_t is the target value in the DDQN, which can be computed using Eq. (5)

$$y_t = r_t + \gamma Q_{\theta'}\left(s_{t+1}, \underset{a'}{argmax} Q_\theta(s_{t+1}, a')\right) \tag{5}$$

where γ is the discount factor; θ' is a parameter of the target Q-network; and $\underset{a'}{argmax} Q_\theta(s_{t+1}, a')$ denotes that the action a' with the largest Q-value in state s_{t+1} is selected.

Therefore, by minimising the difference between the estimated Q-value (current Q) and the target Q-value, the current policy can be iteratively refined towards the optimal policy. Updating the parameters θ' and θ to improve the performance of a self-seeking optimal control model for pig building environments using the adaptive moment estimation (Adam) to minimise the loss function.

3.3. Model evaluation

Average reward, maximum reward, convergence time, and stability are used to evaluate the overall performance of the models of DQN and DDQN during training, as well as to assess learning efficiency and stability during the testing phase. The average reward is the mean of the cumulative rewards obtained while performing a task or interacting

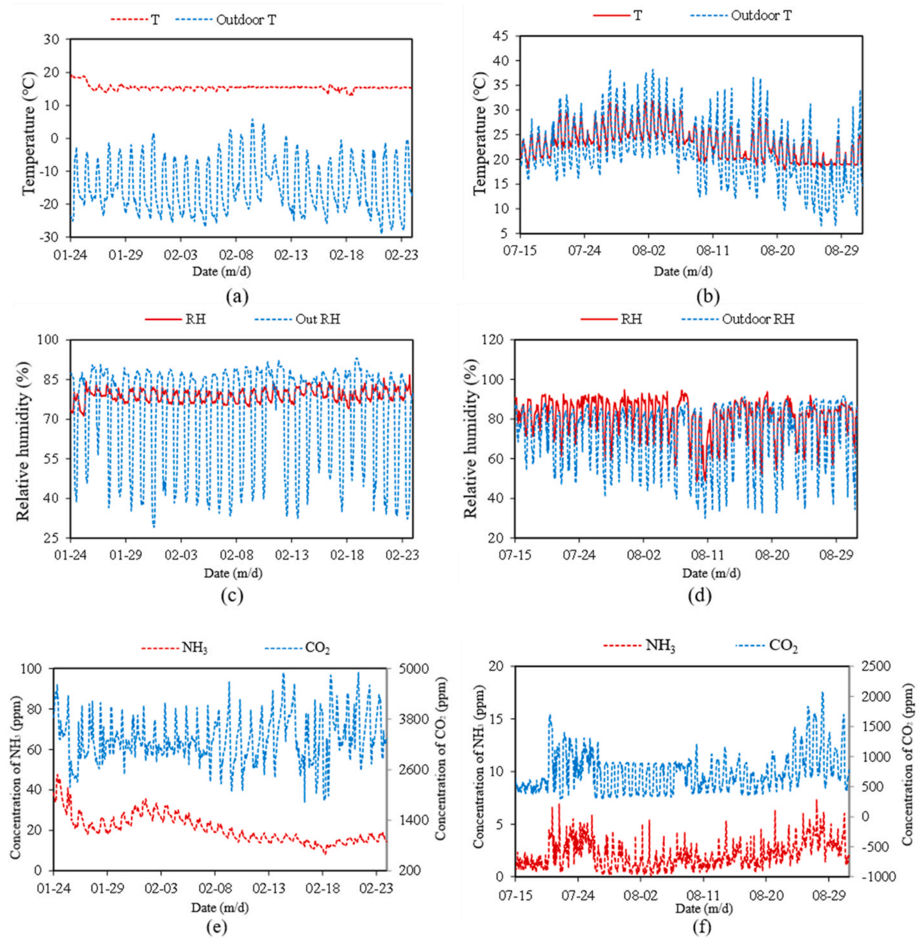

Fig. 4. Hourly mean data in summertime and wintertime: (a) Average hourly T and Out T in winter, (b) Average hourly T and Out T in summer, (c) Average hourly RH and Out RH in winter, (d) Average hourly RH and Out RH in summer, (e) Average hourly gas concentration data in winter and (f) Average hourly gas concentration data in summer.

with the environment. The average reward serves as a reflection of the overall model performance, with a higher value indicating a better model performance and is calculated by Eq. (6).

$$R_{avg} = \frac{1}{N}\sum_{i=1}^{N} R_i \tag{6}$$

where R_{avg} is the average reward; N is the total number of test instances; R_i is the return obtained at the ith test moment.

The maximum reward signifies the highest potential reward value attainable by the model under ideal operating conditions. Generally, a higher maximum reward indicates a more favourable performance of the model. Models maximise cumulative rewards by continually taking actions through interactions with the environment. By optimising the model's decision-making strategy and learning algorithms, the model can be gradually brought closer to or reach the level of maximum return, which is shown in Eq. (7).

$$R_{\max} = \max_{i=1}^{N} R_i \tag{7}$$

Convergence time is the time required to obtain a stable learning outcome from the commencement of training. A threshold $R_{avg}(t_i)$ can be established, and the model is deemed to have converged when the discrepancy between the average reward and the maximum average reward ε is lower than $R_{avg}(t_i)$. A faster convergence time implies that the model can learn the features and patterns of the data more quickly, but sometimes an excessively fast convergence time may also mean that the model falls into local optimal solutions. Therefore, it is necessary to comprehensively consider both the model's convergence time and its final performance in the actual training process. The convergence time is calculated as shown in Eq. (8).

$$T_{conv} = \min_{t=1}^{N}\left(t_i \middle| R_{avg}(t_i) \geq (t_i) - \varepsilon\right) \tag{8}$$

Stability reflects the degree of stability of a model. The higher the stability, the broader the model's generalisation ability and application scope. The stability is calculated as shown in Eq. (9).

$$S = \frac{1}{N-1}\sum_{i=1}^{N}\left(R_i - R_{avg}\right)^2 \tag{9}$$

where R_i is the return at the ith test moment; R_{avg} is the average return over all test moments.

3.3.1. Performance comparison of control models

The environmental data used for model training and validation covered a period of 31 days (from July 15 to August 15, 2022), comprising a total of 69784 data records. These are divided into a training set (31,680 records), a validation set (14,400 records), and a test set, following a 7:2:1 ratio. By inputting the on-site environmental data collected from the pig house along with the fan start-stop action data, a reinforcement learning experimental environment is constructed. The model is trained on an NVIDIA 4090 GPU, and the total training step count for the agent is 6000 steps.

Table 4
Summary of environment conditions in pig buildings in summer (Jul. 15 – Aug. 31, 2022) and winter (Jan. 24 – Feb. 23, 2022).

Parameter	winter, Jan. 24 – Feb. 23, 2022			summer, Jul. 15 – Aug. 31, 2022		
	Min	Max	Mean ± STD	Min	Max	Mean ± STD
NH_3 (ppm)	8.0	47.6	20.73 ± 6.7	0.1	7.3	2.1 ± 1.3
CO_2 (ppm)	1826.6	4904.0	3325.7 ± 549.9	296.6	2067.9	741.4 ± 320.6
T (°C)	13.2	19.3	15.5 ± 0.9	17.9	31.9	23.3 ± 3.2
Out T (°C)	−29.0	5.9	−14.7 ± 7.8	6.6	38.2	21.7 ± 6.3
RH (%)	71.2	86.8	79 ± 2.4	48.4	94.8	81.0 ± 9.7
Out RH (%)	29.1	93.2	72.1 ± 19.5	29.9	91.7	72.4 ± 15.6
Ventilation (m^3 min^{-1})	34	14294	7056 ± 5494	33	9731	1704 ± 1683

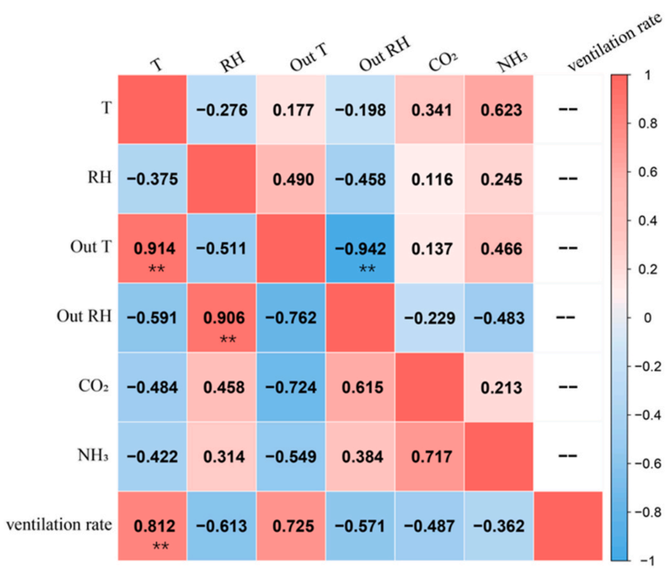

Fig. 5. Correlation heatmap of multiple environmental factors in pig house: the top right half represents correlations obtained in the winter and the bottom left half represents summer-based correlations. ** represents highly significant correlations.

4. Results and discussion

4.1. Data selection

Data in wintertime (from January 24 to February 23, 2022) and in summertime (from July 15 to August 31, 2022) were selected and 1-min resolution data were averaged into 1-hr data for indoor environmental factors variation analysis and control in this study. During these two periods, the mean number of pigs in winter was 80–130 and the mean pig number in summer was 37; the mean pig weights were 190 kg in winter and 165 kg in summer. Environmental conditions during the two periods are shown in Fig. 4 and Table 4.

Combining Table 4 and Fig. 4, it can be observed that during the winter, the concentrations of NH_3 and CO_2 inside the pig house were relatively high, which may be related to the lower ventilation rates. However, in summer, the temperature and humidity fluctuated greatly, while the concentrations of NH_3 and CO_2 were relatively low, with less variability than the winter data. All these indicate that seasonal variations had a significant impact on the environmental conditions in the house.

4.2. Analysis of the correlation and variations of environmental factors in pig house

4.2.1. Correlation analysis of multiple environmental factors in pig house

The Pearson correlation analysis method ($p < 0.01$) was used to analyse the correlations among environmental variables in pig houses in different seasons (Fig. 5). The temperature inside the pig house (T) showed a consistently strong correlation with Out T in both summer and winter, making it a primary driver of internal environmental dynamics.

In winter, NH_3 concentration displayed stronger correlations with other factors, particularly T ($r = 0.62$) and RH ($r = 0.25$), suggesting that reduced ventilation in cold conditions facilitated gas accumulation. In contrast, in summer, CO_2 concentration was more closely linked to environmental changes. Strong correlations with both RH ($r = 0.46$) and Out RH ($r = 0.62$), as well as ventilation rate ($r = 0.49$), were observed. This reflects the increased metabolic activity of pigs under heat stress and the greater air exchange due to higher ventilation rates.

Moreover, the strength and direction of correlations differed between NH_3 and CO_2, depending on the season. These shifting dynamics revealed that the impact of one factor cannot be understood in isolation or assumed to be linear over time. In summary, the interdependence of temperature, humidity, and gas concentrations in pig houses is both non-linear and highly season-specific. These findings provide clear motivation for developing intelligent environmental control systems that can dynamically respond to changing conditions, rather than relying on fixed thresholds or simplistic linear models.

4.2.2. Analysis for seasonal and diurnal variations of environment in pig house

To analyse the diurnal environment factors variations in pig houses, representative environmental data were randomly selected from January to February (winter), and from July (summer) in 2022 (Fig. 6 and Table 5). As shown in Fig. 6(a) to 6(h), Out T and RH followed regular diurnal patterns in both seasons. In summer, T and RH closely tracked outdoor values due to increased ventilation. However, in winter, the confined environment resulted in relatively stable indoor conditions, with higher humidity levels due to pig respiration and management activities.

As shown in Fig. 6(i) and (j), NH_3 and CO_2 concentrations also showed seasonally distinct diurnal patterns. Gas concentrations peaked during feeding periods and were generally higher in winter due to limited ventilation. In summer, concentrations were lower and more variable, reflecting the effects of enhanced airflow. Overnight reductions in both NH_3 and CO_2 were observed in winter, corresponding to lower pig activity and cooler temperatures.

Therefore, the environmental control strategies need to be developed according to the different seasons. In winter, the priority is to balance heat retention with sufficient ventilation to limit gas accumulation. In summer, ventilation must respond dynamically to fluctuations in temperature and humidity. On the basis of reducing energy consumption, the control for fans and other equipment should ensure that the environmental parameters in the pig house are maintained within a suitable range for pig production.

4.3. Validation of multi-objective optimisation control in pig house

4.3.1. Performance comparison of control models

In Table 6, it can be seen that the DDQN model performs better in the three indicators. The average and maximum returns at convergence

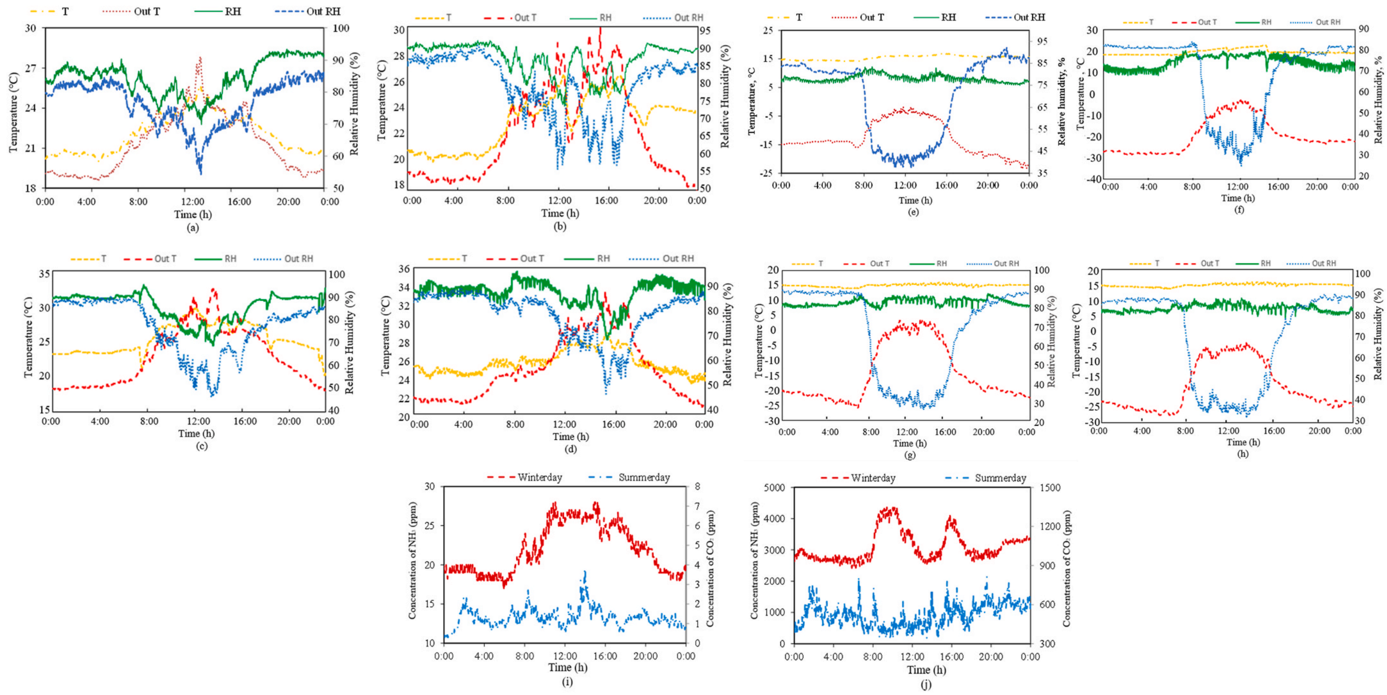

Fig. 6. Examples of diurnal environment variations: (a)~(d) Summer Day (July), (e)~(f) Winter Day (January and February), (c) NH_3 concentration, (d) CO_2 concentration.

were 27.16 and 28.19 for the DDQN model and 20.56 and 23.69 for the DQN model, respectively. The average return at convergence of the DDQN model was better than that of the DQN model by 32.1 %, and the maximum return was better than that of the DQN model by 19 %. This suggested that in the same environment, the DDQN model was able to perform the action better and obtain higher returns. The convergence time step of the DDQN model was slower than that of the DQN model, which was due to the fact that the DDQN algorithm is more complex and slightly more difficult to train compared to the DQN, but the average return at the time of the final convergence of the former model was higher. In terms of the stability of the model, the DDQN model had a slightly higher stability than that of the DQN, which indicates that the DDQN model had stronger robustness and stability.

As shown in Fig. 7(a), the average return for both models of DQN and DDQN initially increased quickly with the number of training steps. The DQN model converged faster due to its relative simplicity and had less difficulty in converging compared to the Double DQN. However, its average return after convergence was lower than that of DDQN because the DQN model encountered the problem of overestimating Q-values, which affected its performance. In contrast, DDQN improved performance through dual Q-networks. Both models exhibited some degree of oscillation after convergence, with the DDQN model showing smoother fluctuations and higher stability.

The loss value changes of the two models during the training process are shown in Fig. 7(b). The loss value of the DDQN model gradually decreased to 0 as the number of training steps increases. In contrast, the loss value of the DQN model decreased rapidly in the initial stages but exhibited significant fluctuations as the training steps increased, indicating poorer stability compared to the DDQN model.

Overall, the DDQN model exhibited better average return, maximum return, and stability during convergence, enabling rapid achievement of higher returns and effective regulation of environmental parameters such as temperature and humidity within suitable ranges.

4.3.2. Verification of indoor environmental control effect

The objectives of ventilation vary across different seasons, consequently influencing the requirements for ventilation volume and wind speed. During the summer, when T tends to be excessively high, increased ventilation is essential to effectively reduce the temperature within the pig house. Conversely, in winter, the focus shifts towards maintaining warmth for pigs, requiring a reduction in both the duration and volume of ventilation. Excessive ventilation during colder months can lead to imbalances between the need for ventilation and the requirement for heat retention. Therefore, to achieve a balanced approach, only one fan with a power rating of 0.75 kW is operated for ventilation adjustments during winter. To verify the control effect of the DDQN model, comparative experiments with the traditional temperature threshold control strategy (TTCS) were conducted in the same pig house for twelve days in August and September under similar outdoor climate conditions (Table 7). The weather conditions and temperature-humidity situations outside the pig house were similar for the comparison experimental groups, characterised by large diurnal temperature variations and relatively high humidity.

As can be seen from Table 8, the DDQN strategy was able to control the temperature closer to the target value of 19 °C on most days, with a deviation range of +1.0 °C to +1.8 °C. In contrast, the TTCS strategy had a larger temperature deviation, ranging from +1.8 °C to +2.1 °C. The DDQN strategy also performed better in humidity control, with deviations ranging from −2.7 % to +0.8 %. The humidity deviation of TTCS strategy ranged from +0.8 % to +4.1 %. In summary, the DDQN strategy was more accurate in the control of these two key parameters (temperature and humidity), and better met the expected conditions of the system.

Taking the contrast test on August 23 and August 24 as an example, the changes of four environmental factors in the pig house under the two control strategies were analysed in detail. The temperature changes in the pig house under the two control strategies are shown in Fig. 8(a) The temperature in the pig house was in the range of 18–25 °C on both days, and did not exceed the upper limit of 27 °C for pregnant sows. The expected value of the system temperature was 19 °C. Under the DDQN and temperature threshold control strategies, the maximum temperatures were 23.5 °C and 24.2 °C, respectively, the minimum temperatures were 18.4 °C and 18.2 °C respectively, the maximum deviation of the temperature from the expected value was 4.5 °C and 5.2 °C respectively, and

Table 5
Moments of peaks and valleys of environmental parameters in pigsties during a day in different seasons.

Factors	Jan 21		Jan 28		Jan 31		Feb 5		Jul 18		Jul 19		Jul 25		Jul 30	
	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
Out T (°C)	12:56 a.m.	5:33 a.m.	12:53 a.m.	11:17 p.m.	1:22 p.m.	7:15 a.m.	1:49 p.m.	5:36 a.m.	2:12 p.m.	4:00 a.m.	2:00 p.m.	11:55 p.m.	2:09 p.m.	0:23 a.m.	1:50 p.m.	11:46 p.m.
Out RH (%)	0:35 a.m.	1:21 p.m.	9:49 p.m.	1:34 p.m.	2:52 a.m.	1:41 p.m.	9:15 p.m.	1:50 p.m.	11:00 p.m.	2:00 p.m.	5:50 a.m.	2:25 p.m.	5:10 a.m.	2:10 p.m.	3:51 a.m.	2:40 p.m.
T (°C)	3:00 p.m.	5:00 a.m.	3:51 p.m.	7:18 a.m.	3:09 p.m.	5:50 a.m.	3:53 p.m.	6:30 a.m.	1:00 p.m.	4:00 a.m.	12:57 a.m.	2:06 a.m.	1:16 p.m.	11:57 p.m.	12:53 a.m.	10:51 p.m.
RH (%)	7:05 p.m.	8:48 a.m.	5:59 p.m.	4:02 a.m.	7:57 p.m.	9:27 a.m.	1:21 p.m.	5:32 p.m.	8:00 p.m.	1:00 p.m.	5:47 a.m.	12:59 a.m.	8:00 a.m.	1:08 p.m.	8:32 a.m.	1:53 p.m.
NH_3 (ppm)	7:55 a.m.	3:44 p.m.	8:04 a.m.	6:41 a.m.	7:50 a.m.	3:21 p.m.	7:18 a.m.	6:37 p.m.	8:00 a.m.	0:00 a.m.	3:12 p.m.	9:00 a.m.	3:00 p.m.	8:57 a.m.	3:21 p.m.	9:14 a.m.
CO_2 (ppm)	12:06 a.m.	2:58 p.m.	10:26 a.m.	5:51 a.m.	11:17 a.m.	2:54 p.m.	8:37 a.m.	2:43 p.m.	9:00 p.m.	9:00 a.m.	8:04 a.m.	4:00 p.m.	4:00 p.m.	4:00 p.m.	4:15 p.m.	9:05 a.m.

Table 6
Comparison of model indicators between DQN and DDQN.

Model	Average return at convergence	Maximum return	convergence timestep	Stability
DQN	20.56	23.69	2812	1.02
DDQN	27.16	28.19	3920	1.09

the maximum relative error was 23.7 % and 27.4 % respectively. Moreover, the mean and standard deviation of the DDQN control strategy (20.5 ± 1.7) °C were better than those of the TTCS control method (20.8 ± 2.1) °C. From 8:00 a.m. to 6:30 p.m., no matter how the fan was regulated, it could only reduce the peak temperature in the house and slow down the temperature rise trend, so it was necessary to add air conditioning and other cooling equipment to regulate the pig house environment to a more appropriate temperature level.

The humidity changes in the pig house under the two control strategies are shown in Fig. 8(b). The humidity in the pig house was relatively high, and the humidity at night was maintained at about 80 %–85 %, which exceeded the suitable humidity range for pregnant sows. The expected humidity of the system was 75 %. Under the DDQN control strategy, the maximum humidity was 84.9 %, the minimum humidity was 60.1 %, the maximum humidity deviation from the expected value was 9.9 %, and the maximum relative error was 13.2 %. Under the TTCS, the maximum humidity was 86.8 %, the minimum humidity was 57.1 %, the maximum humidity deviation from the expected value was 11.8 %, and the maximum relative error was 15.7 %. The mean and standard deviation of humidity was 74.2 % ± 7.8 in the DDQN control strategy and better than those of the TTSC (75.8 % ± 9.5). Due to frequent rainfall in August and the use of water spray guns for floor cleaning, RH remained high. In summer, equipment, such as dehumidifiers, should be considered in the environmental control system of the pig house to more effectively reduce the humidity to an appropriate range while maintaining the temperature of the pig house.

The changes of NH_3 concentration and CO_2 concentration in the pig house under the two control strategies are shown in Fig. 8(c) and (d). Under the DDQN control strategy, the highest concentration of NH_3 was 6.9 ppm and the lowest was 0.7 ppm. Under the TTCS, the highest concentration of NH_3 was 6 ppm and the lowest concentration was 1 ppm. It can be seen that the NH_3 concentration in the pig house was a low level, far less than the NH_3 concentration threshold required by the national standard. NH_3 mainly derives from protein metabolism in the pig house and the decomposition of nitrogen-containing organic matter in faces and other excretions, so the low concentration of NH_3 in pig houses was mainly maintained by the regulation of ventilation system and the regular cleaning of faeces by keepers twice a day. Under the control of the two control strategies, the CO_2 concentration was below 1600 ppm, and the sleeping of pigs at night and the reduction of ventilation often resulted in a high nighttime CO_2 concentration in the house, while the daytime concentration was relatively low. The mean and standard deviation of CO_2 concentration in the pig houses under DDQN control strategy were 772.9 % ± 247.3 ppm and <898.2 ± 373.9 ppm under TTCS. This was because DDQN can comprehensively control the environment of the pig house by considering temperature, humidity and harmful gas concentration, so that the environmental parameters in the pig house were maintained in a more comfortable range. However, the TTCS method only focused on the temperature in the pig house, ignoring the importance of other environmental factors.

4.3.3. Energy consumption analysis

Due to the low Out T in winter, only one fan with a power of 0.75 kw was adjusted, but in summer, the ventilation system in the pig house environment consumed the most energy. Therefore, the comparison of energy consumption between the two control strategies of DDQN model and TTCS was conducted in August and September (late summer/early autumn), 2022. There were three wall fans installed in the pig house.

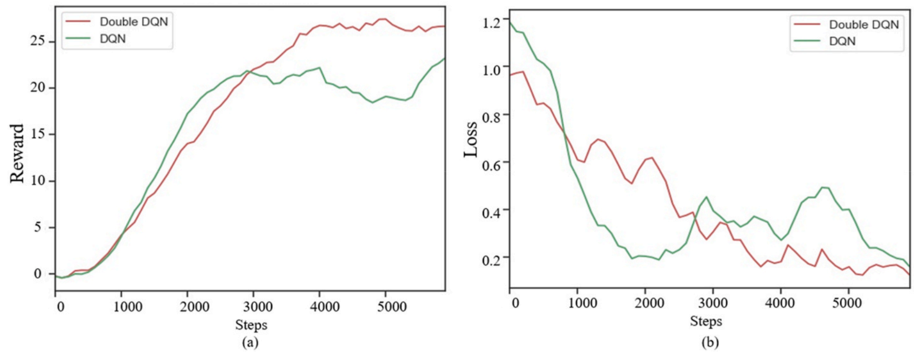

Fig. 7. Change curves during training: (a) change curve of return value during model training, and (b) change curve of loss value during model training.

Table 7
Comparison of the external environment of the experimental house.

Group No.	Date	Out T (°C)	Out RH (%)	Atmospheric pressure (kPa)
1	Aug. 10	12.7–34	28.4–86.5	99.7
	Aug. 11	13.1–34.6	28.6–87.4	99.3
2	Aug. 14	11.9–29.7	43.7–90.3	100.1
	Aug. 15	11.7–28.8	44.1–91	99.8
3	Aug. 20	10.2–30.8	38.8–89.5	97.8
	Aug. 21	9.9–30.6	39.8–89.9	97.3
4	Aug. 23	9.9–31.7	30.3–88.1	98.4
	Aug. 24	9.7–32.1	28.8–89.9	97.4
5	Aug. 26	8.8–25.7	41.4–91	97.4
	August 27	9.1–26.2	42~90.5	97.5
6	Sept. 2	13~25.2	23.5–89.1	98.2
	Sept. 3	12~26.4	24.4–88.7	98.8

The power of the three wall-mounted fans, Fan 1, Fan 2, and Fan 3, was 0.37 kW, 0.37 kW, and 0.55 kW, respectively.

The energy consumption comparison of the two groups of control strategies is shown in Table 9. As can be seen from Table 9, the energy consumption on most days under the control strategy of DDQN was lower than that of TTCS. These data show that DDQN, as an advanced control strategy, had better performance in terms of energy consumption and effectively reduced the energy consumption of system. A contrast analysis was made between August 23 and August 24 as an example. On August 23, 2022, the pig house environmental control strategy based on DDQN was adopted, with three fans running cumulatively for 28.01 h in one day and a total power consumption of 11.4 kW h; On August 24, the pig house environmental control strategy based on TTCS was adopted. The three fans operated for a cumulated total of 29.73 h in one day, and the total power consumption was 12.31 kW h. Compared with the TTCS, the total running time (RT) of fans under the DDQN control strategy was shortened by 1.72 h, and the total power consumption was saved by about 7.39 % in one day (Table 10).

Due to the influence of Out T, T was higher from 8:00 to 18:30 on both days, and the ventilation system worked continuously during this time, which consumed more electricity than at night. Taking the same period from 3:23 p.m. to 4:34 p.m. on August 23 and August 24 as an example, a comparative analysis of the real-time energy consumption of the fan system under the two control strategies was conducted. During this period, the initial temperature on both days was 22.9 °C and the final temperature was 22.7 °C. Under the control strategies of DDQN and the temperature threshold, the total operating time of the three fans was 2.55 h and 3.27 h, and the total electricity consumption of 1.1 kW h and 1.41 kW h, respectively. The average temperature and standard deviation during this period over the two days were (22.7 ± 0.1) °C and (23.0 ± 0.2) °C, respectively. Under the DDQN control strategy, the average T was closer to the desired value with smaller temperature fluctuation; compared to the TTCS, the total operating time of the fans was reduced by 0.72 h, and electricity consumption decreased by 0.31 kW h, saving approximately 22 % of energy consumption.

In summary, the DDQN control strategy can not only use multiple environmental factors to jointly regulate the pig house environment but also optimise the start-stop combinations of three fans. Compared to a control strategy based on temperature threshold, this approach reduces the power consumption of the ventilation system and minimises the relative energy loss, thereby achieving a balance between effective ventilation and energy savings. At the same time, the fan start-stop frequency based on the control strategy of DDQN is slow, which helps to reduce the influence on the service life of the fan.

Table 8
Mean value and variance of environmental factors in pig house.

Group No.	Strategy	T (°C)	RH (%)	NH_3 concentration (ppm)	CO_2 concentration (ppm)
1	DDQN	20.4 ± 1.6	73.5 ± 4.3	2.3 ± 0.3	704.6 ± 204.0
	TTCS	21.1 ± 2.0	77.6 ± 5.3	2.7 ± 1.1	875.4 ± 238.4
2	DDQN	20.5 ± 1.7	73.7 ± 5.0	2. 3 ± 0.7	703.2 ± 214.4
	TTCS	21.1 ± 2.0	78.2 ± 8.7	2.6 ± 1.0	887.4 ± 245.6
3	DDQN	20.63 ± 1.8	72.5 ± 5.4	2.1 ± 0.8	697.0 ± 213.2
	TTCS	21.2 ± 2.3	79.1 ± 9.5	2.6 ± 1.0	864.2 ± 230.8
4	DDQN	20.5 ± 1.7	74.2 ± 7.9	2.5 ± 1.0	773.0 ± 247.3
	TTCS	20.8 ± 2.1	75.8 ± 9.5	2.6 ± 1.0	898.2 ± 373.9
5	DDQN	20.5 ± 1.4	73.4 ± 4.9	2.4 ± 0.7	686.1 ± 222.5
	TTCS	21.1 ± 2.1	77.6 ± 9.0	2.5 ± 1.0	875.2 ± 369.9
6	DDQN	20.0 ± 1.5	72.3 ± 6.3	2.2 ± 0.8	692.8 ± 245.3
	TTCS	21.1 ± 2.1	79.0 ± 9.0	2.6 ± 1.0	869.4 ± 370.0

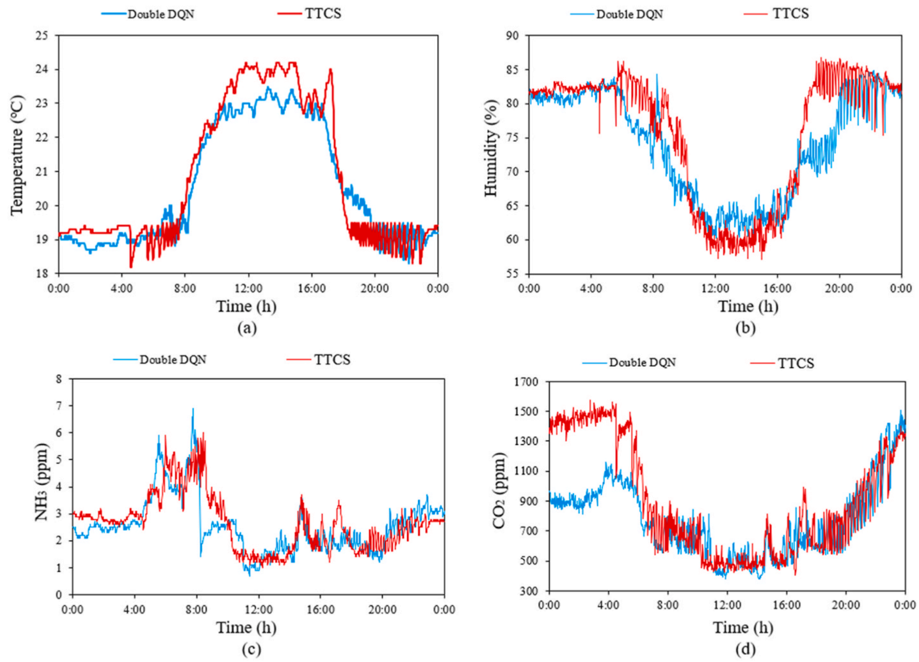

Fig. 8. Changes in environmental factors in pig houses under two control strategies: (a) Temperature, (b) Humidity, (c) NH_3 concentration, and (d) CO_2 concentration.

Table 9
Comparison of energy consumption between two control strategies (DDQN and TTCS).

Group No.	Control strategy	standard	Fan 1	Fan 2	Fan 3	Total
1	DDQN	RT, h	10.86	13.1	5.22	29.18
		EC, kW·h	4.02	4.85	2.9	11.77
	TTCS	RT, h	11.4	13.28	7.06	31.74
		EC, kW·h	4.22	4.91	3.92	13.05
2	DDQN	RT, h	10.91	14.09	4.49	29.49
		EC, kW·h	4.04	5.21	2.49	11.74
	TTCS	RT, h	11.1	14	6.01	31.11
		EC, kW·h	4.11	5.18	3.33	12.62
3	DDQN	RT, h	9.5	12.74	5.87	28.11
		EC, kW·h	3.52	4.71	3.26	11.49
	TTCS	RT, h	10.36	12.06	6.96	29.38
		EC, kW·h	3.83	4.45	3.86	12.14
4	DDQN	RT, h	9.7	12.59	5.72	28.01
		EC, kW·h	3.59	4.66	3.15	11.4
	TTCS	RT, h	10.53	11.95	7.25	29.73
		EC, kW·h	3.9	4.42	3.99	12.31
5	DDQN	RT, h	9.4	11.96	5.23	26.59
		EC, kW·h	3.48	4.42	2.90	10.8
	TTCS	RT, h	10.12	11.78	6.13	28.03
		EC, kW·h	3.74	4.36	3.40	11.5
6	DDQN	RT, h	8.9	12.09	5.28	26.27
		EC, kW·h	3.29	4.47	2.93	10.69
	TTCS	RT, h	9.11	11.9	6.15	27.16
		EC, kW·h	3.37	4.40	3.41	10.91

RT = Running time; EC = Electricity consumed; DDQN = Double Deep Q-Network; TTCS = Traditional temperature threshold control strategy.

Table 10
Changes in the pig building environment after ventilation for 15 min in winter.

Environmental factors	Initial value	Final value	Difference
T (°C)	19.8	16.2	3.6
RH (%)	79.1	72.7	6.4
NH_3 concentration (ppm)	49.6	37.9	11.7
CO_2 concentration (ppm)	4538	2584	1954

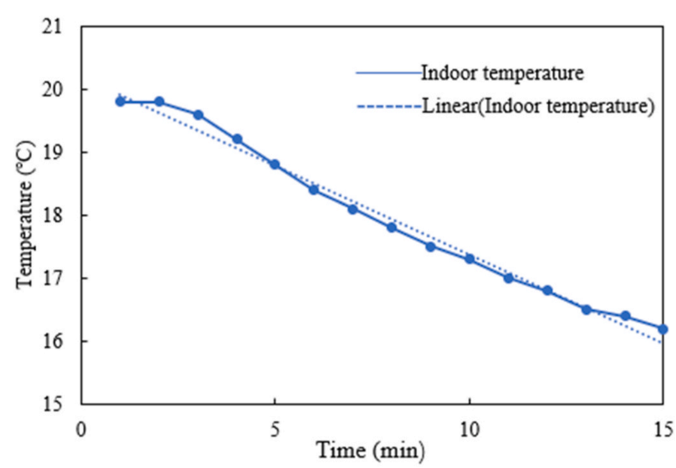

Fig. 9. Relationship between indoor temperature and ventilation time in pig house in winter.

4.4. Relationship between ventilation and temperature dynamic changes

Ventilation is a critical part of environmental control in the pig house (Ni et al., 2016), it affects not only T, but also indoor air quality. Therefore, exploring the relationship between ventilation and indoor temperature variation is a basic way to achieve an effective and costless environmental control. In this study, different ventilation rates were operated both in winter and summer to establish the heat loss and dissipation for keeping a suitable indoor environment in the pig house.

4.4.1. Relationship between ventilation and temperature changes in winter

In winter, to maintain T in the pig house, only minimal ventilation (Fan 0 mode) is employed to reduce heat loss. The variation of T with minimum ventilation rates is shown in Fig. 9. Before the fan was turned on, T was 19.8 °C, while the RH was 79.1 %, the NH_3 concentration was 49.6 ppm, and the CO_2 concentration was 4538 ppm. The T gradually decreased as the fan's running time increased. After continuous

Table 11
Changes in the pig building environment after ventilation for 15 min in summer.

Environmental factors	Fan 2			Fan 1+Fan 2			Fan 1+Fan 2+Fan 3		
	initial	finial	difference	initial	finial	difference	initial	finial	difference
T (°C)	27	26.6	0.4	26.8	25.8	1	29.6	28.2	1.4
RH (%)	74.3	69.2	5.1	87.7	85.6	2.1	72.7	70.6	2.1
NH_3 concentration (ppm)	3.6	1.7	1.9	12.4	5.2	7.2	6.6	2.2	4.4
CO_2 concentration (ppm)	742	459	283	1607	650	957	909	372	537

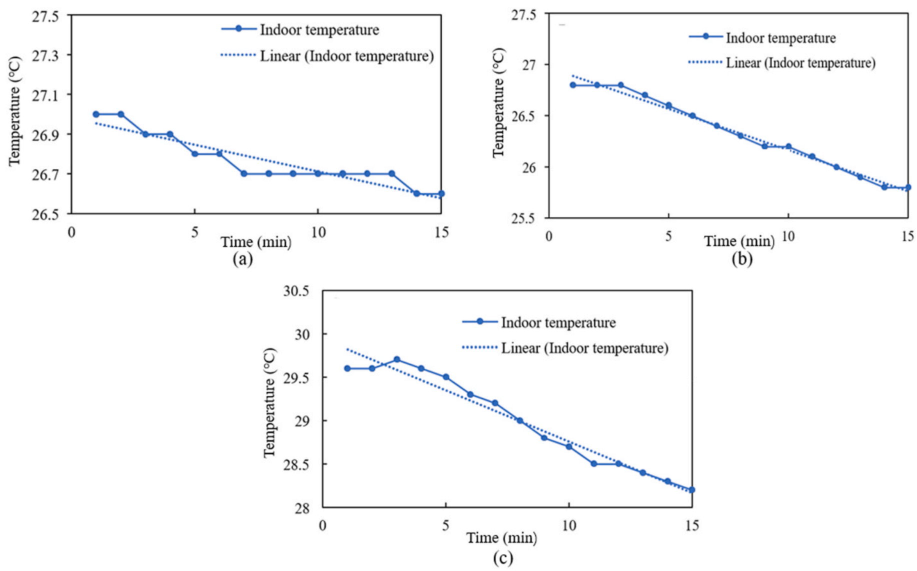

Fig. 10. Indoor temperature variations under three ventilation modes in summer: (a) Fan2 ventilation mode, (b) Fan 1+Fan 2 ventilation mode, (c) Fan 1+Fan 2+Fan 3 ventilation mode.

operation of the fan for 15 min, T dropped by 3.6 °C, temperature variation rate was 19.18 %, RH decreased by 6.4 %, RH variation rate was 8.1 %, and the concentrations of NH_3 and CO_2 were affected greatly by the ventilation (dropping by 11.7 ppm and 1954 ppm with variation rates of 23.6 % and 43.1 %, respectively).

The linear relationship between T and ventilation time was established as shown in Eq. (10). When Fan 0 is turned on, the variation rates of T was −0.2818 °C min^{-1}. The rate of temperature change inside the pig house over time was −0.0047 °C per second.

$$y_{Fan0} = -0.2818x + 20.201 \quad (10)$$

where, x represents the ventilation time, min; and y_{Fan0} represents the indoor temperature, °C。

Obviously, ventilation improved the indoor air quality, but also brought the problem of heat loss. Therefore, a compensation is needed for the heat loss to maintain a suitable T.

The heat loss Q caused by the indoor temperature drop due to ventilation is depicted by Eq. (11).

$$Q = C \cdot M \cdot \Delta T \quad (11)$$

where C is the specific heat capacity 1000 J kg^{-1} °C^{-1};M is the mass of air in the pig house, kg, calculated as $M = V \cdot \rho$, where V is the volume of the pig house and ρ is the density of air, assuming $\rho = 1.29$ kg m^{-3}; ΔT is the temperature variation rate, °C。

Therefore, in winter, when the indoor temperature decreased by 1 °C, there was a heat loss of ~1.42 × 10^3 kJ. To maintain the indoor temperature, heating equipment needs to supply at least an equivalent amount of heat to compensate for the heat loss caused by the ventilation system.

4.4.2. Relationship between ventilation and temperature changes in summer

In summer, through the different operation combinations of Fan 1, Fan 2 and Fan 3, three different ventilation modes for the pig house, Fan 2, Fan 1 + Fan 2, and Fan 1 + Fan 2 + Fan 3, are formed to explore the changes of environmental factors in the pig house after 15 min of ventilation, as shown in Table 11.

As shown in Table 11, all three ventilation modes resulted in varying degrees of decline in various environmental factors within the pig house in summer. Within 15 min, the temperature drop efficiencies in the pig house under the three ventilation modes were 1.5 %, 3.7 %, and 4.7 %, respectively. For humidity, the drop efficiencies were 6.9 %, 2.4 %, and 2.9 %, respectively. The concentrations of NH_3 and CO_2 were significantly influenced by ventilation. The drop efficiencies of NH_3 concentration were 52.8 %, 58.1 %, and 66.7 %, respectively, while the drop efficiencies of CO_2 concentration are 38.1 %, 59.6 %, and 59.1 %, respectively. The indoor temperature under different ventilation modes in summer changed with ventilation time (Fig. 10). By performing linear fitting on the temperature and ventilation time in the pig house under three ventilation modes, the linear relationship between the indoor temperature and ventilation volume was established, as shown in Eqs. (12)–(14).

$$y_{\mathrm{Fan\ 2}} = -0.0268x + 26.981 \quad (12)$$

$$y_{\mathrm{Fan\ 1+Fan\ 2}} = -0.0807x + 26.972 \quad (13)$$

$$y_{\mathrm{Fan\ 1+Fan\ 2+Fan\ 3}} = -0.1182x + 29.939 \quad (14)$$

where x is the ventilation time in minutes; $y_{\mathrm{Fan\ 2}}$, $y_{\mathrm{Fan\ 1+Fan\ 2}}$, $y_{\mathrm{Fan\ 1+Fan\ 2+Fan\ 3}}$ are the indoor temperatures under ventilation modes of Fan 2, Fan 1+Fan 2, and Fan 1+Fan 2+Fan 3, respectively, °C.

From Fig. 10, it can be observed that the indoor temperature decreased proportionally with ventilation time and the fastest temperature decrease was with the ventilation mode using all three fans, i.e., Fan 1+Fan 2+Fan 3. However, as the Out T continued rising in summer, even operation at the maximum ventilation mode struggled to achieve the desired cooling effect. Taking August 1, 2022, as an example, the highest T reached 32.1 °C at 12:08, the Out T was 35.2 °C. Although, under the maximum ventilation mode, all three fans were operated, T could not be maintained in the suitable range. Therefore, it was necessary to use cooling equipment to control T in a proper range. According to Eq. (11), in summer, the ventilation or cooling equipment needs to remove 0.63×10^3 kJ of heat for every 1 °C above the setting value.

5. Conclusions

In this study, it was demonstrated that there is a strong correlation and seasonal dependence among multiple environmental factors in the pig house, and that the DDQN-based control strategy significantly enhanced environmental regulation performance in pig houses when compared with both the traditional temperature threshold method and the standard DQN model. The DDQN model achieved more stable and precise environmental control, resulting in closer alignment with target values and reduced energy consumption. The observed relationships between ventilation and thermal variation provided practical insights for seasonal control optimisation, particularly in colder regions. Therefore, these findings provide a scientific foundation for the development of intelligent and energy-efficient ventilation control systems in pig housing.

CRediT authorship contribution statement

Xiaofei Sun: Writing – original draft. **Shengchao Wang:** Writing – original draft. **Qiuju Xie:** Conceptualization, Supervision. **Congcong Sun:** Writing – review & editing. **Haiming Yu:** Resources. **Wenfeng Wang:** Data curation.

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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