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Review

Indoor Thermal Comfort Sector: A Review of Detection and Control Methods for Thermal Environment in Livestock Buildings

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Abstract: The thermal environment is crucial for livestock production. Accurately detecting thermal environmental conditions enables the implementation of appropriate methods to control the thermal environment in livestock buildings. This study reviewed a comprehensive survey of detection and control methods for thermal environments in livestock buildings. The results demonstrated that temperature, humidity, velocity, and radiation are major elements affecting the thermal comfort of animals. For single thermal environmental parameters, the commonly employed detection methods include field experiments, scale models in wind tunnels, computational fluid dynamics (CFD) simulation, and machine learning. Given that thermal comfort for livestock is influenced by multiple environmental parameters, the Effective Temperature (ET) index, which considers varying proportions of different environmental parameters on the thermal comfort of livestock, is a feasible detection method. Environmental control methods include inlet and outlet configuration, water-cooled floors, installation of a deflector and perforated air ducting (PAD) system, sprinkling, etc. Reasonable inlet configuration increased airflow uniformity by more than 10% and decreased ET by more than 9 °C. Proper outlet configuration improved airflow uniformity by 25%. Sprinkling decreased the temperature by 1.1 °C. This study aims to build a comprehensive dataset for the identification of detection and control methods in research of the thermal environment of livestock buildings.

Keywords: thermal environment; detection methods; control methods; livestock buildings; CFD; equivalent temperature

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1. Introduction

The livestock sector is important within the agricultural industry, contributing approximately 40% of the total net agricultural value worldwide. In some countries, such as Mauritania and New Zealand, the total net value rate of the livestock sector can exceed 80% compared with the total net value of agriculture [1]. The thermal environment plays a crucial role in livestock production and animal welfare [2]. Due to excessively high or low ambient temperatures, like in many regions worldwide where the maximum ambient temperature is more than 35 °C in summer and the minimum is less than −20 °C in winter, the failure of thermal environment regulation leads to billions of dollars loss in livestock production [3]. The detection and control of thermal environments in livestock buildings are of great importance.

Temperature, humidity, and airflow are the main parameters affecting the thermal environment in livestock buildings. Detection of the above parameters serves as the foundation for environment control. Currently, the most employed detection methods include field experiments, scale models with wind tunnel measurement, as well as computational fluid dynamics (CFD) simulations. The emerging method of machine learning has also started to be utilized. Field experiments are conducted directly on-site, making them closest to real-world scenarios [4], but the limitations of limited measurement points, high costs, and long cycles exist. A scale model with wind tunnel measurement allows for precise control of experimental conditions, which are less affected by the external environment and provide relatively high-precision results. However, it may fail to accurately represent real-world phenomena, as the wind fluctuations produced in a wind tunnel differ from actual situations [5]. As for CFD, it can both enable the precise control of boundary conditions and handle complex geometries at full scale. Meanwhile, with the advance in computer capability, all environmental data in the computational domain can be provided [6]. However, the accuracy of simulation results is influenced by model simplification, mesh type, turbulence models, etc. In terms of machine learning, an emerging research method, it has advantages such as high efficiency, strong adaptability, the ability to handle complex problems, and the capability to process large-scale data. While it demands a substantial volume of data and heavily relies on data. Insufficient availability of representative data may result in decreased performance of the model [7]. Considering the distinct features of various research methods, it is extremely necessary to select the appropriate research method based on the actual situation and specific needs.

Additionally, given that the thermal comfort of livestock is influenced by temperature, humidity, wind speed, and thermal radiation for cows with exercise yards, it is more objective to detect the thermal environment in livestock buildings by considering the combined effects of multiple environmental parameters. The Effective Temperature (ET) index, which considers the varying proportions of different environmental parameters on the thermal comfort of livestock, is a practical and feasible method for detecting the thermal environment. Furthermore, the ET index and suitable ranges are classified according to the species, considering the varying heat tolerance of different livestock species.

Based on the accurate research and evaluation of the indoor environment, it is possible to determine the thermal comfort of animals and regulate the indoor environment of livestock housing. The control methods include inlet and outlet configuration, water-cooled floors, deflector installation, and fixed air supply through perforated air ducting systems, among others. The strategies vary with the type of livestock housing and ventilation patterns, like open, semi-open, or closed house, mechanical, or natural ventilation. Intensive studies indicate that with appropriate control methods, the indoor environment has been improved including increased airflow speed and airflow distribution uniformity, as well as reduced hazardous gas concentration [8]. The physiological health of animals has ameliorated, like respiratory rate and skin temperature reductions during summer [9]. In such a way, the production performance has enhanced with increased feed intake and accelerated daily weight gain [10]. As a result, appropriate environmental control methods have a direct impact on the production performance of livestock, making them the most significant factor influencing their economic efficiency.

This study provides a comprehensive review of detection and control methods of thermal environments in livestock housing. Detection methods serve as the foundation for obtaining the thermal environmental condition, which can provide a theoretical foundation to determine the thermal comfort status of animals and the need for environmental control methods. Based on the detection results, it is imperative to adopt effective environmental control methods to ensure the thermal comfort of animals and improve economic benefits. The relationship between the variables is shown in Figure 1.

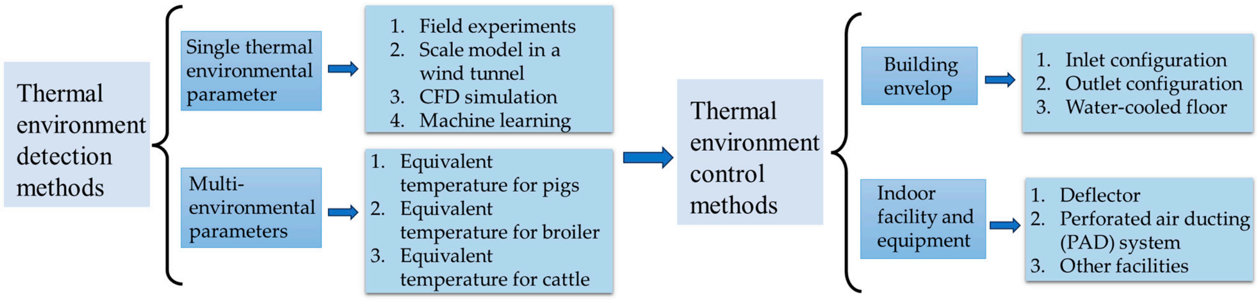


Figure 1. Flowchart of relationship between the detection and control methods.

This study serves as a comprehensive guide for researching the thermal environment in livestock buildings. However, it is rare to come across literature that thoroughly explores the detection methods with single and multiple environmental parameters, as well as control methods associated with the thermal environment in animal buildings, both nationally and internationally. The objective of this research is to create a comprehensive dataset tailored for the identification and implementation of detection and control methods in the field of thermal environment research for livestock buildings. The primary goal is to enhance animal welfare and improve overall productivity by optimizing the thermal conditions in these buildings.

2. Research Methodology

This study adopted a systematic literature review (SLR) method that can be used to collect, screen, and synthesize published studies to assess a specific research field. The research questions for this study were as follows: (1) What are the main environmental parameters that influence the thermal environment in livestock buildings? (2) What are the detection methods for single thermal environmental parameters in livestock buildings? (3) What detection methods can consider multiple thermal environmental parameters simultaneously? (4) What control measures should be implemented to maintain a thermoneutral environment in livestock buildings?

To answer these questions, a literature search was conducted using two categories of keywords: (i) "thermal comfort" or "thermal environment"; "detection methods" or "control measures", and (ii) "livestock" or "livestock building environment"; "poultry house", "pig house" or "cow shed". The databases used for the literature search included IEEE Xplore, Science Direct, Google Scholar, and Taylor & Francis Online. Each database went through 10 rounds of searching, resulting in 251 articles after removing duplicates. From these articles, those belonging to the fields of computer science or engineering, agriculture, and biological sciences were included, whereas patents and articles without complete versions were excluded, reducing the collected papers to 182.

Subsequently, a detailed review of document quality was conducted to ensure relevance to the research question. For example, in a study on the thermal environmental conditions in livestock buildings, each article was examined to meet one of the following requirements:

application of field experiments in collecting thermal environmental data from livestock buildings;

application of scale model and wind tunnel to study thermal environmental conditions in livestock buildings;

application of CFD simulation in thermal environmental management research in livestock buildings; and

application of machine learning and deep learning in thermal environmental control in livestock buildings.

After screening, 100 articles were selected for further analysis. These 100 articles provide representative samples of the impact, research and control of environmental conditions inside livestock buildings.

3. Thermal Environment Detection Methods in Livestock Buildings

3.1. Main Thermal Environmental Parameters in Livestock Buildings

To maintain thermal comfort, various mechanisms such as convection, conduction, radiation, and evaporation heat transfer were adopted. According to the research, heat transfer quantity increased with airflow speed [11], while decreasing with temperature and humidity. In the study of Li et al. and Wang et al., the convective heat transfer coefficients all increased by approximately 1.5 times when airspeed rose from 1 to 2 m s^{-1} for pigs and cows [11]. According to the research of Huang et al., the conductive heat transfer quantity from sows to floor systems accounted for approximately 6% to 19% of the total heat loss of sows at 20 °C, whereas this percentage reduced to 5% to 11% when the temperature rose to 30 °C [12]. As for humidity, it is reported that when the humidity increased from 48% to 84% at 33.3 °C, with reduced heat loss, the rectal temperature increased by 0.3 °C [13]. Furthermore, Brown et al. found that beef cattle exposed to solar radiation in summer had significantly lower feed intake, slower weight gain, and more severe heat stress than beef cattle exposed to sunshade [14]. Hence, in order to assess the thermal comfort of animals, it is recommended to take into account various environmental parameters such as temperature, humidity, airflow velocity, and solar radiation.

3.2. Single Thermal Environmental Parameter Detection Methods for Livestock Buildings

The thermal environment plays a vital role in determining animal welfare and production performance [15]. When the thermal environment is beyond the thermoneutral zone, animals will experience heat or cold stress, resulting in decreased reproductive performance, growth rates, health problems, and even increased mortality [16]. Field measurements, wind tunnel experiments, and CFD simulations are three commonly used methods to detect single environmental parameters in livestock buildings. With technological developments, machine learning has also been applied. Considering the efficiency, accuracy, cost, and other factors, different detection methods have been applied to various scenarios.

3.2.1. Field Experiments

Field experiments are the most common and direct methods to detect the thermal environment in livestock buildings. Kova'cs et al. measured relative humidity and air temperature to estimate the thermal stress in 7-week-old Holstein bull calves [17]. To conduct a comprehensive comparison between conventional laying hen housing systems and various alternative systems, Zhao et al. also conducted on-site temperature and humidity measurements [18]. To study the impact of the thermal environment on milk yield, Hill et al. conducted measurements of temperature, humidity, and wind speed [19]. Ding et al. measured the temperature, humidity, airspeed, and solar radiation to evaluate the cooling effect on beef cattle of spraying combined with fans [20]. However, the cost of field experiments is relatively high. To conduct a quantitative analysis of air temperature distribution in a hybrid ventilated finisher pig shed, Gautam et al. used 28 sensors in a comprehensive arrangement [21].

3.2.2. Scale Model in a Wind Tunnel

Compared to field experiments, a scale model in a wind tunnel makes it easier to control thermal environmental parameters such as velocity and turbulence intensity and obtain useful data that are translatable to real-life situations [22]. Hudson and Ayoko demonstrated that wind tunnels had a higher likelihood of simulating changes in airflow states [23]. Accordingly, the application of scale models in wind tunnels has been widely utilized for a variety of aerodynamic studies. Rong et al. studied the effects of airflow and liquid temperature on mass transfer above an emission surface in a wind tunnel, using a supply and return tank model [24]. Ye et al. placed a scaled pig pen model in a wind tunnel to investigate the airflow characteristics above the manure surface in a storage pit [25]. Wu et al. measured air velocities in a 1:8 scale pit model placed in a wind tunnel [26,27]. Yi et al. researched the airflow characteristics downwind of a naturally ventilated pig shed using a laser Doppler anemometer (LDA) in a large boundary layer wind tunnel [28]. However, wind tunnels have certain limitations, specifically regarding the control of wind fluctuations. In realistic scenarios, wind conditions may vary greatly, which cannot be accurately replicated in a wind tunnel environment [29].

3.2.3. CFD Simulation

Computational fluid dynamics is a powerful and versatile tool to evaluate complex thermal conditions. It gathers data under various conditions and analyses airflow patterns both quantitatively and qualitatively, which would be challenging or impossible to analyze experimentally. However, various factors including model simplification, mesh quality, and numerical methods can affect the accuracy and reliability of evaluation results [6].

(1) Model simplification

a. Animal model. Geometric modeling of animals can be challenging and often impractical. In many studies, to reduce mesh density and computational complexity, animal models have been simplified by neglecting certain small parts, such as legs, ears, noses, and tails. Gebremedhin and Wu developed a model of 10 cows using the body-fitted geometry of the actual configuration and size when simulating the flow field in a building; however, some minor parts were neglected, such as the ears and nose [30]. Cheng et al. calculated the airflow resistance of caged hens using a full-geometry hen model while neglecting the legs, beak, and comb [31]. These anatomical features often require high-aspect-ratio polygons in CFD models. The exclusion of nonessential details can strike a balance between accuracy and computational efficiency in the simulation.

Furthermore, simplifying animal models into easier geometries to avoid excessive amounts of meshes has become more widespread. Li et al. reported that a cylinder can be used to represent a pig for heat transfer research [32], and a sphere can be adopted to represent a chicken to predict convective heat transfer coefficients [33]. However, for a high-density hen house, it is impossible to model all the hens separately. Seo et al. assumed that no space exists among broilers raised on the ground; hence, the Animal-Occupied Zone (AOZ) was treated as solid [34]. Hui et al. suggested that a Caged-hen Occupied Zone (CZ) can be directly simplified to a solid because of the high density of laying hens [35].

b. Facility model. For facilities with complex geometries, such as slatted floors and feeding zones, porous media modeling is considered a feasible simplification method. Wu et al. studied the potential of porous media models (POM) when simplifying slatted floors; the results indicated it is viable to estimate mean air velocity and turbulent kinetic energy in the core of pit headspace [26]. Rong et al. also found that the POM could appropriately predict the airspeed below a slatted floor [36]. In the feeding zone, Mondaca and Choi found that the AOZ can be treated as a porous medium when evaluating aerodynamics in dairy cow sheds apart from AOZ [37]. Cheng validated the feasibility of treating CZ as a porous medium when simulating the airflow and temperature in a hen house [38].

(2) Mesh type

For thermal environmental research on animal buildings, mesh type was a crucial factor affecting simulation accuracy. Commonly used types include hexahedral, tetrahedral, and hybrid meshes. The results calculated using a hexahedral mesh are known to be more accurate than those calculated using a tetrahedral mesh [39]. However, the number of cells in a tetrahedral mesh must be larger than that in a hexahedral mesh of the same size, which leads to increased computation time [40]. Moreover, hexahedral meshes are suitable for relatively simple geometries, whereas tetrahedral meshes can capture boundaries with intricate surfaces. Concerning the above issues, a hybrid mesh, which combines both hexahedral and tetrahedral elements, offers a practical solution by reducing the computation time and ensuring accuracy. To study the thermal convection effects in a mechanically ventilated pigsty, Li et al. adopted a hybrid mesh. This shows that the hybrid mesh is a viable alternative for enabling accurate simulation results for animal buildings with complex geometries without encountering difficulties in mesh generation [41]. Similarly, Seo et al. used hybrid meshes to investigate air distribution in a pigsty [42].

(3) Turbulence model

Because the turbulence model relates to an additional term of the turbulence pulsation value to the mean time value, it is one of the principal elements influencing simulation precision. It comprises three methods: direct numerical simulation (DNS), Reynolds-averaged Navier–Stokes (RANS), and large eddy simulation (LES). Because DNS directly calculates high-degree complex turbulent flow, it is rarely applied in simulations because of the difficulty in satisfying hardware requirements.

Because LES can calculate the motion state of large-scale vortices in nonsteady and nonequilibrium processes, the precision of the simulation results obtained by LES is higher than that of RANS. Walton et al. compared the accuracy of RANS (k-ε model) and LES using experimental data. The results showed that the LES approach achieved the closest agreement with the measured results, indicating its superior accuracy in modeling aerodynamics [43]. A study by Rong et al. also revealed that the RANS model generally exhibited poor performance in predicting velocity fluctuations, which arises from its inability to resolve the non-isotropic nature of the flow field [44]. However, performing LES for high-Reynolds-number industrial flows demands a substantial allocation of computational resources, along with the requirement of precise spatial and temporal discretization. The LES was applied in the simulation with high-precision requirements and a relatively simple geometric model. Wu et al. used an LES model to examine airflow and ammonia transportation dynamics in the presence of a slatted floor [26].

Considering the computational resources and accuracy requirements of the results, RANS was widely adopted in this study. The most commonly used RANS equations included the standard k-ε model (SKE), renormalization group k-ε model (RNG k-ε), realizable k-ε model (RKE), and shear stress transport K-ω model (SST K-ω). The SKE is frequently used in industrial flow and heat transfer simulations but is valid only for fully turbulent flows [45]. The RNG k-ε added refinements to realize greater accuracy and reliability for a wider class of flows, especially for flows with recirculation [46]. The RKE was enhanced to incorporate the transport of the primary turbulent shear stress. Specifically, the SST K-ω model was considered for its capability to predict the transfer phenomenon occurring within the boundary layer [47]. For different cases, various turbulence models were required because of their variations in suitability and effectiveness in accurately characterizing flow conditions. Specific turbulence models applicable in thermal environment research are listed in Table 1.

Table 1. The specific turbulence models applicable in thermal environment researches.

Software	Turbulence Model	Research Domain	Research Object	Study
STAR CCM+	Realizable k-ε	Sow pen with slatted floor	Heat loss of sows	Huang et al. [12]
Ansys Fluent	Realizable k-ε	Multi-floor animal building	Indoor thermal environmental condition	Wang et al. [48]
STAR-CCM+	Standard k-ε	Dairy building	Airflow discharge coefficient of an opening	Yi et al. [49]
Ansys Fluent	Standard k-ε	Laying hen house	Airflow distribution	Cheng et al. [50]
Ansys Fluent	RNG k-ε	Swine building	Airflow velocities and patterns	Tong et al. [51]
Ansys Fluent	RNG k-ε	Greenhouse with a tomato crop	Ventilation rates, airflow patterns and temperature	Bartzanas et al. [52]
----	SST k-ω	Virtual wind tunnel with cow model	Convective heat transfer of cows	Wang et al. [11]
Ansys Fluent	SST k-ω	Virtual wind tunnel with pig model	Convective heat transfer from pig models	Li et al. [32]
Ansys Fluent	Large eddy simulation	Slatted floor	Airflow patterns	Wu et al. [26]

3.2.4. Machine Learning

Recently, machine learning has been applied in the study of the thermal environment in livestock buildings. It analyzes large amounts of data to identify patterns and regularities, with advantages that include the ability to handle big data, strong predictive capabilities, automation, and continual improvement. Based on these characteristics, Mora et al. adopted Random Forest (RF) modeling to assess the effects of environmental control strategies on daily egg production fluctuations [53]. Huang et al. used response surface methodology (RSM) in combination with the Box–Behnken design (RSM-BBD) and neural networks (NN) to assess the efficacy of individualized ventilation strategies (IV) for sows housed in confined environments [54]. Lee et al. used recurrent neural network (RNN) models to predict the internal air temperature and relative humidity of mechanically and naturally ventilated duck houses [7]. These findings demonstrate that machine learning can accurately model the thermal environment in livestock buildings.

Moreover, the accuracy of the predictions was influenced by the selection of the machine learning algorithm. Yeo et al. compared the performance of three different machine learning models (ElasticNet, RF, and support vector regression (SVR)) to predict the temperature in a pigsty and found that RF provided superior prediction performance [55].

3.3. Detection Methods of Thermal Environment Based on Multi-Environmental Parameters

Since thermal comfort is influenced by multiple factors, to evaluate the thermal environment objectively, numerous effective temperature (*ET*) indices have been proposed. The temperature–humidity index (*THI*) was proposed as an *ET* index, which used the dry bulb temperature and relative humidity [56]:

$$THI = 0.8T + rh(0.99T - 14.3) + 46.3 \tag{1}$$

where rh is the relative humidity, %; T is air dry bulb temperature, °C.

Although *THI* was initially used for environmental assessment of human activity areas, it has been widely adopted in evaluating thermal conditions in livestock buildings. The *THI* thresholds in various livestock buildings have been summarized. Mayer et al. reported that the upper and lower critical *THI* values for dairy cattle were 78 and 72, respectively [57]. In beef cattle sheds, Amundson et al. concluded that the optimal THI for 0–60-day-old calves was 68 and that for pregnant cows should not exceed 72.9 [58]. In contrast, Brown-Brandl et al. found that the upper and lower limits of THI for fattening cattle were 84 and 74, respectively [14].

However, air velocity, radiation, and physiological reactions were not included in the THI. To address this issue, various thermal indices that consider more elements have been proposed to assess thermal comfort. Additionally, because of differences in sensitivity to the environment and the varied feeding conditions of animals, the indices were classified according to animal species.

3.3.1. Equivalent Temperature for Pigs

Brandt et al. proposed an effective temperature model for gestating sows (ET_{gs}):

$$ET_{gs} = T + a(rh - 50)T - c(v^e - 0.2^e) \tag{2}$$

where v is air velocity (m s^{-1}).

Regarding skin temperature, the values for a, c, and e were as follows: a = 0.0005, c = 3.2 and e = 0.52. According to the research of Brandt et al., an increase in relative humidity from 50% to 70% led to a corresponding increase in *ET* of 0.9 °C. In contrast, an increase in air velocity from 0.2 to 1.0 m/s resulted in a decrease in *ET* of 1.2 °C [13].

Specifically, for pig rearing on a solid floor, Bjerg et al. put forward an *ET* equation for the lying area of pigs [59]:

$$ET = T + 0.0015(rh - 50)T \tag{3}$$

To develop an *ET* model that comprehensively considers environment and dynamic heat balance within a sow's body, a 2-node mechanistic thermo-physiological model was developed. It is comprised of a passive system that mimics the heat transfer processes that occur within the body core and on the surface of the skin. It also included an active system that monitored the thermoregulatory system and adjusted it when the core temperature deviated positively from its reference value under thermally neutral conditions [60]. In a passive system, heat transfer can be described by the following energy balance equations:

$$Q_{SC} = C_{PC} \cdot \frac{\mathrm{d}T_c}{dt} \cdot A_{sk}^{-1} = Q_M - Q_t - Q_{bl} - Q_{res} \tag{4}$$

$$Q_{ssk} = C_{P_{sk}} \cdot \frac{\mathrm{d}T_{sk}}{dt} \cdot A_{sk}^{-1} = Q_{bl} + Q_t - Q_{conv} - Q_{rad} - Q_{diff} \tag{5}$$

where Q_{SC} is heat storage in the core segment, W m^{-2}; Q_{SSK} is heat storage in the skin segment, W m^{-2}; C_{PC} and C_{Psk} are heat capacities of the core segment and skin segment, respectively, J °C $^{-1}$; *Tc* is the core temperature, °C; T_{sk} is the skin temperature, °C; A_{SK} is the skin surface area of the pig, m^2; Q_M is metabolic heat production, W m^{-2}; Q_t is heat conduction from the core body segment to the skin segment, W m^{-2}; Q_{bl} is the convection via peripheral skin blood flow, W m^{-2}; Q_{res} is the heat loss through respiration, W m^{-2}; Q_{conv} is the heat release via convection between the skin surfaces of sows and ambient air, W m^{-2}; Q_{rad} is the radiation to/from the surrounding surfaces, W m^{-2}; and Q_{diff} is the diffusion heat loss from skin surfaces, W m^{-2}.

In an active system, it imitates thermoregulatory reactions, including vasodilatation, panting, and metabolic heat production in the central nervous system. The active system manages the rate of heat transfer in the passive system by regulating the body temperature. The workflow of the 2-node model is presented in Figure 2a; the calculation was performed iteratively until the heat storage values approached zero. The final outputs were the rectal and skin temperatures. Since the 2-node model linked the majority of thermo-physiological processes in pigs, it facilitated a more thorough understanding of pig thermoregulation.

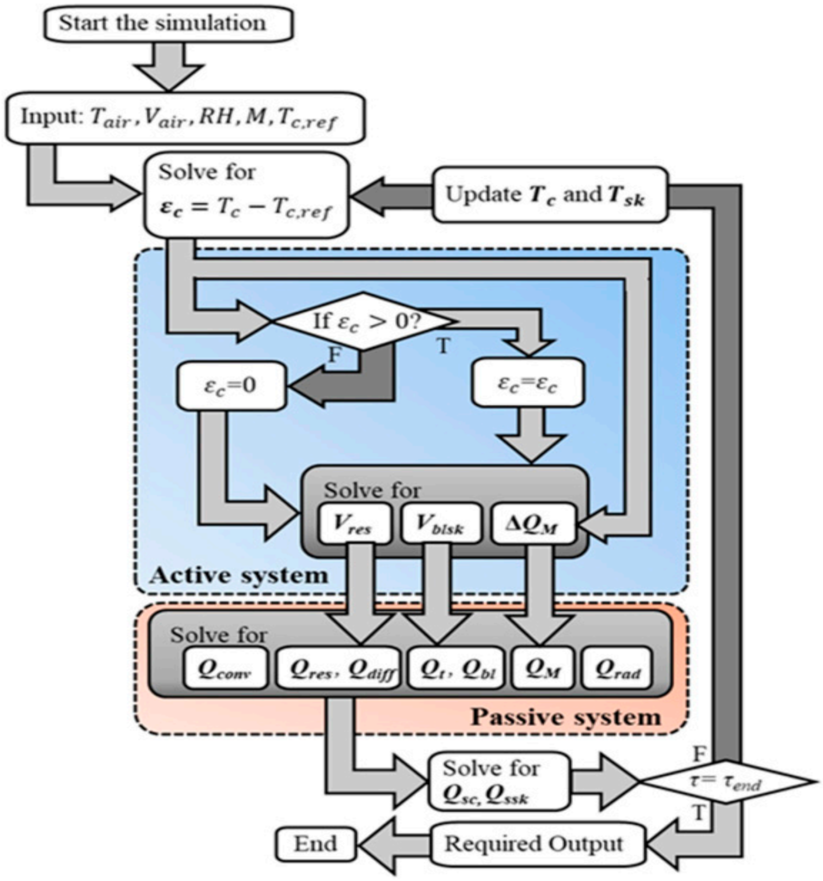
Based on the 2-node model, a second-order dynamic deterministic ET model is shown in Figure 2b. The 2-node model was employed to determine the metabolic heat production under the augmented standard condition $Q_{M,s}$ and the actual condition $Q_{M,a}$. The calculations were performed iteratively. When the difference between $Q_{M,s}$, and $Q_{M,a}$ was less than 0.01 W, the model could be regarded as a convergence. The output value was the effective temperature of the sows (*ETS*). The results showed that the ETS achieved from the 2-node model can effectively reflect the thermal status of sows, as supported by the physiological parameters measured in sow experiments [61].

3.3.2. Equivalent Temperature for Broiler

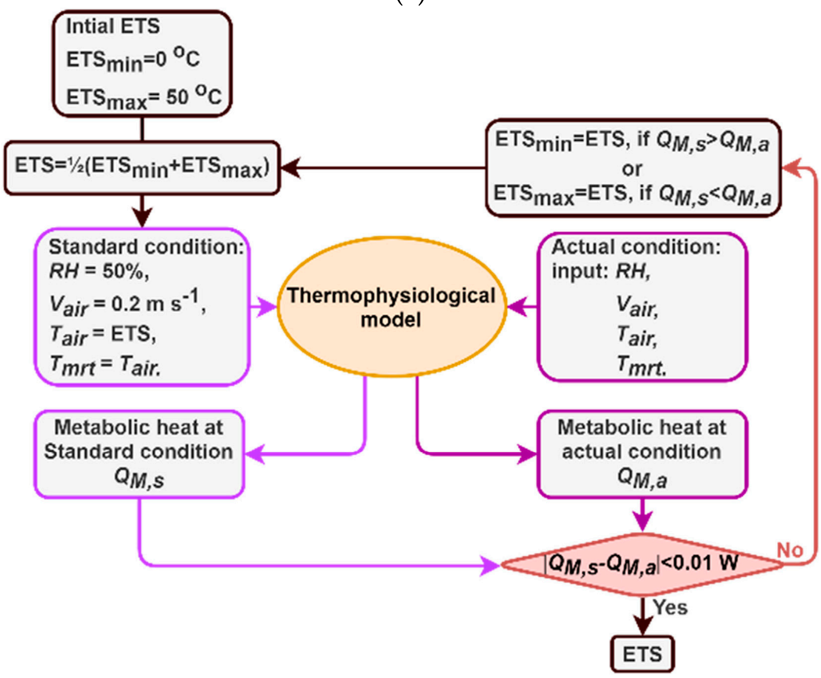
Tao et al. proposed a temperature–humidity–velocity index (*THIV*) using a broiler test that considered temperature, humidity, and airflow velocity [62].

$$THVI = (0.15 \times T + 0.85 \times T_W) \times v^{-0.058} \tag{6}$$

where T_W is wet bulb temperature, °C.



(**a**)



(**b**)

Figure 2. (**a**) Dynamic simulation processes of the 2-node model; (**b**) schematics of algorithm to obtain the ETS using the 2-node model.

3.3.3. Equivalent Temperature for Cattle

Compared to pigs and broilers, cattle spend more time at pasture. Therefore, thermal radiation is an important factor that affects beef cattle production. Given this, *ET* indices that take into account solar radiation have been proposed.

Wang et al. developed a specific thermal index for cattle called the equivalent temperature index (*ETIC*). This index considers the air dry bulb temperature, relative humidity, air velocity, solar radiation, and their interactions, as shown in the following equation:

$$ETIC = T - 0.0038 \times T(100 - rh) - 0.01173 \times v^{0.707} \times (39.2 - T) + 1.86 \times 10^{-4} \times T \times sr \quad (7)$$

where *sr* is solar radiation (W m^{-2}) [63].

After conducting numerous experiments, Mayer et al. proposed the black globe humidity index (*BGHI*) for dairy cows [57]:

$$BGHI = t_{bg} + 0.36t_{dp} + 41.5 \quad (8)$$

where t_{bg} is the black globe temperature, °C; t_{dp} is the dew point temperature, °C.

4. Thermal Environment Control Methods in Livestock Buildings

The thermal environment is vital for livestock production. Numerous studies have demonstrated that building envelope configurations significantly affect thermal comfort. In addition, to regulate the environment within the thermoneutral zone, a series of supplementary facilities and equipment were investigated, and extensive studies were undertaken.

4.1. Building Envelop

4.1.1. Inlet Configuration

It is reported that the airflow states, including airspeed and inlet angle, significantly influence the air movement and its penetration into AOZ [64]. Given that inlet configuration is one of the major factors determining the airflow state, the inlet is crucial to regulate the air motion and distribution in the building [65,66].

In mechanical ventilation, location and ancillary facility are two primary components influencing indoor airflow speed and distribution. For the location, compared with inlets near the edges of the wall, the ventilation rate of inlets near the center is higher, and the pattern was steadier for cross ventilation [67]. For tunnel ventilation in summer, Cheng et al. found the airflow speed increased by 0.37 m s^{-1}, and distribution uniformity added by 11% with increased distance between the sidewall inlet and cages in the hen house [68]. For the ancillary facility, the slot openings beneath the ceiling with a hinged flap were adopted in cross-ventilation [69], which can generate attached air jets to preheat the cold inlet air in winter. A study of a 20 °C temperature difference between indoor and inlet air was reported after adopting bottom-hinged flaps at the rear of the inlet [70,71]. Likewise, Bjerg et al. elucidated that in comparison with the diffuse ceiling only, the ceiling jet inlet could regulate air speed in the AOZ of a pig house more effectively, as the same ET could be obtained when the outdoor temperature was 9 °C higher [59].

In naturally ventilated buildings, both ventilation rate and airflow pattern are considerably dependent on opening configurations [72], like opening ratio(r) and location [73]. Yi et al. found that in dairy buildings, the airspeed and turbulent kinetic energy in AOZ went up linearly with added r values. The corresponding Pearson's correlation coefficients were approximately 0.8 and 0.9, respectively [74]. When the r increased from 18.6% to 62.7%, the discharge coefficient (C_d) varied from 0.67 to 0.94. Especially when r > 42.5%, the impact was more sensitive [75,76]. Meanwhile, when r < 62.71% and the opening was positioned below the eaves, an airflow pattern called "upward jet" was observed. In the absence of sidewalls installed below the AOZ, the air passed through the AOZ without mixing with the surrounding air. In contrast, when the heights of the sidewalls were lower than the height of AOZ, air speed heterogeneity was observed [74]. It can be inferred that the r-value and location of ventilation systems should be adapted to accommodate seasonal fluctuations, as the demands for ventilation and airflow organization vary accordingly.

4.1.2. Outlet Configuration

While the significance of outlet configuration in regulating indoor air contaminant concentrations is generally lower than that of the inlet [77], it plays a crucial role in determining the ventilation rate. Wang et al. found that, for a multi-floor animal building (MFAB), compared with the ventilation rate of a building with fans on each floor, the rate of a building with an outlet in the end wall and fans installed on the top of the shaft was approximately 25% lower [78]. Meanwhile, prolonging the width after the outlet could increase the output volume of fans, which can mitigate the negative effect of multiple floors on ventilation rates in MFAB, especially for the lower floor [48]. In this way, for multistoried buildings, placing outlets separately on each floor and increasing the distance between the outlet and shaft are recommended to improve the air exchange rate.

4.1.3. Water-Cooled Floor

The water-cooled floor is laying water pipes underneath the surface of the animals' lying area. When cold water flows through the water pipes, the surface temperature of the floor reduces, thereby taking away the heat generated from sows by conducting heat dissipation. It has been widely adopted in pig houses. Brandt et al. analyzed the effect of floor cooling on pig welfare and found that after the installation of floor cooling, the respiration rate (RR) of finishing pigs reduced by 4.7 breaths per minute (bpm), and the proportion of pigs lying on the ground increased by 2.3% [79]. Cabezón et al. also discovered that when the ambient temperature reached 35 °C, the water-cooled floor could significantly reduce the respiratory rate of lactating sows by 77 breaths/min, and decrease the vaginal temperature, rectal temperature, and skin temperature by 0.9, 1.0, and 0.8 °C, respectively [80]. Meanwhile, floor cooling can modify animal behavior to improve welfare. Parois et al. found that water-cooled floors significantly reduced the drinking and standing time of sows by 3% and 2.8%, respectively, and increased the lying time by 9% [81]. The study of Wagenberg et al. also revealed that when the inlet water temperature was 17 °C, the water-cooled floor significantly increased daily feed intake by 0.6 kg and growth rate by 20 g per day of nursing sows [82]. Based on this, the implementation of a floor cooling system can be considered as an effective method to mitigate the negative impact of excessively high temperatures.

4.2. Indoor Facility and Equipment

4.2.1. Deflector

The main function of a deflector is to increase the airspeed or change the airflow direction. Deflectors are mainly installed under the ceiling, behind the inlet, or in the pit. Cheng et al. researched the influence of a ceiling deflector on the airflow distribution in a hen house with tunnel ventilation. As shown in Figure 3, the deflectors could effectively direct airflow downwards to the CZ and aisle zone. Compared to buildings without deflectors, the air speed in the CZ and aisle zone increased by 0.66 m s^{-1} and 0.91 m s^{-1}, respectively [50].

In similar studies for cow sheds with deflectors compared to those without deflectors, Harner and Smith found that air speed in the AOZ increased from 0.9–1.3 m s^{-1} to 2.7–3.6 m s^{-1}. Dairies had better laydown rates and a corresponding increase in milk production [83]. Chen found that wind speed in the AOZ increased by 0.3–0.6 m s^{-1} [84]. Deng et al. also indicated that the average wind speed in the AOZ increased by 52.8% [85]. The location and height of the deflectors are key parameters affecting the airflow pattern in a barn. Ikeguchi et al. found that the most suitable location for the installation of deflectors was 9.5 m from the inlet sidewall at a height of 2.5 m in a low-profile cross-ventilated barn (LPCV) [86]. However, adding a ceiling deflector to an animal barn increases the static pressure in the building and affects the fan efficiency. According to the research of Purswell et al., nine ceiling deflectors with a spacing of 12.2 m were installed in a broiler house. The flow rate of the ventilator was reduced by 11%, and the static pressure in the building increased by 11.2 Pa [87].

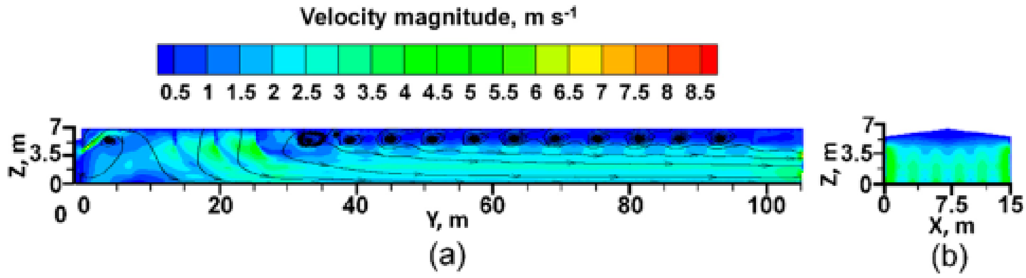


Figure 3. Airflow streamlines and air speed distribution for the (**a**) longitudinal section and (**b**) cross-section in the hen house with ceiling deflectors.

Deflectors have been placed behind the inlet or pit. Ye et al. investigated the effect of the deflector and curtain on the air exchange rate in a slurry pit in a model pigsty. The results showed that the deflector angles and curtain numbers affected the airflow patterns, air velocities, and turbulence intensities in the room space near the slatted floor and in the headspace of the pit [88]. In a laying hen house, Cheng et al. investigated the effect on the indoor environment of a deflector behind the inlet. The results indicated that the deflector increased the air speed and decreased the temperature, while it reduced the airflow distribution uniformity [68].

4.2.2. Perforated Air Ducting (PAD) System

A perforated air supply system is used to guide fresh air through tubes and directs it downward onto the AOZ through smaller diameter holes [89]. Currently, the system has been widely adopted to alleviate heat stress in animals. Perin et al. demonstrated that using a PAD system with a cold air supply of 250 m^3/h per lactating sow significantly increased the feed intake and weaning weight of piglets [90]. Cheng et al. found that the respiratory rates and skin temperatures of beef cattle decreased by 22 beats/min and 1.04 °C, respectively, when applying the PAD system in an open-sided beef cattle barn [91]. Eliene et al. also observed that with a PAD system in a sow pen, the respiratory rate of sows decreased by 16 beats/min and sensible heat loss increased by 74 W [92].

Furthermore, Wang et al. found that adjusting the air supply angle is the most effective method for improving cooling performance [93]. Adding deflectors is a viable approach to achieve this. Cao et al. investigated the effect of deflectors on the jet flow and cooling performance of PAD systems. The airflow and convective heat transfer rates, with deflectors in the form of rectangular tubes (D1) and rectangular plates (D2), were compared with those without deflectors (D0). As shown in Figure 4, the PAD systems that included deflectors achieved a greater airflow rate deviation than those without deflectors. The average convective heat transfer rate by cows was achieved under D1, at 98.37 W m^{-2}, which was 13.7% and 14.7% higher than that under D0 and D2, respectively. This can be explained as the deflectors in D1 altered the trajectory of the jet flow, enhancing the directional accuracy and ensuring complete coverage of the cow's surface [94]. Hence, the efficiency of the PAD system can be improved by integrating auxiliary equipment that effectively controls the jet flow pattern within an optimal range.

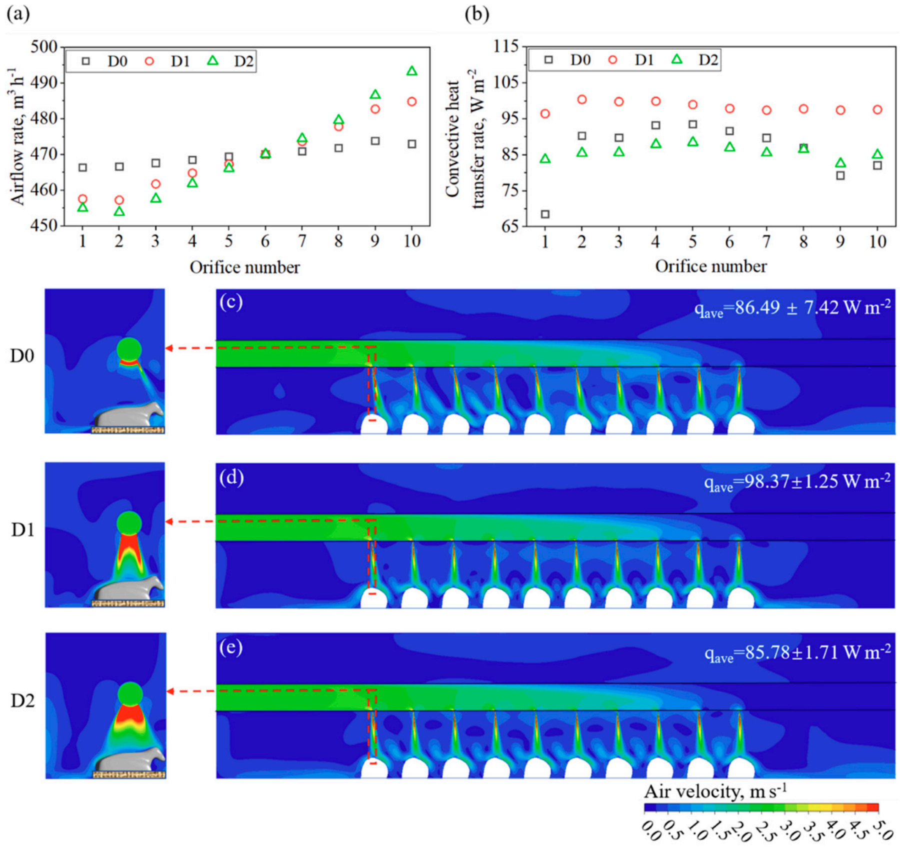


Figure 4. The airflow rates (**a**) and convective heat transfer rates (**b**) associated with the original PAD system without deflectors (D0) and with two different deflectors (D1 and D2), corresponding jet flow patterns (**c**–**e**).

4.2.3. Other Facilities

An earth–air heat exchanger (EAHE) uses a compressor in the ground source heat pump unit to facilitate the vapor–liquid transformation cycle in the refrigeration state. This technology can effectively reduce the cooling load of livestock buildings on hot days. Wang et al. researched the cooling performance of EAHE and discovered that air velocity, tube length, and temperature difference between the inlet air and undisturbed soil are all positively correlated with the air temperature difference between the tube inlet and outlet. Moreover, the cooling capacity initially increased, stabilized, and then increased again with an increase in tube diameter [95]. Similarly, Kim et al. developed an air-recirculated ventilation system for a piglet shed that could recycle the internal thermal energy of a pigsty [96].

Another cooling method is sprinkling, in which heat is absorbed via water evaporation. Kendall et al. found that sprinkling in dairy buildings reduced respiratory frequency and body temperature by 60% and 0.5 °C respectively, while a combination of sprinkling and shading further reduced them by 67% and 0.6 °C, respectively [97]. Collier et al. reported an average daily temperature drop of approximately 1.1 °C when a high-pressure spray cooling system was used in cow sheds [98]. However, spraying may lead to damp ground, which can promote the growth of pathogenic bacteria and microorganisms, potentially causing diseases such as piglet diarrhea. Therefore, this system may not be suitable for suckling pig sheds.

5. Problems and Research Prospects of Detection and Control Methods for Thermal Environment in Livestock Buildings

As for the current thermal environment detection methods, field experiment relies heavily on the accuracy of the equipment, requiring substantial time, manpower and resources. The number of measurement points is limited, and the result is restricted by the choice of point [99]. A scale model in a wind tunnel experiment is subject to scale effects and is mostly based on the assumption of one-dimensional flow, whereas real flow in actual wind fields is typically multidimensional, leading to limitation in the experimental result. Currently, there are no standards or benchmarks for validation of CFD models [100]. And simplified models used in the simulation process may overlook uncontrollable variables, resulting in inaccurate simulation results that fail to fully consider the changing characteristics of real environments. Mathematical models used in machine learning and multi-factor detection possess a strong theoretical foundation, while due to uncertainty in actual production, there may be disparities in the accuracy of these models. Moreover, the simplicity of the model structure makes it difficult to capture the influences and variations in multi-factor interactions. As a result, it is challenging to apply and generalize these models in practical production.

In addressing the above issues, research can focus on improving sensor accuracy and exploring methods to reduce costs as well as energy consumption of field experiments. Additionally, several emerging trends such as cloud computing, big data, and the internet of things (IoT) should be integrated into field experiments. For a wind tunnel experiment, it is necessary to explore more advanced scale modeling techniques and develop methods to simulate multidimensional flow. Introducing more control measures and devices to simulate real-world scenarios would also be beneficial. For CFD simulations, the combination of different detection methods can be considered, and the reliability of the models can be validated through field experiments. Furthermore, transient simulations can be adopted to enhance the real-time continuous monitoring capability in simulations. For a mathematical model, it can consider the interaction of multiple environmental factors. Building upon a theoretical foundation, variables can be added based on practical needs, allowing for a more comprehensive analysis of the thermal environment.

In terms of thermal environment control technology, envelope configuration design is the foundation. With proper design of the envelope, environmental control can be enhanced with the additional facilities. However, traditional environmental control techniques like sprinkling and water-cooled floors often rely solely on temperature sensors for regulation, which does not accurately measure and control factors such as humidity and airflow velocity. As a result, it fails to meet the precise requirements of different livestock species and growth stages for optimal thermal conditions. Furthermore, energy consumption has always been a crucial concern in environment control of livestock buildings. Energy is required for the operation of devices like PAD and sprinkling. Deflectors increase ventilation resistance, leading to higher energy consumption by the fans.

Based on the aforementioned issues, it is worth considering the utilization of technologies such as Internet of things (IoT), big data, and artificial intelligence (AI) to guide the monitoring and control of the thermal environment in livestock buildings towards intelligent systems. For instance, real-time monitoring of temperature, humidity, oxygen, ammonia, and other indicators can be achieved through sensors, enabling the analysis of big data to predict environmental changes. Combined with automatically regulating ventilation, heating, cooling and other devices, a rational thermal environment can be achieved. In line with the growing trends of energy conservation and emission reduction, promoting the application of green and sustainable methods for thermal environment control in livestock buildings is crucial. The utilization of renewable energy sources such as solar and geothermal energy for heating and cooling can reduce the reliance on fossil fuels and electricity consumption, therefore lowering carbon emissions. The researches mentioned above are also crucial directions for the development of thermal environment control technologies in the future.

6. Conclusions

This study reviewed a comprehensive survey of detection and control methods of the thermal environment in livestock buildings. The following conclusions can be drawn:

(1) Temperature, humidity, and airflow speed are the main parameters affecting the thermal environment in livestock buildings.
(2) For single parameter detection, a field experiment is the most commonly used method. A scale model in a wind tunnel can effectively control experimental conditions and has been extensively applied in aerodynamics studies. But it fails to accurately represent the real situation. CFD simulation analyzes the thermal environment in both quantitative and qualitative manners, while model simplification, mesh, and turbulence models may affect its accuracy. Machine learning is an emerging detection method, and its precision is influenced by the data and model.
(3) For detecting the thermal environment based on multi-environmental parameters, an effective temperature index is a feasible detection method. It considers varying proportions of different environmental parameters and is classified according to livestock species.
(4) For thermal environment control methods, the inlet configuration significantly affects the air motion and distribution, while the outlet determines the ventilation rate. The water-cooled floor can effectively decrease surface temperature. Deflectors beneath the ceiling can effectively increase airspeed, while deflectors behind inlets or pits affect airflow patterns and turbulence intensity. A PAD system significantly increases the air speed in AOZ. EAHE significantly mitigates the heat load of livestock housing. Sprinkling removes heat from livestock buildings through evaporation but concurrently elevates humidity levels.

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