Review

Methodologies of control strategies for improving energy efficiency in agricultural greenhouses

The corrections made in this section will be reviewed and approved by a journal production editor.

Shanhong Zhang[a,b,c], Yu Guo[a,b,c], Huajian Zhao[a,b,c], Yang Wang[a,bc,*] andy_yangwang@cau.edu.cn, David Chow[d], Yuan Fang[e]

[a]College of Information and Electrical Engineering, China Agricultural University, 100083, Beijing, China

[b]National Innovation Center for Digital Fishery, China Agricultural University, 100083, Beijing, China

[c]Beijing Engineering and Technology Research Center for Internet of Things in Agriculture, China Agricultural University, 100083, Beijing, China

[d]School of Architecture, University of Liverpool, L69 3BX, Liverpool, UK

[e]Fraunhofer Institute for Building Physics, 70569, Stuttgart, Germany

*Corresponding author. College of Information and Electrical Engineering, China Agricultural University, 100083, Beijing, China.,

Handling Editor: Prof. Jiri Jaromir Klemeš

Abstract

The greenhouse sector accounts for the largest portion of total final energy consumption in agriculture in most countries. One efficient way to minimize the total energy consumption in greenhouses is through the acceptable and efficient control strategy. The control strategy plays a very important role in maintaining comfortable inside climate and reducing energy consumption for the greenhouse, which could effectively adjust the equipment such as the heating/cooling, ventilation, shading system, and coordinate them with low energy operation. The objective of this article is to systematically review the methodologies of control strategies for improving energy efficiency in agricultural greenhouses, particularly for the low energy greenhouses. The methods section, including review methodology and brief methodology description for control strategies in greenhouses, have been first presented. Subsequently, results section introduces the significance of control strategy and types of control strategies in greenhouses; detailed methodologies of greenhouse control strategies including mathematical modelling study; physical experimental study; numerical simulations and parametric sensitivity analysis have been then systematically reviewed. Furthermore, more than 30 parameters affecting greenhouse performance have been analyzed and evaluated. This review could provide a guidance to probe into the advanced control strategies to reduce the energy consumption for the greenhouse and maintain suitable growing environment simultaneously. This work has also demonstrated several control perspectives on the future low energy greenhouse trends.

Keywords: Low energy greenhouse; Control strategy; Control performance; Control methods; Parametric sensitivity study; Hybrid control

1 Introduction

It is well known that the greenhouse provides the controlled environments for better plant growth and food production. According to the latest statistics, there is an estimated 3.64 million hectares of greenhouses worldwide (McNulty, 2017). However, energy consumption in agriculture is mainly derived from greenhouses in most countries. Meanwhile, emissions from agricultural production presently account for around 11% of global greenhouse gas emissions and have risen 14% since 2000 (ClimateWatch, 2020). With the expansion of greenhouse areas, the challenge of greenhouse energy consumption and cleaner production will dramatically increase in the coming years.

Energy embodied in agricultural greenhouses is divided into direct and indirect energy (Aguilera et al., 2015). Not only the greenhouse energy consumption is large and at a high cost for lighting, heating, cooling and mechanical ventilation etc. (direct energy use), which could result in more carbon emissions; but also indirect energy use, i.e., upstream energy requirement for producing greenhouse materials (e.g. plastics, metals etc.), is even higher than direct energy use. (Aguilera et al., 2015). From the life cycle point of view, the cumulative energy demand (CED) of an agricultural product also represents direct and indirect energy use. Bartzas et al. (2015) found that CED for lettuce cultivated in open-field and greenhouse in Italy are 2.98 MJ/FU (functional unit) and 3.15 MJ/FU, CED for Barley in Spain are 2.11 MJ/FU and 3.47 MJ/FU, respectively.

Moreover, around 65–85% of total energy consumed by heating in greenhouses, the rest portion is applied in electricity and transportation (Ahamed et al., 2019). Meanwhile, costs for heating (mostly) and cooling in greenhouses account for approximately 70–85% of total operating costs except those costs relevant to labor (Ahamed et al., 2019; Anifantis et al., 2017). It is thus imperative to improve the greenhouse energy conservation and cleaner production in the agricultural greenhouses. There are many ways to improve energy efficiency or reduce unnecessary energy consumption in greenhouses, for example, storing the thermal energy by phase change material (PCM) (Baddadi et al., 2019; Najjar and Hasan, 2008), designing the suitable greenhouse constructions for optimal energy efficiency (Djevic and Dimitrijevic, 2009), exploring the novel covering materials for the thermal insulation and endothermic function (Zhang et al., 1996), increasing the precision of sensors in the control system to indirectly influence the energy consumption (Bontsema et al., 2011), and exploring the control strategy in the greenhouse control system for optimal adjusting the inside climate (Zhang et al., 2019; Li et al., 2017).

Baddadi et al. (2019) designed a new solar air heater with latent storage energy system using the PCM to improve energy efficiency in the hydroponic greenhouse in Borj Cedria, Tunisia. However, its payback period of proposed latent storage energy system using PCMs was a little longer, i.e., 6 years. The covering materials were popular as the thermal protection in recent years, the design of the covering material improved the inside temperature but also negatively influenced on the lighting conditions (Zhang et al., 1996). The high-precision sensors were expensive, although they could assist controller with precise control and then save energy in greenhouses (Aiello et al., 2018; Bontsema et al., 2011).The development of new control strategies to improve energy efficiency and reduce energy consumption is another possibility in agricultural greenhouse production. The greenhouse energy conservation methods using control system mainly involve hardware facilities and control strategy. The hardware of control system is mainly composed of sensors, controller and actuators. The precision of three above parts has indirectly influence on the greenhouse energy consumption. Due to the complex agricultural greenhouse microclimate, the application of novel control strategy on greenhouses could not only coordinate each equipment operating efficiently with high energy efficiency and low costs, but also provide a comfortable environment for meeting a cleaner production of different crops in real time (Zhang et al., 2019). Normally, the advantages of control strategies include wide fields of application, high compatibility, user-friendly operation and low cost, in particular for the greenhouse energy savings (Alhusari et al., 2018).

From the end of last century, research on the greenhouse energy conservation by exploring the optimization of control strategies has started. With the development of computer technology, greenhouse energy optimization has been greatly improved based on the control strategy. The control strategy/algorithm in agricultural greenhouses mainly includes Bang-Bang control, PID (Proportional-integral-derivative) control, fuzzy control, feedforward control, optimal control and model predictive control (MPC) etc. Those strategies aim to improve the energy efficiency and enhance cleaner production for the crops in greenhouses.

Up to now, the optimization and application of control strategies or algorithms to improve greenhouse energy efficiency and cleaner production are becoming more and more significant, which has been studied by a large number of scholars (Van Beveren et al., 2015a; Zhang et al., 2019; Li et al., 2017; Xu et al., 2019; Alhusari et al., 2018). However, there is no attempt made so far to review, even investigate systematically control strategies or algorithms in greenhouses. In particular, for the low energy greenhouses (LEG), it is very necessary to explore the suitable control strategies, which could not only keep the stable inside climate conditions for the crops growth and production, but also minimize the energy consumption in greenhouses. The novelty of the paper is to systematically review the methodologies of control strategies for energy efficiency improvement in agricultural greenhouse production: the selective numerical reconstruction method, including mathematical modelling study; physical experimental study; numerical simulations; and parametric sensitivity study, is very advantageous.

In this work, under the condition of maintaining the greenhouse microclimate for crop growing within a comfortable range, advanced control strategies or algorithms aiming to save energy or improve energy efficiency for cleaner production in greenhouses will be focused and reviewed. In Section 2, the methods, including review methodology and brief description of methodologies for control strategies in greenhouses, have been first presented. Section 3 introduces results of review including significance of control strategy, types of control strategies, methodologies of greenhouse control strategies, control performance, and energy saving via control strategies in greenhouses. Section 4 is discussion. The last part mainly draws the conclusion and future work.

2 Methods

2.1 Review methodology

An intensive literature review was conducted from September 2019 to January 2020 in order to explore methodologies of control strategies for improving energy efficiency in agricultural greenhouses production. Suitable control strategies applied in greenhouses not only maintain suitable growing environment but also have low energy using in operation and maintenance.

The literature selected in this work mainly derived from the following databases: *Web of Science*, *Scopus*, *Science Direct*, *Research Gate* and *Google Scholar*. Main keywords for the review were selected to determine the suitable scientific papers including three categories: “agricultural greenhouse”, “control” and “energy efficiency”. The following search strings based on the above keywords have been employed in the aforementioned databases – [(“agricultural greenhouse” OR “greenhouse”) AND (“control” OR “controller” OR “control strategy” OR “control method” OR “control algorithm”) AND (“energy efficiency” OR “energy saving” OR “energy consumption”)]. The Boolean search terms AND OR have been applied to incorporate different combinations aiming to obtain the suitable literature for the review.

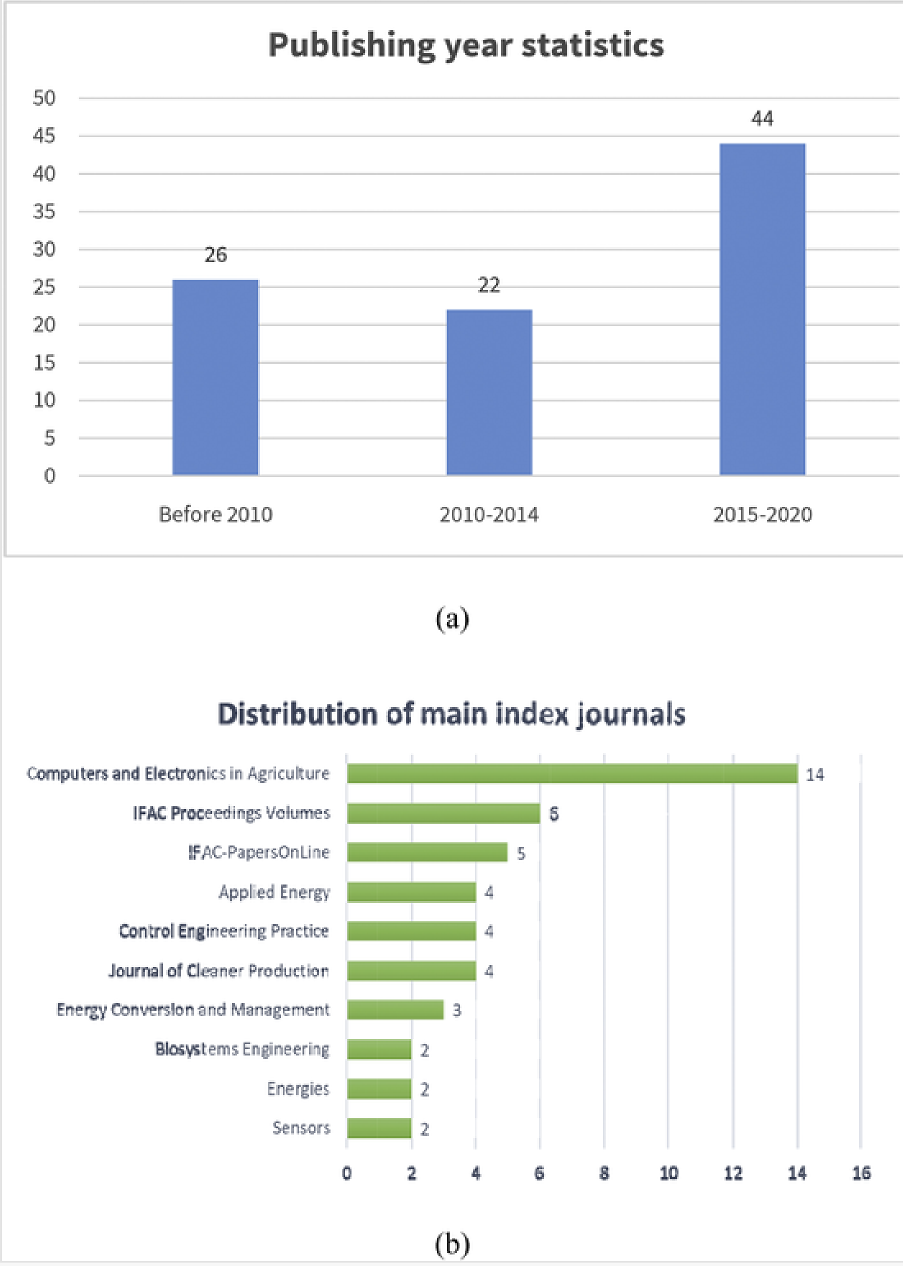
The published time of selected literature in this work has been limited to the latest 25 years, i.e., from 1996 to 2020. These studies focus only on the low energy consumption or energy efficiency in agricultural greenhouses production using suitable control strategies. After relevance analysis and selection based on the abovementioned criteria for keywords and published time, up to 100 articles have been determined and intensively reviewed, particularly considering the methodologies of control strategies for improving energy efficiency in agricultural greenhouses production.

The valuable and scientific information was extracted from the selected articles in this work as follows: 1) main controller types applied in greenhouses, software/model/programming/measurements used for those selected researches, and controlled objects/components have been compared and summarized; 2) comparison of parametric sensitivity study and the corresponding investigation results have been conducted; 3) control performance including control accuracy, response time, robustness, sensitivity, adaptability, smoothness and convergence for those controllers applied in greenhouses has been compared and analyzed.

Fig. 1(a) and (b) illustrate the publishing year statistics and distribution of main index journals for those selected articles, respectively. Seen from Fig. 1(a), it could be concluded that, in the past five years, the studies on low energy consumption or energy efficiency in agricultural greenhouses production using control strategies have been paid more attention. Fig. 1(b) indicates that the most popular publishing journal related to aforementioned study is *Computers and Electronics in Agriculture* with 14 articles.

alt-text: Fig. 1

Fig. 1



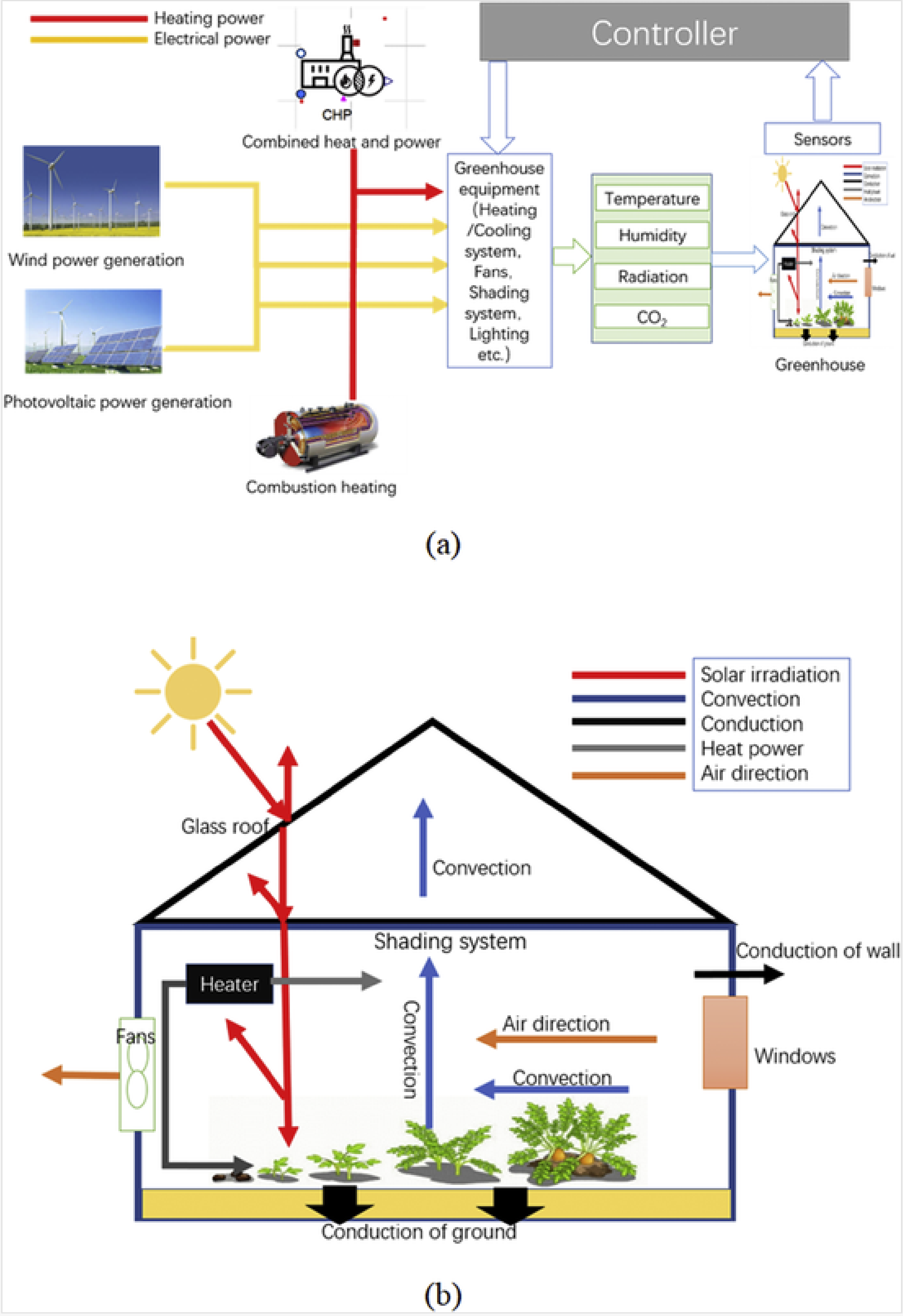
Publishing year statistics (a) and distribution of main index journals (b) for those selected articles in this work.

2.2 Methodology description for control strategies in greenhouses

From the summary of the review literature, there are various control strategies and studies applied in greenhouses in order to maintain optimal growing environments while saving energy as shown in Supplementary Table S.1. There are different investigating methodologies for control strategies used in greenhouses, including mathematical modelling study; physical experimental study; numerical simulations; and parametric sensitivity study. Fig. 2(a) indicates the relationship between controller, actuators supplied by thermal and electrical energy, controlled environmental factors (temperature, humidity etc.) and sensors in the greenhouse. Fig. 2(b) demonstrates the detailed thermal environment inside the greenhouse.

alt-text: Fig. 2

Fig. 2



Relationship among controller, greenhouse equipment supplied by thermal and electrical energy, controlled environmental factors (temperature, humidity etc.) and sensors in the greenhouse (a), detailed thermal environment inside the greenhouse (b).

3 Results

3.1 Significance of control strategy in greenhouses

Greenhouse environment plays a vital role in crops quality and yield. Control system with the high precision and low energy consumption is acceptable path to govern the microclimate inside greenhouses and maintain a stable microclimate.

For the inside environmental management of greenhouses, suitable control strategy could 1) ensure a comfortable greenhouse environment for increasing crop yields; 2) coordinate the greenhouse complex energy system how to function, including heating, ventilation and lighting systems, when required; 3) maintain the environmental parameters within acceptable range, such as temperature, humidity; 4) protect the inside environment from the severe weather conditions; 5) manage the greenhouse equipment systems to achieve high efficiency; 6) minify the greenhouse energy consumption, operation cost and carbon emissions for cleaner production.

3.2 Types of control strategies in greenhouses

There are many categories for control strategies to achieve the low energy in greenhouses, some methods are just as follows: based on controlled components, controlled parameters, controlled mode, and controller or control algorithm. As shown in Table S1, it is a summary of control strategies for greenhouse energy saving and high yield.

alt-text: Table 1

Table 1

The table layout displayed in this section is not how it will appear in the final version. The representation below is solely purposed for providing corrections to the table. To preview the actual presentation of the table, please view the Proof.

Comparison of parametric sensitivity study and the corresponding investigation results.

Control methods	Parameter	Measurement instrument	Study/results	Reference
Adaptive Feedback Linearization-based Predictive Control	Effect of non-linearity, uncertainties and time-varying parameters	Sensor network	The influence of high non-linearity, uncertainties and time-varying parameter could be coped with through the use of UKF (unscented Kalman filter) for parameter and online state estimation	Chen et al. (2018)
Adaptive Feedback Linearization-based Predictive Control	Effect of measurement noise	Sensor network	The measurement noise Ra could be deduced from the precision of the proposed sensor network	Chen et al. (2018)
Adaptive Fuzzy Control	Effect of approximation errors	Sensors	Employing a novel smooth robust control term can cancel out the effect of the approximation errors.	Su et al. (2016)
Adaptive particle swarm optimization and geneticalgorithms	Effect of uncertain parameters of energy model	Four sensors distributed uniformly inside the greenhouse	The uncertain parameters of energy model are collected through sensitivity analysis, and are then calibrated by APSO-GA based on real energy demand of greenhouse	Chen et al. (2016)
Optimal control	Effect of number of collocation points	N/A	Influence of different numbers of collocation points could be through calculating the smallest number of collocation points, and then using the obtained solution as a new initial guess to optimize the following number of collocation points	Van Beveren et al. (2015a)
Adaptive neuro-fuzzy control	Effect of nonlinearity problem of greenhouse	N/A	The capability of adaptive neuro-fuzzy inference system (ANFIS) controller could eliminate the effect of nonlinearity problem of greenhouse modelling	Hu et al. (2010)
Model-based predictive control	Effects of steady state errors	N/A	A minimal structure for disturbance model will avoid the steady state errors, when process model is non-linear	Blasco et al. (2007)
PSO-MPC	Effect of reference temperature tracking	N/A	The backward horizontal control helps further accurately tracking temperature of all algorithms	RAMDANI et al. (2015)
Predictive control	Effects of infrequent large noise signals	Capacitor sensors, low-cost optoelectronic sensors, an infrared gas analyser, anemometer	The effects of infrequent large noise signals could be reduced via substituting for the prediction error applied in the estimator law	Coelho et al. (2005)
Nonlinear PID	Effect of water in greenhouses	N/A	The water could directly influence the temperature and humidity for the greenhouse air	Hu et al. (2014)
Fuzzy Logic Control	Effect of disturbance rejection	N/A	Employing the decoupling nonlinear methods could avoid the disturbance rejection impact	Bounaama and Draoui (2011)
Fuzzy Adaptive Control	Effect of disturbances	N/A	Effect of external disturbances could be eliminated by the proposed robust control term	Su et al. (2017)
Hybrid neuro-fuzzy control	Effects of the inherent delay time, such as climate	N/A	Compensating delay time could be through the precise prediction of greenhouse temperature and humidity	Yousefi et al. (2010)
Adaptive control	Effects of non-linearity, errors, and parameter variations	Sensors	Effects of non-linearity, errors, and parameter variations were well solved by the proposed fuzzy logic controller.	Nicolosi et al. (2017)
MPC control	Effect on the irradiance	Sensors	The irradiance disturbance effect on the membrane distillation system will be	Gil et al.

	disturbance		reduced by the proper use of a storage system	(2019)
Optimum control	Effect of shading orientations	Solar radiation sensors	Individually controlling the shadings depending on different orientations can affect solarium on the plants in greenhouses	Bastien and Athienitis (2012)
Optimum control	Effect of different weather conditions	Temperature sensors	To reduce the negative impact of weather conditions, time periods with similar average external temperatures and solar radiation were selected for the comparison	Chen et al. (2015)
Fuzzy Logic Control	Effect of temperature error bandwidth	N/A	Reducing the error bandwidth of temperature has an indirect effect on energy consumption	Caponetto et al. (1998)
Nonlinear feedback control	Effects of time constant and time scales	Temperature and humidity measurement	The effects of both parameters could be regarded as the slowly varying disturbances	Pasgianos et al. (2003)
PID Control	Effect of PID gains	N/A	The gains of PID controller have a direct impact the control performance	Ashida et al. (2016)
Adaptive hierarchical control	Effect of the heating system, the ventilation system, and outside disturbances	N/A	Temperature dynamics can be represented as dynamic hybrid systems for compensating the disturbances. The external disturbances strongly affect the air flow, especially the wind speed and external air temperature (Rodríguez et al., 2008).	Rodríguez et al. (2008)
PID Control	Effect of load disturbances	Temperature and humidity sensors	The effect of load disturbances was compensating via adding the additional feedback loop (Gurban and Andreescu, 2014).	Gurban and Andreescu (2014)
Optimum control	Effect of the crop on the air temperature	N/A	The effect of crops on air temperature is mainly the latent heat generated by the plant transpiration	Rodríguez et al. (2002)
Adaptive particle swarm optimization and genetic algorithms	Effect of plant canopy variables	N/A	The elimination of negative impact of plant canopy variables from plant growth could be through performing monitoring meteorological data and actual energy sources on the continuous days to verify and optimize energy demand model of greenhouse	Chen et al. (2016)
Optimum control	Effect of climate variables, e.g., temperature, humidity and CO_2 bounds	N/A	The higher the degree of freedom of the climate variables is, the higher the potential energy savings are	Van Beveren et al. (2015b)
Optimal Control	Effect of modifications in trajectory definitions	Sensor	Modifications in trajectory definitions have a definite impact on the energy and other resources consumption, as well as on the crop growth and development	Van Straten and Henten (2010)
Robust control	Effect of fogging	Sensors	Fogging indirectly affects air enthalpy through humidity ratio	Linker et al. (2011)
Optimal control	Effect of fluctuating disturbances	N/A	Fast fluctuating disturbances were difficult to predict and had a strong effect on the system's economic performance, finally, would result in large difference in dynamic times	Van Henten and Bontsema (2009)
Predictive control	Effect of constraints and real disturbances	Commercial Davis Weather Station	The constraints and real disturbances mainly included the biological constraints, the MPC methods could optimize the each time step from the process of constraints	Piñón et al. (2005)
Nonlinear optimal control	Effect of nonlinear optimization	N/A	The nonlinear optimization problem could be eliminated through the Branch-and-Bound algorithm	RAMDANI et al. (2015)
Optimal control	Effect of trajectory of the heating set-point	N/A	The trajectory of the heating set-point had influence on minimizing the total energy consumption	Chalabi et al. (1996)
Optimal control	Effect of outside climate	N/A	The effect of extreme climate could be minimized by establishing the upper and lower bounded for the climate state variables	Xu et al. (2019)
Automatic control	Effect of the nonlinear relationship and disturbance	Sensors	Combining the Bayesian networks with the control system was suitable to solve the influence of nonlinear relationship and disturbance in the greenhouse	Del Sagrado et al. (2016)
Fuzzy control	Effect of bi-linearity model such as operating the windows and heating systems at the same time	N/A	Takagi-Sugeno (T-S) fuzzy model could reduce the influence of bi-linearity of greenhouse models	Nachidi (2006)
Feedback linearizing control	Effect of disturbance and actuators saturation	Semiconductor sensors	The influence of disturbance and actuators saturation could be eliminated through a model predictive control combined with a feedforward compensator (Rodríguez et	Rodríguez et al.

			al., 2010).	(2010)
Generalized predictive control	Effect of measurable disturbances	N/A	Compensating for measurable disturbances effects on the process variable in advance, the future control signal was taken into account of the future variation of disturbances	Pawlowski et al. (2011)

3.2.1 Controlled components

For the complexity of the environment inside greenhouse, the components of the control systems are various. Especially the environment in greenhouses has to meet the requirement of different crops, control components in greenhouses mainly include as follows: heating system (El Ghoumari et al., 2005; Nachidi et al., 2006; Zou et al., 2010; Xu et al., 2020), ventilation system (Rodríguez et al., 2008; Su et al., 2016), shading system (Van Beveren et al., 2015a; Zhang et al., 2019), fogging system (Linker et al., 2011), CO_2 injection unit (El Ghoumari et al., 2005; Li et al., 2017; Chaudhary et al., 2019), fans and spraying facility (Kuang and Shen, 2010 ; Alhusari et al., 2018) etc. As shown in Table S1 from recent literature, the heating system was extensively used in greenhouses as controlled component for inside temperature regulation.

3.2.2 Controlled parameters

Controlled parameters play an important role in the environment management, since it can directly adjust the internal environment. There are many controlled parameters in greenhouses, mainly including temperature (Boaventura Cunha et al., 1997; Salazar et al., 2007; Kuang and Shen, 2010; Zeng et al., 2012; Su et al., 2016; Singhal and Kumar, 2016; Li et al., 2017; Chen et al., 2018b, c), relative humidity (Tantau, 1998; Salazar et al., 2007; Trejo-Perea et al., 2009; Nicolosi et al., 2017), CO_2 concentration (Zou et al., 2010; Su and Xu, 2015; Su et al., 2017) and air flow velocity (Rodríguez et al., 2008; Alhusari et al., 2018). As shown in Table S1, indoor temperature and humidity control have been widely investigated by almost up to 60% of the latest literature related to the greenhouse energy and crops yield. Meanwhile, it is noticed that some environmental parameters have strong coupling characteristics in greenhouses, such as temperature and humidity (Azaza et al., 2015), temperature and air flow velocity (Alhusari et al., 2018) or multi-parameter coupling (Paraforos and Griepentrog, 2013), which will be a new and important research field. It then requires the control strategy more accurate for low energy greenhouse, for the complex greenhouse environment, it is worth exploring the multi-parameter coupling not just two parameters. Aiming to achieve the low energy greenhouse considering various coupling parameters, the control strategy is complicated and hard to simulate for the real crop environments.

3.2.3 Control mode

From the point view of control mode, there are some simple controls in greenhouses, such as manual control and on/off control, automatic control system (Park et al., 2011), intelligent control system, hybrid control (Yousefi et al., 2010), and derivative control modes, e.g., greenhouse internet of things (Çaylı et al., 2017), and smart greenhouse wireless monitoring (Azaza et al., 2016), which is based on the wireless data monitoring, the smart greenhouse has the significant effect on the energy and water saving.

3.2.4 Controller and control algorithm

For designing the control system to reduce energy consumption in greenhouses, different control algorithms have been developed and explored in the past years, including PID control (Zeng et al., 2012; Bounaama and Draoui, 2011; Hu et al., 2014), fuzzy control (Kuang and Shen, 2010; Atia and El-madany, 2017), model predictive control (Ferreira, 2008; Coelho et al., 2005; Chen et al., 2018a), Multi-objective compatible control (Hu et al., 2011; Xu et al., 2009), artificial neural network (ANN) (Salazar et al., 2007), optimal control (Van Beveren et al., 2015a), and mixed control, e.g., neuro-PID (Hu et al., 2010, 2014), PSO-MPC (Zou et al., 2010), non-linear predictive control (Gruber et al., 2011), as shown in Table S1. Seen from Table S1, optimal control strategy is widely applied, which could keep the comfortable inside climate for the crop growth under the low energy. For meeting the requirement of crops, many researches proposed that an advanced controller combined with artificial neural networks is fully satisfying in achieving the high precision and low energy. In addition, minimizing the inertia of inside climate, ANN seems to be a trend to save energy and achieve the high accuracy, especially combined with the traditional control algorithm (such as PID, fuzzy control, MPC), there will be more prevalent in the future greenhouse energy.

3.2.5 Novel control methodology

There are recently some novel control methodologies used in agricultural greenhouses, such as combining advanced controller developed by MATLAB with other simulators, e.g., ANSYS (Piscia et al., 2015; Xiao et al., 2013), and DYMOLA (Rodríguez et al., 2002) etc., which could explore the optimal control algorithm and exhibit vividly the thermal status (3D/4D temperature, air flow and CO_2/O_2 concentration distributions) of greenhouse at the same time. The primary intention of this novel optimal control parameters aims to assist with developing accurate and low energy model, which not only represents the energy performance (via demonstrating temperature/pressure/airflow distributions) in greenhouses significantly but also fully displays the evolving processes of the microclimate variables.

3.3 Methodologies of control strategies applied in greenhouses

3.3.1 Mathematical modelling study

Many mathematical models of control strategies/algorithms applied in greenhouses have been investigated in literature. Several mathematical models of typical controls will be introduced in this section.

3.3.1.1 PID control

Proportional-integral-derivative control, referred as PID control for short, is one of the earliest and traditional developed control strategies. Because of its simple algorithm, good robustness and high reliability, it is widely used in greenhouse process control. Up to now, about 90% of control loops still have PID structure.

Hu et al. (2014) proposed a new tuning methodology to coordinate multiple PID controllers, aiming to incorporate multiple performance based on non-dominated sorting genetic algorithm-II (NSGA-II). The new controller is used for reducing energy consumption and saving water costs, based on a nonlinear thermodynamic law model for a number of system variables.

Meanwhile, a two-input and two-output continuous time non-linear PID control system was founded to maintain the inside temperature and humidity within appropriate ranges, which combined with RBF (radial basis function) network, the energy function and parameters of PID could be presented as follows:

$$\mathrm{E}(\mathrm{K}) = \frac{1}{2}e(k)^2 \tag{1}$$

$$\mathrm{K_P}(k) = K_P(k-1) + \eta_p e(k)\frac{\partial y}{\partial u}(e(k) - e(k-1)) \tag{2}$$

$$\mathrm{K_i}(k) = K_i(k-1) + \eta_i e(k)\frac{\partial y}{\partial u}e(k) \tag{3}$$

$$\mathrm{K_d}(k) = K_d(k-1) + \eta_d e(k)\frac{\partial y}{\partial u}(e(k) - 2e(k-1) + e(k-2)) \tag{4}$$

Where k is iterative step, $\mathrm{K_P}$, $\mathrm{K_i}$ and $\mathrm{K_d}$ are the gains of the proportional, integral and derivative terms of a PID controller, $\frac{\partial y}{\partial u}$ is the Jacobian information of the controlled plant, η_p, η_i and η_d are learning rate parameters of the proportional, integral and derivative terms, $e(k)$ is the error signal, $\mathrm{E}(\mathrm{K})$ is energy function.

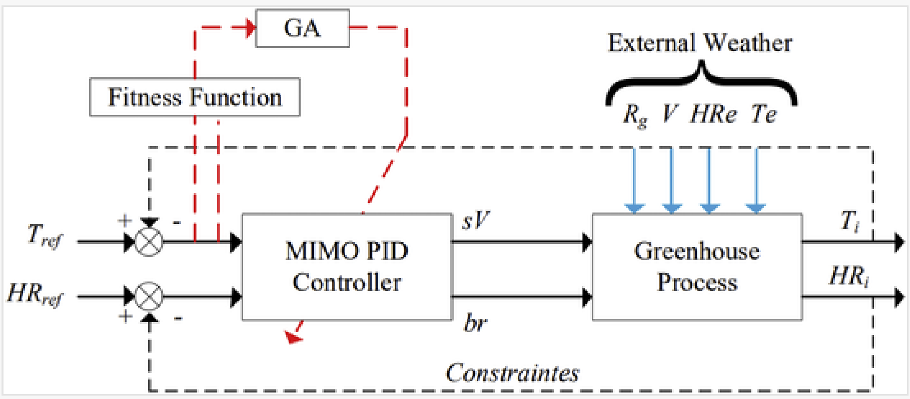
$$J_2 = J_{energy} + J_{water} = \frac{1}{2}\xi_1 \sum_{k=1}^{N}\left(\sum_{i=1}^{2}\eta_i \mu_i^2(k)\right) + \frac{\xi_2}{60}\sum_{k=1}^{N}\mu_2(k)\, V_{TH} \tag{5}$$

Where ξ_1 and ξ_2 are weights which obtained from the relationship between energy price and water price.

Due to the complex inside climate, the multi-input and multi–output control methods could fully describe the complex model for the greenhouse environment. Bounaama and Draoui (2011) proposed a MIMO PID controller to govern the inside environmental variables. Under the decoupling system with genetic algorithms, this controller provides the optimal tuning values to coordinate the ventilation/cooling and moisturizing system. Coupling objectives in this simulation mainly included the inside air temperature and relative humidity. For minimizing the big inertia of inside climate, the variables were sampled once a minute for the system. The result showed that proposed controller has useful performance in energy saving especially during the night**.** The process of MIMO PID controller is shown in Fig. 3 as follows:

alt-text: Fig. 3

Fig. 3



MIMO PID controller for the indoor greenhouse environment: variable T_i means the indoor temperature and HR_i represents the indoor relative humidity, sV and br are the vents opening wind speed and moistening, and measurable disturbances are solar radiation Rg, wind speed V, outside temperature Te, outside relative humidity HRe (Bounaama and Draoui, 2011).

Physically, indoor temperature level was influenced by the vents opening-wind speed and moistening control signals, but the moistening command for the vents opening-wind speed had more impact on the controlled variable indoor relative humidity than indoor temperature variable.

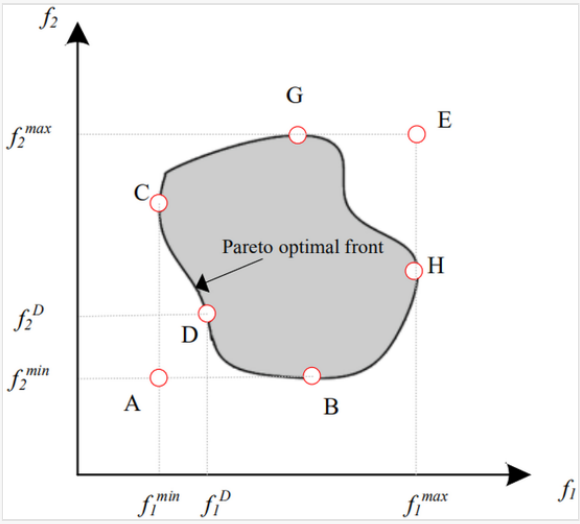
3.3.1.2 Feedback control

Based on feedback control structure, Hu et al. (2011) employed Multi-Objective Compatible Control (MOCC) strategy to solve multi-objective conflict between the low energy consumption and high control precision. For this proposed control strategy, the principle of compatible control algorithm aimed to replace a point objective with an interval or region objectives, which avoids the difficulty of finding the optimal points and is useful to expand the interval of energy saving under the optimal control strategies.

Meanwhile, the result also demonstrates a good performance on the energy saving in the greenhouse production. An area consisting of two variable intervals is regarded as compatible objective regions, compatible objective regions are described in the coordinates that the x-axis and y-axis represent two variable intervals, respectively. Under constraints, the shadow area represents the optimization interval, as shown in Fig. 4.

alt-text: Fig. 4

Fig. 4



Compatible objective regions for two-objective conflict control problem (Hu et al., 2011).

The energy consumption objective function is defined below:

$$f_{energy}(t) = \sum \omega(u\hat{u}max)^2 = \sum_{i=1}^{m} \omega_i \left(u_i u_i^{max}\right)^2 \quad (6)$$

$$\sum_{i=1}^{m} \omega_i = 1 \quad m = 1,2,3 \quad 0 \le u_i \le 1; 0 \le \omega_i \le 1 \quad (7)$$

$$u^{max} = \left(Q_{heater}^{max} \;\; Q_{fog}^{max} \;\; Q_R^{max}\right)^T \quad (8)$$

Where u^{max} are maximal energy consumption of control input and ω is the weight, selected by experience and power of respective equipment. Employing the Multi-Objective Compatible Control (MOCC) strategy could effectively eliminate the conflict between the control precision and low energy using. The simulation result shows that the controller could dramatically improve in the precision of control system and reduce the energy consumption.

According to the feedback control, Chen et al. (2018) proposed the predictive control model combined with adaptive feedback linearization to manage the inside temperature in greenhouses. Focusing on the reference deviation and energy consumption, the authors designed the cost function, which could trade off the weighted sum between control accuracy and heating input for the greenhouse. The detailed cost function is defined by

$$\mathrm{J} = \sum_{i=1}^{N} \left[e^T(k+1)\, Qe\left(k+1+u(k+i-1)^{\prime} TRu(k+i-1)\right]\right. \quad (9)$$

Where e is the error between the set point and inside temperature estimation, and Q and R represent the weighting factor for tracking error and control variable, respectively.

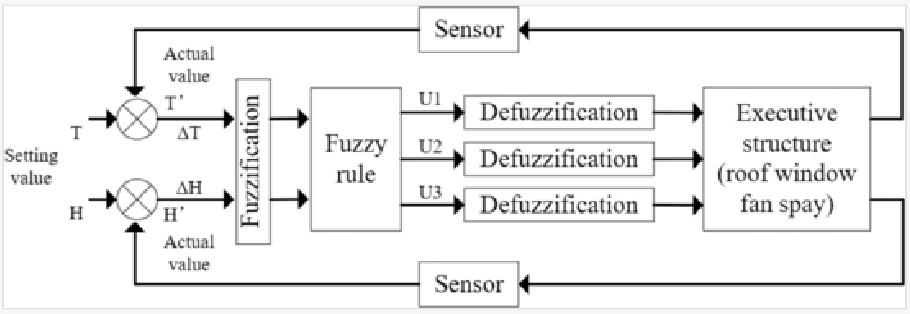
3.3.1.3 Fuzzy control

Greenhouse internal environment management has characteristics of non-linearity, variable and time-lagging in terms of control. It is appropriate to employ the fuzzy control instead of the precise mathematical model to regulate the complex inside climate, meanwhile, the previous research results illustrate the good performance in greenhouse energy conservation.

Kuang and Shen (2010) proposed the fuzzy control with the MIMO model to manage the inside temperature and humidity in greenhouses. To simplify control without effect on the control precision, the input of fuzzy control system was discretized and graded in the proposed controller. Meanwhile, the process of control system has the automatic adjust function according comfortable inside environment, which is helpful to reduce the power consumption. The simulation result represents that the control system has the high accuracy, the low-cost, easy-operation and convenient installation. The frame of fuzzy control is illustrated in Fig. 5, the fuzzy control system included two inputs (temperature and humidity) and three outputs (from the roof window, fans and the sprays). The sensor could collect the deviation of actual value from the setting value amounts for the controller output.

alt-text: Fig. 5

Fig. 5



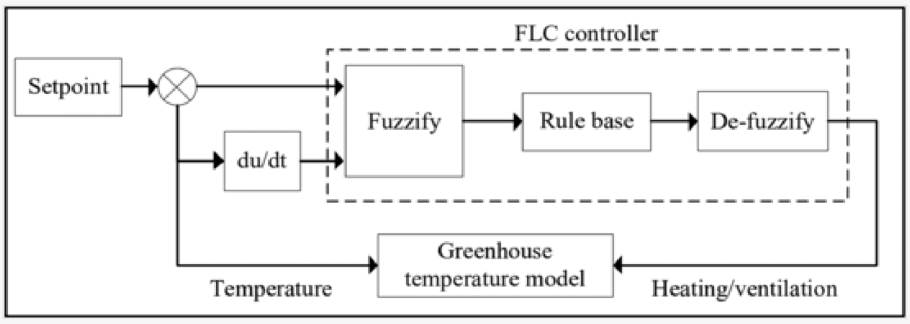
Frame of novel decoupling fuzzy control (Kuang and Shen, 2010).

In order to control accurately and reduce energy consumption in greenhouses, Azaza et al. (2015) designed a novel decoupling fuzzy controller to optimize the microclimate, which is the highly coupling between the temperature and humidity. The decoupling fuzzy logic controller has a good performance, which could obtain acceptable energy saving level though reducing the number of actuator commutations and the time of actuator operation. When the greenhouse would need to be heated or ventilate, the proposed controller will have different responses with reference to the scene within day and night.

Combining with a self-tuning fuzzy logic structure, Xu et al. (2006) developed a genetic algorithm controller to manage the inside temperature of greenhouse. According to the set point of greenhouse temperature and input energy, the temperature variation and input error were optimized through genetic algorithm. The proposed self-tuning fuzzy logic control (FLC) could enhance the control precision and minimize input energy. The overall framework of proposed method could be demonstrated in Fig. 6.

alt-text: Fig. 6

Fig. 6



Framework of optimizing FLC (Xu et al., 2006).

3.3.1.4 Adaptive control

Given that crops could adapt a short period of environmental change, small environmental variable errors are acceptable by the greenhouse control, Su et al. (2016) developed an adaptive fuzzy control of a class of MIMO nonlinear system and integrated the control inputs with known control gains. Meanwhile, the Taylor-series expansion was used to solve the nonlinear functions. An energy management strategy was used to solve the conflict that the heating and cooling system work simultaneously. Depending on the heater, fog and the ventilation systems, their functions illustrated the real control signals and climatic variables, which are given as follows:

$$Q_{heater}(t) = f_h\left(u_{heater},\ T_{in}\right) \tag{10}$$

$$Q_{fog}(t) = f_g\left(u_{fog}\right) \tag{11}$$

$$V_R(t) = f_v\left(u_{vent},\ T_{in},\ T_{out},\ v_{wind}\right) \tag{12}$$

Where $u_{heater},\ u_{fog},\ u_{vent}$ are normalized control variables of heater, fog and ventilation, respectively. v_{wind} is the speed of outside wind.

Nicolosi et al. (2017) proposed an adaptive control system to regulate microclimate. The controller was combined with neuro-fuzzy model to regulate the indoor temperature and relative humidity. The proposed control system could actually measure variables and predict the climate change conditions, which could provide the better performance for the greenhouse climate with improving energy saving or crop production, compared with other traditional controls.

3.3.1.5 MPC

El Ghoumari et al. (El Ghoumari et al., 2005) proposed a model predictive control (MPC) to regulate the temperature in the greenhouse. From the control performance and energy saving points of view, the advantages of the proposed MPC were exhibited by the real greenhouse experiments and simulation. The manipulated components, such as heating and ventilation, were regulated by the MPC controller. The test results showed that the proposed MPC control has a good performance in regulating highly nonlinear greenhouse climate, and the set-point temperature tracking level has been fully improved by the proposed MPC controller. Considering the limitations of heating system temperature setting and the energy loss level, the energy loss function was described as follows:

$$Q = f(A)(T_i - T_{out}) \Rightarrow Q_{\lim} = \mathrm{f}(A_{\lim})(T_i - T_{out}) \tag{13}$$

Where Q is the energy loss, A is windows opening, f is the function, T_i/T_{out} is inside/outside temperature, the energy loss function with the constraints of heating system temperature limits $Q_{\lim}$ was mentioned in Eq. (13), which is helpful to save energy, when the window system and the heating system operate alternately.

Ferreira et al. (2008) developed the Branch-and-Bound search algorithm to optimize MPC control. Under the predicting of external disturbances and optimizing input, the proposed optimal MPC control could reduce the computational time without affecting control accuracy. A simpler cost function was designed with the on-line adjustable coefficients, which aims to regulate the energy consumption and inside temperature. The cost function was defined as follow:

$$\begin{gathered} J_{1:PH}(k) = \left(\sum_{i=k+1}^{k+PH} \widehat{J}(I)\right)\Big|_{U(k)} \\ \min_{U(k)\in u_{PH}} J_{1:PH} \end{gathered} \tag{14}$$

Where PH is the prediction horizon, u_{PH} is the set of all sequences of size prediction horizon formed. $U(k)$ depends on the $J_{1:PH}$.

Zou et al. (2010) employed the model predictive control with the particle swarm optimization (PSO) to achieve the low cost, through advantage of the MPC flexibility to achieve the control targets. Meanwhile, the proposed method is not only suitable for greenhouse inside temperature, but also suitable for controlling the humidity and CO_2 concentration, which provides a good performance, e.g., within the acceptable control accuracy. The proposed control strategy of MPC with PSO could describe energy cost functions flexibly and solve the nonlinear process problem. Taking into account of the energy consumption, the cost function is proposed to minimize its value, its detailed definition is as follows (Zou et al., 2010).

$$\mathrm{J}(\mathrm{X}) = J_1(\mathrm{x}_1) + J_2(\mathrm{x}_2) = \lambda_1 \sum_{j=1}^{n_1} V(k+j) + \lambda_2 \sum_{j=1}^{n_2} H(k+j) \tag{15}$$

$\mathrm{J}(\mathrm{X})$ represents the energy consumption with the control system. $J_1(\mathrm{x}_1)$ and $J_2(\mathrm{x}_2)$ mean the energy consumption from opening windows and the heating system, respectively. n_1 and n_2 are control horizon of the two manipulated variables. λ_1 and λ_2, are the weighting factors for each term.

Blasco et al. (2007) developed a genetic algorithm(GA) combined with the model predictive control (MPC) for minimizing energy and water consumption, under an accurate non-linear model (NLM), both two elements (MPC and NLM) were adjusted through the GA to reduce the energy and water consumption. The controller could maintain the inside climate conditions in the adaptive ranges, through adjusting the window and fog systems, instead of maintaining the set points of temperature and humidity. The large reduction in energy and water using by the cooling system were then obtained.

The proposed cost function also included the fog system, window system and heating system, the detailed cost function is defined by:

$$\mathrm{J}(\bar{U}) = J_1(\overline{U_1}) + J_2(\overline{U_2}) + J_3(\overline{U_3}) \tag{16}$$

$J_1(\overline{U_1})$ represents the energy consumption from opening windows, $J_2(\overline{U_2})$ is the energy consumption from fog system for water used. $J_3(\overline{U_3})$ represents the energy consumed by heating system.

3.3.1.6 Optimal control

The advantage of optimal control was able to get the time trajectories of the energy flux aiming to minimize the total energy input. Based on the climate variables and control constraints in greenhouses, Van Beveren et al. (Van Beveren et al., 2015a) proposed the minimizing cost function, as shown below.

$$\min_{Q_E, g_V} J(Q_E, g_V) = \int_{t_0}^{t_f} Q_E^2 dt \tag{17}$$

Where t_0 is the initial time and t_f is the final time. Q_E means the aggregated controllable energy flux, g_V is the specific ventilation.

The optimization receding horizon control is proposed by Singhal and Kumar (2016). The receding horizon control for inside temperature is covered by the constraints on operating variables, The cost function is described as follows:

$$\mathrm{J} = \lambda_1 \sum_{i=1}^{N_P} \left| Q(i) * (T_{ref}(i) - T_{gh}(i)) \right| + \lambda_2 \sum_{i=0}^{N_P - 1} \left| R(i) * \Delta u(i) \right| \tag{18}$$

Where the cost function factors λ_1, λ_2 are the weights to reference temperature trajectory and change in control effort, respectively, and are set as $\lambda_1 = 1.0$ and $\lambda_2 = 0.1$. Q and R are weighted diagonal matrix, which mean the exponentially decreased diagonal elements.

3.3.1.7 Hybrid control

To fully make full use of the advantages of each control strategy, many scholars proposed the hybrid control methods to govern the complex inside climate in greenhouses. Some kinds of traditional control strategies were combined with each other, it will fully meet the control requirement such as the plant environment, climate disturbance. Meanwhile, traditional control methods could combine with the advanced neural networks (Hu et al., 2010), genetic algorithms, and particle swarm optimization algorithms, which are also good at improving the energy efficiency of control systems in greenhouses.

Montoya et al. (2016) used a hybrid control method to cooperate the forced-air heaters and aerial pipe systems for maintaining the inside suitable temperature during the night in greenhouses. The proposed controller could calculate and obtain the optimal control signals, according to the power consumption and minimizing commutation. The result illustrates the hybrid controller has better control performance while having smaller incremental energy costs, compared with a single controller. For example, in order to obtain the better control performance, the following objective function J is taken and shown below:

$$min_{\{u,\delta,z\}_0^{N-1}} \mathrm{J}\left(\{u,\delta,z\}_0^{T-1}, \mathrm{x(t)}\right) \triangleq \left\|Q_{xN}(x(N|t)-x_r)\right\|_p + \sum_{k=1}^{N-1} Q_x(x(k)-x_r)_p + \sum_{k=0}^{N-1} \left\|Q_u(u(k)-u_r)\right\|_p$$

$$+||Q_z(z((k|t)-z_r))||_p + ||Q_y(y((k|t)-y_r))_{||p} \tag{19}$$

Where N is the control horizon, $x(N|t)$ is the vector of the continuous and discrete states predicted at time$(\mathrm{t+k})$ produced by the input $(\mathrm{t+k})$, $y(k|t)$ is the output, $z(k|t)$ and $d(k|t)$ are continuous and discrete auxiliary variables.

It is very important to improve the energy efficiency of greenhouse based on the predicting energy consumption. Shen et al. (2018) also proposed a hybrid control strategy to optimize the greenhouse energy using. The proposed hybrid control consisted of the optimization algorithm and predictive control. After performing the hybrid control, the difficulty of parameter identification could be determined in the energy consumption model. At the same time, the prediction model, based on the weather data, could forecast the greenhouse energy consumption in the coming week. The experiments illustrate that the proposed hybrid control can reduce energy costs by 9% during cold days. Greenhouse energy consumption function was also designed. Its definition is indicated by

$$\mathrm{J(x)} = \sum_{i=7}^{7} \left(Q_{heat}\left(T_{Di}\right)\right) x = \left(T_{D1}, T_{D2}, T_{D3}, T_{D4}, T_{D5}, T_{D6}, T_{D7},\right) \tag{20}$$

The objective function $\mathrm{J(x)}$ represents the total energy consumption of one week with different daily average temperatures. $Q_{heat}\left(T_{Di}\right)$ means the energy consumption prediction, and $x = \left(T_{D1},\ T_{D2},\ T_{D3},\ T_{D4},\ T_{D5},\ T_{D6},\ T_{D7},\right)$ represents seven daily average temperatures.

Coelho et al. (2005) proposed a new hybrid control, which is composed of the particle swarm optimization algorithm and the model-based predictive control. The proposed controller is able to predict the greenhouse inside environment and the outside weather conditions. The outside weather condition is predicted through the mathematical models, whose probabilistic cost function is introduced by:

$$J = \lambda_1 \sum_{j=h_{min}}^{h_{max}} \left[\varepsilon(k+j|k)\right]^2 + \lambda_2 \sum_{j=1}^{h_c} \left[\Delta u(k+j-1)\right]^2 \tag{21}$$

where $\varepsilon(k+j|k)$ is the prediction error between the future trajectory and expected output, $u(k+j-1)$ represents the control effort, λ_1 and λ_2 are the weighing factors for each component, respectively, h_{max} and h_{min} represent the maximum and minimum prediction horizon, respectively, and h_c is the control horizon. Constants h_{max} and h_{min} represent the instant limits.

This proposed method can be applied for the greenhouse temperature prediction, even the air humidity and CO_2 concentration regulation.

3.3.2 Physical experimental study

In order to validate the incredibility of mathematical models and numerical simulation for control strategies, physical experiment investigation in the real greenhouse is more significant. There are useful physical experimental set-ups in greenhouses, including greenhouse facilities, e.g., the sensor, detector, controller and the actuator. Some real experimental greenhouses with control systems were used for different environmental requirements of plants such as the rose (Van Beveren et al., 2015a), tomato (Van Beveren et al., 2015a; Márquez-Vera et al., 2016) and fruits (Ferreira, 2008). However, there still exists the errors between the real experiment data and simulation results. Until now, the real greenhouse experiment studies related to the control strategies are few in recent literature. Some typical experimental cases are introduced in this article.

Chen et al. (2016) studied the Venlo-type greenhouse where is located in Jiangyin city. Covering material is the single 4 mm glass for the greenhouse, which was equipped with Surface Water Source Heat Pump System (SWSHPS), 3 heat pumps, 116 fan coin acceptors and four sensors in the greenhouse. The sensors mainly measured the inside air temperature and relative humidity. The optimized prediction algorithm used in the real greenhouse can accurately adjust the uncertain parameters of control system and achieve high control precision. In order to speed up the convergence of the algorithm, the controller changes the weight of the adjustment factor in the optimization process, meanwhile, the adaptive operator adjusts the particle ratio of the particle swarm and the genetic algorithm. The proposed model could reduce the load and regulate greenhouse energy using to minimal level. Moreover, the controller applied in the real greenhouse could accurately predict the energy demand and peak load of the model.

Van Beveren et al. (Van Beveren et al., 2015a) has also built a Venlo-type greenhouse in Bleiswijk, Netherlands. The greenhouse systems consist of the shading with black-out screen, artificial lighting, natural ventilation, pipe rail heating, and heat exchangers. The greenhouse installed newly dynamical controller with an optimal control algorithm, which expanded the region of greenhouse temperature and humidity. Meanwhile, it minimized requirements of energy input and reduced heating through more natural ventilation during the hotter weather conditions. This proposed controller could minimize the input of total energy per year. The experimental model can be applied to different greenhouse configurations for different types of crops. The measurement data indicated that the optimal control is not only obviously energy-saving, but also beneficial to crop growth.

Bounaama and Draoui (2011) conducted physical experiments, which was used to validate the control models, in a greenhouse, located at the INRA Bioclimatology station, Avignon, France. The experiment focused on measuring the solar radiation, wind speed, dry bulb temperature in the greenhouse. Regarding the greenhouse as the multi-inputs and multi-outputs model, a proposed PID controller was employed to regulate the inside environmental under the actuation constraints, which is based on the decoupling system with the low frequency point. The aims to keep the inside air temperature and relative humidity with suitable range through regulating the ventilation and cooling systems.

3.3.3 Numerical simulations

As shown in Table S1, Matlab/Simulink was widely used to explore greenhouse control algorithms and novel controllers, aiming to maintain the comfortable environment for the greenhouse crops while saving energy. MATLAB simulations could not only verify the energy-saving control algorithms, but also reduce the physical experimental costs and period. Moreover, numerical simulation could provide the high accuracy in theory according to the mathematical model. There are some typical studies related to control strategy based on Matlab/Simulink.

Chen et al. (2018) probed an adaptive feedback linearization-based predictive control using Matlab, which can provide fast and accurate tracking effect on temperature. The simulation environment variables mainly included the outside solar radiation, outside temperature and the solar radiation. The simulation results showed that the proposed control method has a good energy efficiency based on precise temperature control.

For the greenhouse, as a complicated nonlinear system, Atia and El-madany (Atia and El-madany, 2017) employed the MATLAB/Simulink to compare the performance of controllers used in the greenhouse, which mainly included the PI control, fuzzy logic control, artificial neural network control and adaptive neuro-fuzzy control. The process of simulation also took into account of environmental disturbances consisted of air temperature, wind speed and relative humidity.

The effect of infiltration loss and condensation loss on total greenhouse heat was explored by Villarreal-Guerrero (Villarreal-Guerrero et al., 2012), who established a new control strategy simulation model. The simulation experiment aimed to evaluate the contribution of crop humidification and cooling. The results illustrated the proposed control strategy could save 36% water and consume 30% less electric energy. Trejo-Perea et al. (2009) adopted the MATLAB to explore the energy consumption of greenhouse. MATLAB simulation model is mainly used to predict energy consumption base on a proposed multi-layer neural network controller. The effects of weather spectral characteristics and crop tolerance limits on greenhouse energy efficiency were explored by the MATLAB platform designed from Sigrimis et al. (2000). The simulation results of temperature integration use in greenhouses indicated that proposed control system has good feasibility for greenhouse energy saving. Singhal and Kumar (2016) presented a grey wolf optimization algorithms based on the simulation model to optimize the control in the greenhouse. Simulation result showed that the proposed control strategy not only achieves energy saving but also has smoother control performance.

In order to more accurately achieve the goal of energy saving in greenhouses, the different weights in the control of day and night should be accurately distinguished. Pinon et al. (Piñón et al., 2005) defined the error and control weights of day and night, respectively, based on the simulation platform. The simulation results demonstrate that hybrid control structure, MPC + FL (Model Predictive Control + Feedback Linearization) is a suitable approach to solve nonlinear control problem. The above hybrid control method has a good energy-saving performance and control accuracy.

Except the MATLAB/Simulink, there are a variety of software to model/simulate the aforementioned control strategies in greenhouses, e.g., TRNSYS (Goto et al., 2017; Kolokotsa et al., 2010; Vadiee and Martin, 2014), Computational Fluid Dynamics (CFD) (Piscia et al., 2015; Xiao et al., 2013), DYMOLA (Rodríguez et al., 2002), COMSOL (Ma et al., 2019) and EnergyPLUS (Bastien and Athienitis, 2012; Dahlan et al., 2018). Under the complex inside environment of greenhouse, only MATLAB/Simulink does not fulfil the experimental requirement, e.g., how to visually demonstrate the detailed condition of energy saving based on optimal control strategy. There have been many newly co-simulation methods to explore energy saving with the optimal control strategy in the greenhouse. The researchers have combined MATLAB/Simulink with different kinds of energy simulation software, e.g., CFD and MATLAB (Piscia et al., 2015; Xiao et al., 2013), TRNSYS and MATLAB (Sudhakar et al., 2019), which will be a new trend to explore the more complex problems in low energy greenhouse (LEG).

3.3.4 Parametric sensitivity study

In order to maintain the greenhouse microclimates within acceptable ranges, the parametric sensitivity study aims to evaluate the effects of parameters or variables in greenhouses on control system performance and energy efficiency of the greenhouse. Many researches have carried out parametric sensitivity analysis and are listed in Table 1.

There are many significant parameters including non-linearity, uncertainties and time-varying parameters, measurement noise, various external disturbances, approximation errors, inherent delay time, error bandwidth and time constant, environmental parameters such as crop transpiration, different weather conditions, outside climatic conditions, inside control actuators and crops, temperature, humidity and CO_2 concentration bounds.

It was found that the effect of system noise plays a vital role in the control performance. The system noise mainly comes from the model of errors, the parameter values of errors and the spatial distribution errors. Chen et al. (2018) proposed a solution that matrix of system noise was set to the different values on the diagonal and the rest are zero. Another way is to deduce the system measurement noise Ra is through the measurement accuracy of sensor. For the uncertain parameters effect of the energy model, there are adaptive way to save computation time by calibrating from unclear internal parameters (Chen et al., 2016). However, the uncertain parameters could not influence on the convergence speed. The optimal control algorithm could adjust the proportion of particles and optimize the weight of particles to achieve a higher convergence rate. In order to solve the nonlinearity problem, there are a series of tools such as the artificial neural network (ANN) and adaptive neuro-fuzzy control. The elimination of negative impact of plant canopy variables from plant growth could be through performing monitoring meteorological data and actual energy sources on the continuous days to verify and optimize energy demand model of greenhouse (Chen et al., 2016).

Under the indirect adaptive fuzzy control, the approximation errors could be cancelled out by the robust control, while aiming to maintain a stability control system (Su et al., 2016). The error bandwidth plays the indirect role in the energy using, meanwhile, fuzzy logic membership functions also demonstrate the good control performance (Caponetto et al., 2000).

The external disturbances, such as the solar radiation, outdoor temperature and wind speed, have also influences on the control performance and greenhouse energy using. For maintaining the controller stability and robustness, there are useful methods to meet the environmental requirement through regarding the external disturbances as the constant (Linker et al., 1998). The effect of load disturbances was compensating via adding the additional feedback loop (Gurban and Andreescu, 2014). For the disturbance, the simulations results from the proposed control with the Takagi-Sugeno (T-S) fuzzy model showed that a good approximation around the preset point and improving the accuracy of the setting point (He et al., 2018). The influence of disturbance and actuators saturation could be eliminated through a model predictive control combined with a feedforward compensator (Rodríguez et al., 2010).

In the greenhouse, the crops could indirectly affect the control system through its own state of growth. For example, the crop could have an impact on the air temperature, plant canopy variables and crop transpiration, and could seem as an important disturbance for the process gain, time constant and inherent delay time. The elimination of negative impact of plant canopy variables from plant growth could be through performing monitoring meteorological data and actual energy sources on the continuous days to verify and optimize energy demand model of greenhouse (Chen et al., 2016) Moreover, the influence of the crop transpiration is also considered as the latent heat factor in the objective function.

3.4 Control performance

The control performance, which determines energy efficiency level, mainly includes control accuracy, response time of control system, robustness, sensitivity and convergence etc. Table 2 demonstrates the comparison of control performance for a series of control strategies. Meanwhile, Table 2 also includes if recommends the proposed control strategy as the low energy greenhouse (LEG) or not. Many typical control strategies reported from recent literature were listed in Table 2, mainly including adaptive neuro-fuzzy control, neuro-PID, model predictive control (MPC), PSO-MPC, receding horizon control, two-layer multi-objective compatible control (MOCC), T-S fuzzy control, fuzzy adaptive control, feedback linearization-based predictive control, adaptive particle swarm optimization and genetic algorithms etc.

alt-text: Table 2

Table 2

The table layout displayed in this section is not how it will appear in the final version. The representation below is solely purposed for providing corrections to the table. To preview the actual presentation of the table, please view the Proof.

Comparison of control strategies in greenhouses.

Type of control	Impact on greenhouse energy consumption and crop yield	Accuracy	Other performance (response time/robustness/sensitivity/adaptability/smoothness)	Convergence	Recommendation for LEG (low energy greenhouse)
Optimal control (Van Beveren et al., 2015a)	Minimizing total external energy input over the year	Accurate	Optimal calculation time	Improving convergence	Yes
Adaptive neuro-fuzzy control (Atia and El-madany, 2017)	High yield, high quality and low costs	Accurate	Fast response time	Much faster convergence	Yes
Neuro-PID (Hu et al., 2010)	Low production costs	Accurate	Good adaptability, strong robustness	Speeding up convergence	Yes
Model predictive Control (Ferreira, 2008)	Reducing energy consumption without impact on control accuracy	Accurate	N/A	N/A	Yes
Multi-Objective Compatible Control (Xu et al., 2009)	Developing environmental control strategies to pursue lower energy costs	Accurate	N/A	Convergence	Yes
Fuzzy logic control (Revathi and Sivakumaran, 2016)	Better improvement in temperature inside greenhouse and reducing the crops and production losses	Accurate	Good robustness	N/A	Yes
Decoupling fuzzy control (Azaza et al., 2015)	Fuzzy controller effectively managing the indoor climate of the greenhouse, which may also have an impact on energy conservation	Accurate	High performance	N/A	Yes
PSO-MPC (Zou et al., 2010)	Saving energy in operating the greenhouse climate system.	Accurate	N/A	N/A	Yes
GA-model-based predictive control (Blasco et al., 2007)	Minimizing energy and water costs aiming to keeping the temperature and relative humidity performance within the guaranteed target range.	Accurate	Good performances	.N/A	Yes
MPC (El Ghoumari et al., 2005)	Energy savings	Accurate	Robustness and stability	N/A	Yes

Receding horizon Control (Singhal and Kumar, 2016)	Better power saving	Accurate	Smoother	Convergence	Yes
Two-layer multi-objective compatible control (MOCC) (Xu et al., 2007)	Optimizing energy efficiency by the compatible control system in the second layer	Accurate	Robustness	N/A	Yes
Model predictive control (Coelho et al., 2005)	Having a good performance in energy saving	Accurate	Robustness	N/A	Yes
PID control (Hu et al., 2014)	Ensuring the indoor environment within reasonable target range to minimize energy and water costs	Accurate	Robustness	N/A	Yes
MIMO PID (Bounaama and Draoui, 2011)	Saving energy during the night	Accurate	Better robust performance	N/A	Yes
Neural Networks control (Trejo-Perea et al., 2009)	Energy consumption predicted by multi-layer perceptron neural network	Accurate	N/A	N/A	Yes
PID control (Chaudhary et al., 2019)	Optimizing the energy efficiency and water use	N/A	N/A	N/A	Yes
Fuzzy control (Alhusari et al., 2018)	lower energy consumption	N/A	Good performance	N/A	Yes
Fuzzy adaptive control (Su et al., 2017)	Energy saving through reducing the corresponding error requirement	High accuracy	Stability	Convergence	Yes
Optimal control (Yousefi et al., 2010)	Saving energy	Accurate	N/A	High speed convergence	Yes
Fuzzy control (Kuang and Shen, 2010)	Low-cost	Accurate	High precision	N/A	Yes
Multi-Objective Compatible Control (Hu et al., 2011)	Energy-saving	Accurate	Good robustness	N/A	Yes
Hybrid control (Montoya et al., 2016)	Significant energy-saving	Accurate	Higher flexibility	Good convergence	Yes
Artificial Neural Network (Salazar et al., 2007)	Saving the energy and water	Highly accurate	N/A	N/A	Yes
Feedback Linearization-based Predictive Control (Chen et al., 2018)	Improving the energy efficiency	Accurate	Fast and accurate tracking of setting points	N/A	Yes
Adaptive Fuzzy Control (Su et al., 2016)	Operations with lower energy consumption	Accurate	Stability, good tracking	convergence	Yes
Predictive control (Su and Xu, 2015)	Energy saving by simplifying the model to control the ventilation system	Accurate	N/A	N/A	Yes
Adaptive particle swarm optimization and genetic algorithms (APSO-GA) (Chen et al., 2016)	Reliable to predict energy demand and peak load of greenhouses	Accurate	Less optimization time	Accelerating	Yes
Single Neuron PID (Chen et al., 2018d)	N/A	Accurate	Stable and robust	N/A	N/A
Fuzzy model predictive control (RAMDANI et al., 2015)	N/A	Accurate	Good tracking performance	N/A	Yes
Adaptive fuzzy hierarchical control (Wang and Zhang, 2018)	N/A	Accurate	N/A	N/A	N/A

Model predictive control (Chen et al., 2018a)	N/A	Accurate	Robustness	N/A	Yes
Linear Quadratic Optimal Control (Chen et al., 2018c)	Same tracking RMSE and consuming less energy	Accurate	N/A	N/A	Yes

Observed from Table 2, the following is valuable to note: Kuang and Shen (2010) presented a fuzzy controller to adjust the temperature and humidity levels. The investigation result demonstrated the proposed fuzzy controller has a high precision and reliability performance. Hu et al. (2011) carried out the multi-objective compatible control (MOCC) to regulate temperature and humidity levels, which illustrated MOCC has high control precision, good robustness and good distribution convergence. Su and Xu (2015) proposed a robust predictive controller to regulate the inside temperature, humidity and CO_2 concentration in greenhouses. The study results indicated that the proposed robust predictive controller has the high accuracy control performance. Chen et al. (2016) studied the adaptive particle swarm optimization and genetic algorithms (APSO-GA) to fulfill the ventilation system control requirement, which has a high accuracy improvement with a 95.6% significant level and demonstrates good performance, e.g., less optimization time.Hu et al. (2010) designed a nonlinear adaptive neuro-PID controller to govern the greenhouse climate. The proposed controller indicated good adaptability, strong robustness for the complex and nonlinear time-varying environment.

3.5 Energy saving achieved by control strategy

Greenhouse control not only requires the controller to have good control performance, but also needs to reduce greenhouse energy consumption by optimizing the parameters of control system while keeping the greenhouse microclimate stable. Seen from Tables 1 and 2, it could be concluded that the control strategy plays a vital role in the greenhouse energy consumption. There are some typical examples will be introduced below.

For improving energy efficiency and saving the energy in greenhouses, Kuang and Shen (2010) designed a fuzzy controller, which is used to adjust the roof window opening, the sprays and fans operation. The control to save energy is specific description that the starting the roof window when the inside temperature beyond the average, opening the fans and roof windows while the temperature and the humidity exceeds normal level. When the humidity was below the default value, proposed controller will instruct the actuator to open the window and start sprays. Fuzzy controller in the paper was also employed to adjust the heating operating time, while the inside temperature was very low, especially in the winter. Villarreal-Guerrero et al. (2012) developed a new control strategy for greenhouse cooling, which could save 36% water and consume 30% less electric energy. Coelho et al. (2005) proposed a MPC with PSO, which demonstrated a good low energy performance, such as it could reduce heating consumption 1.2%, and running time by 14%, compared with GA. Shen et al. (2018) developed a hybrid control strategy to optimize the greenhouse energy using. The experiments illustrate that the proposed hybrid control could reduce energy costs by 9% during cold days.

Montoya et al. (2016) provided a reasonable trade-off between the control performance and running costs, compared with a traditional controller. A Hybrid Model-Based Predictive Controller was proposed, which could save energy through coordinating two different heating systems. The mathematical model of proposed control adopted the weights ratio to optimize the energy allocation, when governing the nocturnal greenhouse temperature. Meanwhile, it is worth generalizing that the running costs were evaluated through the running time of each system in the investigated greenhouse.

Van Beveren et al. (Van Beveren et al., 2015a) developed the greenhouse dynamic model and built the minimizing cost function for total energy input. The cost function included the crop transpiration model. The air temperature and humidity were maintained within the acceptable ranges, the proposed optimal control demonstrated the good energy-saving performance because of the less input of total energy consumption around the year. Meanwhile, there was another energy saving method to consider the number of collocation points within satisfactory control performance.

4 Discussion

After analysis of the state of the arts, it is found that control strategies play the key role in the low energy greenhouses, which also affect crops yield and costs. More attention has been paid on energy conservation in greenhouses through advanced control strategies or algorithms.

There is a conflict between low cost and high accuracy control system. It is thus a challenge to balance the relationship between both of them. Unlike human thermal environment, greenhouses have to provide indoor environment for meeting various crop requirements, which should be considered and concentrated by the designer or engineer of control system.

5 Conclusions and future work

In this work, recent literature related to methodologies of control strategies aiming to improve energy efficiency and cleaner production in greenhouses has been intensively and systematically reviewed. The main valuable and concise conclusions are as follows:

1) Most literature (around 60% of selected articles) consider the temperature and humidity as controlled parameters in greenhouse climate, which directly affect the crops yield, and are the major energy consumption variables.
2) The most popular methodology to investigate the control strategy in greenhouses is numerical simulation using MATLAB/Simulink (around 30% of selected literature). However, the real physical experiment methods, which could validate the incredibility of mathematical models and numerical simulation for control strategies, are very few.
3) A traditional control strategy (e.g. PID/Fuzzy) combined with the Artificial Neural Networks (ANN)/intelligent algorithms has become a new trend in reducing the energy consumption for cleaner production and adjusting the inside microclimate in greenhouses into suitable growing environment for crops simultaneously since 2010s.

In the future, with the development of big data, artificial intelligence and machine learning, it will be a revolution in the greenhouse energy management combining the abovementioned technologies with traditional and advanced control strategies, meanwhile, if considering renewable energy and passive house technologies, energy consumption in agricultural greenhouses would be net zero, which seems like Net ZEB (zero energy buildings).

Our project of Energy-saving Optimization and Regulation of Multi-temporal-spatial-scale Greenhouses from Thousand Youth Talents Program has been investigated by the present authors. Optimization and regulation of energy conservation for a novel and cleaner food production system – aquaponics in greenhouses will be carried out soon.

Uncited reference

Uncited reference.

Uncited reference

Arvanitis et al., 2000, Ben Ali et al., 2016, Berenguel et al., 2003, Boughamsa and Ramdani, 2018, Heidari and Khodadadi, 2017, Jomaa et al., 2019, Liang et al., 2018.

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.

Acknowledgments

This research was financially supported by Thousand Youth Talents Plan from the Organization Department of CCP Central Committee (China Agricultural University, China, Grant No. 62339001), China Agricultural University Excellent Talents Plan (Grant No. 31051015), National Innovation Center for Digital Fishery, and Beijing Engineering and Technology Research Center for Internet of Things in Agriculture. The authors also appreciate constructive and valuable comments provided by reviewers.

Appendix A Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.122695.

Abbreviations

ANN	Artificial neural network
APSO-GA	Adaptive particle swarm optimization and genetic algorithms
CED	Cumulative energy demand
CFD	Computational Fluid Dynamics
FL	Feedback Linearization
FLC	Fuzzy logic control
FU	Functional unit, the production of one kg of fresh (lettuce) or grain (barley) marketable product
GWO	Grey wolf optimization
HMPC	Hybrid model predictive control
LEG	Low energy greenhouses
MIMO	Multi-inputs multi-outputs
MOCC	Multi-objective compatible control
MOEA	Multi-objective evolutionary algorithm
MPC	Model predictive control
NLM	Non-linear model
NMPC	Nonlinear model predictive control
NSGA-II	Non-dominated sorting genetic algorithm-II
PCM	Phase change material
PID	Proportional-integral-derivative
PSO-MPC	Particle swarm optimization model predictive control
RBF	Radial basis function
RMSE	Root mean square error
SWSHPS	Surface Water Source Heat Pump System
T-S	Takagi-Sugeno
UKF	Unscented Kalman filter
ZEB	Zero energy buildings

Symbols

A	windows opening
Br	moistening
$d(k\|t)$	discrete auxiliary variables
$\mathrm{E}(\mathrm{K})$	energy function
g_V	the specific ventilation
HR_i	the indoor relative humidity

h_{max}	maximum prediction horizon
h_{min}	minimum prediction horizon
h_c	the control horizon
h_{max}	the maximum instant limits
h_{min}	the minimum instant limits
J (X)	the energy consumption with the control system
J (x)	the total energy consumption of one week
$J_1\left(\overline{U_1}\right)$	the energy consumption from opening windows
$J_2\left(\overline{U_2}\right)$	the energy consumption from fog system for water used.
$J_3\left(\overline{U_3}\right)$	the energy consumed by heating system
k	iterative step
$\mathrm{K_d}$	the gains of the derivative
$\mathrm{K_P}$	the gains of the proportional
$\mathrm{K_i}$	the gains of the integral
N	the control horizon
PH	the prediction horizon
Q	the weighting factor for tracking error; the weighted diagonal matrix; the energy loss
$Q_{heat}\left(T_{Di}\right)$	the energy consumption prediction
Q_E	the aggregated controllable energy flux
R	the weighted diagonal matrix
Rg	the solar radiation
sV	the vents opening wind speed
Te	outside temperature
T_i	the indoor temperature
T_i/T_{out}	inside/outside temperature
V	the wind speed
ξ_1	the weights
u^{max}	the maximal energy consumption of control input
ω	the weight
e	the error
u_{heater}	normalized control variables of heater
$u_{fog,}$	normalized control variables fog
u_{vent}	ventilation
v_{wind}	the speed of outside wind
u_{PH}	the set of all sequences of size prediction horizon formed
t_0	the initial time
t_f	the final time
$x\left(N\|t\right)$	the vector of the continuous
(t + k)	discrete states predicted
$y\left(k\|t\right)$	the output
$z\left(k\|t\right)$	the continuous auxiliary variables
$d\left(k\|t\right)$	the discrete auxiliary variables
$\varepsilon\left(k+j\|k\right)$	the prediction error
$u\left(k+j-1\right)$	the control effort

References

The corrections made in this section will be reviewed and approved by a journal production editor. The newly added/removed references and its citations will be reordered and rearranged by the production team.

etc. Aguilera, E., Guzman, G.I., Infante-Amate, J., Soto, D., 2015. Embodied Energy in Agricultural Inputs. Incorporating a Historical Perspective. University of Jaen, Spain.

Ahamed, M.S., Guo, H., Tanino, K., 2019. Energy saving techniques for reducing the heating cost of conventional greenhouses. Biosyst. Eng. 178, 9–33.

Aiello, G., Giovino, I., Vallone, M., Catania, P., Argento, A., 2018. A decision support system based on multisensor data fusion for sustainable greenhouse management. J. Clean. Prod. 172, 4057–4065. doi:10.1016/j.jclepro.2017.02.197.

Alhusari, R., Fadel, M., Omar, F., 2018. Temperature control of MIMO system by utilizing ground temperature and weather conditions. In: 2018 IEEE Electrical Power and Energy Conference (EPEC). pp. 1–7. doi:10.1109/epec.2018.8598448.

Anifantis, A.S., Colantoni, A., Pascuzzi, S., 2017. Thermal energy assessment of a small scale photovoltaic, hydrogen and geothermal stand-alone system for greenhouse heating. Renew. Energy 103, 115–127.

Arvanitis, K.G., Paraskevopoulos, P.N., Vernardos, A.A., 2000. Multirate Adaptive temperature control of greenhouses. COMPUT ELECTRON AGR 26, 303–320. doi:10.1016/s0168-1699(00)00082-x.

Ashida, Y., Hayashi, K., Wakitani, S., Yamamoto, T., 2016. A Novel Approach in Designing PID Controllers Using Closed-Loop Data. American Automatic Control Council (AACC), pp. 5308–5313. doi:10.1109/acc.2016.7526501.

Atia, D.M., El-madany, H.T., 2017. Analysis and design of greenhouse temperature control using adaptive neuro-fuzzy inference system. Journal of Electrical Systems and Information Technology 4, 34–48. doi:10.1016/j.jesit.2016.10.014.

Azaza, M., Echaieb, K., Tadeo, F., Fabrizio, E., Iqbal, A., Mami, A., 2015. Fuzzy decoupling control of greenhouse climate. ARAB J SCI ENG 40, 2805–2812. doi:10.1007/s13369-015-1719-5.

Azaza, M., Tanougast, C., Fabrizio, E., Mami, A., 2016. Smart greenhouse fuzzy logic based control system enhanced with wireless data monitoring. ISA Trans. 61, 297–307. doi:10.1016/j.isatra.2015.12.006.

Baddadi, S., Bouadila, S., Ghorbel, W., Guizani, A., 2019. Autonomous greenhouse microclimate through hydroponic design and refurbished thermal energy by phase change material. J. Clean. Prod. 211, 360–379. doi:10.1016/j.jclepro.2018.11.192.

Bartzas, G., Zaharaki, D., Komnitsas, K., 2015. Life cycle assessment of open field and greenhouse cultivation of lettuce and barley. Information Processing in Agriculture 2 (3–4), 191–207.

Bastien, D., Athienitis, A.K., 2012. A control algorithm for optimal energy performance of a solarium/greenhouse with combined interior and exterior motorized shading. Energy Procedia 30, 995–1005. doi:10.1016/j.egypro.2012.11.112.

Ben Ali, R., Aridhi, E., Abbes, M., Mami, A., 2016. Fuzzy logic controller of temperature and humidity inside an agricultural greenhouse. In: Proceeding of IEEE Congress on Renewable Energy. pp. 1–6. doi:10.1109/irec.2016.7478929.

Berenguel, M., Yebra, L.J., Rodriguez, F., 2003. Adaptive control strategies for greenhouse temperature control. In: Proceeding of IEEE European Control Conference. pp. 2747–2752. doi:10.23919/ecc.2003.7086457.

Blasco, X., Martínez, M., Herrero, J.M., Ramos, C., Sanchis, J., 2007. Model-based predictive control of greenhouse climate for reducing energy and water consumption. COMPUT ELECTRON AGR 55, 49–70. doi:10.1016/j.compag.2006.12.001.

Boaventura Cunha, J., Couto, C., Ruano, A.E., 1997. Real-time parameter estimation of dynamic temperature models for greenhouse environmental control. CONTROL ENG PRACT 5, 1473–1481. doi:10.1016/s0967-0661(97)00145-7.

Bontsema, J., van Henten, E.J., Gieling, T.H., Swinkels, G.L.A.M., 2011. The effect of sensor errors on production and energy consumption in greenhouse horticulture. COMPUT ELECTRON AGR 79, 63–66. doi:10.1016/j.compag.2011.08.008.

Boughamsa, M., Ramdani, M., 2018. Adaptive fuzzy control strategy for greenhouse micro-climate. Autom. Contr.. doi:10.1504/ijaac.2018.10007843.

Bounaama, F., Draoui, B., 2011. Greenhouse environmental control using optimized MIMO PID technique. Sensors & Transducers 133 (10), 44–52.

Caponetto, R., Fortuna, L., Nunnari, G., Occhipinti, L., 1998. A fuzzy approach to greenhouse climate control. In: Proceeding of IEEE American Control Conference. pp. 1866–1870. doi:10.1109/acc.1998.707343.

Caponetto, R., Fortuna, L., Nunnari, G., Occhipinti, L., Xibilia, M.G., 2000. Soft computing for greenhouse climate control. IEEE T FUZZY SYST 8, 753–760. doi:10.1109/91.890333.

Çaylı, A., Akyüz, A., Baytorun, A.N., Boyacı, S., Üstün, S., Kozak, F.B., 2017. Sera çevre koşullarının nesnelerin i?nterneti tabanlı i?zleme ve analiz sistemi ile denetlenmesi. Turkish Journal of Agriculture - Food Science and Technology 5, 1279–1289. doi:10.24925/turjaf.v5i11.1279-1289.1282.

Chalabi, Z.S., Bailey, B.J., Wilkinson, D.J., 1996. A real-time optimal control algorithm for greenhouse heating. COMPUT ELECTRON AGR 15, 1–13. doi:10.1016/0168-1699(95)00053-4.

Chaudhary, G., Kaur, S., Mehta, B., Tewani, R., 2019. Observer based fuzzy and PID controlled smart greenhouse. J. Stat. Manag. Syst. 22, 393–401. doi:10.1080/09720510.2019.1582880.

Chen, J., Yang, J., Zhao, J., Xu, F., Shen, Z., Zhang, L., 2016. Energy demand forecasting of the greenhouses using nonlinear models based on model optimized prediction method. Neurocomputing 174, 1087–1100. doi:10.1016/j.neucom.2015.09.105.

Chen, J.C.J., Xu, F.X.F., Tan, D.T.D., Shen, Z.S.Z., Zhang, L.Z.L., Ai, Q.A.Q., 2015. A control method for agricultural greenhouses heating based on computational fluid dynamics and energy prediction model. APPL ENERG 141, 106–118. doi:10.1016/j.apenergy.2014.12.026.

Chen, L., Du, S., He, Y., Liang, M., Xu, D., 2018. Robust model predictive control for greenhouse temperature based on particle swarm optimization. Information Processing in Agriculture 5, 329–338. doi:10.1016/j.inpa.2018.04.003.

Chen, L., Du, S., et al., 2018. Adaptive feedback linearization-based predictive control for greenhouse temperature. IFAC-PapersOnLine 51, 784–789. doi:10.1016/j.ifacol.2018.08.100.

Chen, L., Du, S., et al., 2018. Linear quadratic optimal control applied to the greenhouse temperature hierarchal system. IFAC-PapersOnLine 51, 712–717. doi:10.1016/j.ifacol.2018.08.112.

Chen, M.C.M., Wang, X.W.X., Zhang, H.Z.H., 2018. Design of temperature and humidity control system in agricultural greenhouse based on single neuron PID. In: International Symposium on Big Data and Artificial Intelligence (ISBDAI). pp. 135–138. doi:10.1145/3305275.3305302.

Climatewatch. https://www.climatewatchdata.org/ghg-emissions/. final access: 3 May 2020.

Coelho, J.P., de Moura Oliveira, P.B., Cunha, J.B., 2005. Greenhouse air temperature predictive control using the particle swarm optimisation algorithm. COMPUT ELECTRON AGR 49, 330–344. doi:10.1016/j.compag.2005.08.003.

Dahlan, N.Y., Z. Sakimin, S., Faizwan, M., Ajmain, N., A. Aris, A., 2018. Automated calibration of greenhouse energy model using hybrid evolutionary programming (EP)-Energy plus. Indonesian Journal of Electrical Engineering and Computer Science 12, 648–654. doi:10.11591/ijeecs.v12.i2.pp648-654.

Del Sagrado, J., Sánchez, J.A., Rodríguez, F., Berenguel, M., 2016. Bayesian networks for greenhouse temperature control. J. Appl. Logic 17, 25–35. doi:10.1016/j.jal.2015.09.006.

Djevic, M., Dimitrijevic, A., 2009. Energy consumption for different greenhouse constructions. Energy 34, 1325–1331. doi:10.1016/j.energy.2009.03.008.

El Ghoumari, M.Y., Tantau, H.J., Serrano, J., 2005. Non-linear constrained MPC: real-time implementation of greenhouse air temperature control. COMPUT ELECTRON AGR 49, 345–356. doi:10.1016/j.compag.2005.08.005.

Ferreira, P.M.R.A., 2008. Discrete model-based greenhouse environmental control using the Branch & bound algorithm. The International Federation of Automatic Control. doi:10.3182/20080706-5-kr-1001.00494.

Gil, J.D., Álvarez, J.D., Roca, L., Sánchez-Molina, J.A., Berenguel, M., Rodríguez, F., 2019. Optimal thermal energy management of a distributed energy system comprising a solar membrane distillation plant and a greenhouse. ENERG CONVERS MANAGE 198, 111791. doi:10.1016/j.enconman.2019.111791.

Goto, E., Ishigami, Y., Okushima, L., 2017. Development of a greenhouse simulation model to estimate energy and resources necessary for environmental controls under various climate conditions. Acta Hortic. 293–300. doi:10.17660/actahortic.2017.1170.35.

Gruber, J.K., Guzmán, J.L., Rodríguez, F., Bordons, C., Berenguel, M., Sánchez, J.A., 2011. Nonlinear MPC based on a Volterra series model for greenhouse temperature control using natural ventilation. CONTROL ENG PRACT 19, 354–366. doi:10.1016/j.conengprac.2010.12.004.

Gurban, E.H., Andreescu, G., 2014. Comparison of modified Smith predictor and PID controller tuned by genetic algorithms for greenhouse climate control. In: 2014 9th IEEE International Symposium on Applied Computational Intelligence and Informatics (SACI). pp. 79–83. doi:10.1109/saci.2014.6840039.

Heidari, M., Khodadadi, H., 2017. Climate control of an agricultural greenhouse by using fuzzy logic self-tuning PID approach. Chinese Automation and Computing Society in the UK - CACSUK 1–6. doi:10.23919/iconac.2017.8082074.

He, Y., Meihui, L., Lijun, C., Xiaohui, Q., Shangfeng, D.U., 2018. Greenhouse modelling and control based on T-S model. IFAC-PapersOnLine 51, 802–806. doi:10.1016/j.ifacol.2018.08.097.

Hu, H., Xu, L., Goodman, E.D., Zeng, S., 2014. NSGA-II-based nonlinear PID controller tuning of greenhouse climate for reducing costs and improving performances. Neural Comput. Appl. 24, 927–936. doi:10.1007/s00521-012-1312-8.

Hu, H., Xu, L., Wei, R., 2010. Nonlinear adaptive Neuro-PID controller design for greenhouse environment based on RBF network. In: Proceeding of IEEE International Joint Conference on Neural Networks. pp. 1–7. doi:10.1109/ijcnn.2010.5596982.

Hu, H., Xu, L., Zhu, B., Wei, R., 2011. A compatible control algorithm for greenhouse environment control based on MOCC strategy. SENSORS-BASEL 11, 3281–3302. doi:10.3390/s110303281.

Jomaa, M., Abbes, M., Tadeo, F., Mami, A., 2019. Greenhouse modeling, validation and climate control based on fuzzy logic. Eng. Technol. Appl. Sci. Res. 9, 4405–4410.

D. Kolokotsa, G. Saridakis, K. Dalamagkidis, S. Dolianitis, I. Kaliakatsos. Development of an intelligent indoor environment and energy management system for greenhouses. https://doi.org/10.1016/j.enconman.2009.09.007, 2010.

Kuang, Y., Shen, Y., 2010. A greenhouse temperature and humidity controller based on MIMO fuzzy system. In: Proceeding of IEEE International Conference on Intelligent System Design and Engineering Application. pp. 35–39. doi:10.1109/isdea.2010.80.

Li, L., Cheng, K.W.E., Pan, J.F., 2017. Design and application of intelligent control system for greenhouse environment. In: 2017 7th International Conference on Power Electronics Systems and Applications - Smart Mobility, Power Transfer & Security (PESA). doi:10.1109/pesa.2017.8277762.

Liang, M., Chen, L., He, Y., Du, S., 2018. Greenhouse temperature predictive control for energy saving using switch actuators. IFAC-PapersOnLine 51, 747–751. doi:10.1016/j.ifacol.2018.08.106.

Linker, R., Kacira, M., Arbel, A., 2011. Robust climate control of a greenhouse equipped with variable-speed fans and a variable-pressure fogging system. Biosyst. Eng. 110, 153–167. doi:10.1016/j.biosystemseng.2011.07.010.

Ma, D., Carpenter, N., Maki, H., Rehman, T.U., Tuinstra, M.R., Jin, J., 2019. Greenhouse environment modeling and simulation for microclimate control. COMPUT ELECTRON AGR 162, 134–142. doi:10.1016/j.compag.2019.04.013.

Márquez-Vera, M.A., Julio, C.R., Luis, F.C., Frédéric, L., Balmat, J., Jorge, I.E., 2016. Temperature control in a MISO greenhouse by inverting its fuzzy model. COMPUT ELECTRON AGR. doi:10.1016/j.compag.2016.04.005.

McNulty, J., 2017. Solar Greenhouses Generate Electricity and Grow Crops at the Same Time, UC Santa Cruz Study Reveals. UC Santa Cruz Magazine November 03.

Montoya, A.P., Guzmán, J.L., Rodríguez, F., Sánchez-Molina, J.A., 2016. A hybrid-controlled approach for maintaining nocturnal greenhouse temperature: simulation study. COMPUT ELECTRON AGR 123, 116–124. doi:10.1016/j.compag.2016.02.014.

M.,A.B.F.T. Nachidi. Temperature and humidity control in greenhouses using the Takagi-Sugeno fuzzy model. https://doi.org/10.1109/cca.2006.286199, 2006.

Najjar, A., Hasan, A., 2008. Modeling of greenhouse with PCM energy storage. ENERG CONVERS MANAGE 49, 3338–3342. doi:10.1016/j.enconman.2008.04.015.

Nicolosi, G.N.G., Volpe, R.V.R., Messineo, A.M.A., 2017. An innovative adaptive control system to regulate microclimatic conditions in a greenhouse. ENERGIES 10, 722. doi:10.3390/en10050722.

Paraforos, D.S., Griepentrog, H.W., 2013. Multivariable greenhouse climate control using dynamic decoupling controllers. IFAC Proceedings Volumes 46, 305–310. doi:10.3182/20130828-2-sf-3019.00064.

Park, D., Park, D., Kang, B., Kang, B., Cho, K., Cho, K., Shin, C., Shin, C., Cho, S., Cho, S., Park, J., Park, J., Yang, W., Yang, W., 2011. A study on greenhouse automatic control system based on wireless sensor network. Wireless Pers. Commun. 56, 117–130. doi:10.1007/s11277-009-9881-2.

Pasgianos, G.D., Arvanitis, K.G., Polycarpou, P., Sigrimis, N., 2003. A nonlinear feedback technique for greenhouse environmental control. COMPUT ELECTRON AGR 40, 153–177. doi:10.1016/s0168-1699(03)00018-8.

Pawlowski, A., Guzmán, J.L., Rodríguez, F., Berenguel, M., Normey-Rico, J.E., 2011. Predictive control with disturbance forecasting for greenhouse diurnal temperature control. IFAC Proceedings Volumes 44, 1779–1784. doi:10.3182/20110828-6-it-1002.00857.

Piñón, S., Camacho, E.F., Kuchen, B., Peña, M., 2005. Constrained predictive control of a greenhouse. COMPUT ELECTRON AGR 49, 317–329. doi:10.1016/j.compag.2005.08.007.

Piscia, D., Muñoz, P., Panadès, C., Montero, J.I., 2015. A method of coupling CFD and energy balance simulations to study humidity control in unheated greenhouses. COMPUT ELECTRON AGR 115, 129–141. doi:10.1016/j.compag.2015.05.005.

Ramdani, M., Hamza, A., Boughamsa, M., 2015. Multiscale fuzzy model-based short term predictive control of greenhouse microclimate. IEEE International Conference on Industrial Informatics INDIN. doi:10.1109/indin.2015.7281931.

Revathi, S., Sivakumaran, N., 2016. Fuzzy based temperature control of greenhouse. IFAC-PapersOnLine 49, 549–554. doi:10.1016/j.ifacol.2016.03.112.

Rodríguez, C., Rodríguez, F., Guzman, J.L., Berenguel, M., Arahal, M.R., 2010. Diurnal greenhouse temperature control with predictive control and online constrains mapping. IFAC Proceedings Volumes 43, 140–145. doi:10.3182/20100329-3-pt-3006.00027.

Rodríguez, F., Guzmán, J.L., Berenguel, M., Arahal, M.R., 2008. Adaptive hierarchical control of greenhouse crop production. INT J ADAPT CONTROL 22, 180–197. doi:10.1002/acs.974.

Rodríguez, F., Yebra, L.J., Berenguel, M., Dormido, S., 2002. Modelling and simulation OF greenhouse climate using DYMOLA. IFAC Proceedings Volumes 35, 79–84. doi:10.3182/20020721-6-es-1901.01322.

Salazar, R., Lopez, I., Rojano, A., 2007. A neural network model to control greenhouse environment. In: Proceeding of IEEE Mexican International Conference on Artificial Intelligence. pp. 311–318. doi:10.1109/micai.2007.33.

Shen, Y., Wei, R., Xu, L., 2018. Energy consumption prediction of a greenhouse and optimization of daily average temperature. ENERGIES 11, 65. doi:10.3390/en11010065.

Sigrimis, N., Anastasiou, A., Rerras, N., 2000. Energy saving in greenhouses using temperature integration: a simulation survey. COMPUT ELECTRON AGR 26, 321–341. doi:10.1016/s0168-1699(00)00083-1.

Singhal, R., Kumar, R., 2016. Receding horizon based greenhouse air temperature control using grey wolf optimization algorithm. In: Proceeding of IEEE Conference on Electrical Computer and Electronics. pp. 32–37. doi:10.1109/upcon.2016.7894620.

Su, Y., Xu, L., 2015. A greenhouse climate model for control design. In: 2015 IEEE 15th International Conference on Environment and Electrical Engineering (EEEIC). pp. 47–53. doi:10.1109/eeeic.2015.7165318.

Su, Y., Xu, L., Goodman, E.D., 2017. Greenhouse climate fuzzy adaptive control considering energy saving. Int. J. Contr. Autom. Syst. 15, 1936–1948. doi:10.1007/s12555-016-0220-6.

Su, Y., Xu, L., Li, D., 2016. Adaptive fuzzy control of a class of MIMO nonlinear system with actuator saturation for greenhouse climate control problem. IEEE T AUTOM SCI ENG 13, 772–788. doi:10.1109/tase.2015.2392161.

Sudhakar, K., Jenkins, M.S., Mangal, S., Priya, S.S., 2019. Modelling of a solar desiccant cooling system using a TRNSYS-MATLAB co-simulator: a review. Journal of Building Engineering 24, 100749. doi:10.1016/j.jobe.2019.100749.

Tantau, H., 1998. Energy saving potential of greenhouse climate control. Math. Comput. Simulat. 48, 93–101. doi:10.1016/s0378-4754(98)00145-1.

Trejo-Perea, M.T.M., Herrera-Ruiz, G.H.G., Rios-Moreno, J.R.J., Miranda, R.C.M.R., Rivas-Araiza, E.R.E., 2009. Greenhouse energy consumption prediction using neural networks models. Int. J. Agric. Biol. 1–6. https://doi:10.3763/ijas.2009.0459.

Vadiee, A., Martin, V., 2014. Energy management strategies for commercial greenhouses. APPL ENERG 114, 880–888. doi:10.1016/j.apenergy.2013.08.089.

Van Beveren, P.J.M., Bontsema, J., Van Straten, G., Van Henten, E.J., 2015. Minimal heating and cooling in a modern rose greenhouse. APPL ENERG 137, 97–109. doi:10.1016/j.apenergy.2014.09.083.

Van Beveren, P.J.M., Bontsema, J., van Straten, G., van Henten, E.J., 2015. Optimal control of greenhouse climate using minimal energy and grower defined bounds. APPL ENERG 159, 509–519. doi:10.1016/j.apenergy.2015.09.012.

Van Henten, E.J., Bontsema, J., 2009. Time-scale decomposition of an optimal control problem in greenhouse climate management. CONTROL ENG PRACT 17, 88–96. doi:10.1016/j.conengprac.2008.05.008.

Van Straten, G., Henten, E.J.V., 2010. Optimal greenhouse cultivation control: survey and perspectives. IFAC Proceedings Volumes 43, 18–33. doi:10.3182/20101206-3-jp-3009.00004.

Villarreal-Guerrero, F., Kacira, M., Fitz-Rodríguez, E., Linker, R., Kubota, C., Giacomelli, G.A., Arbel, A., 2012. Simulated performance of a greenhouse cooling control strategy with natural ventilation and fog cooling. Biosyst. Eng. 111, 217–228. doi:10.1016/j.biosystemseng.2011.11.015.

Wang, L., Zhang, H., 2018. An adaptive fuzzy hierarchical control for maintaining solar greenhouse temperature. COMPUT ELECTRON AGR 155, 251–256. doi:10.1016/j.compag.2018.10.023.

Xiao, H., Feng, L., Zhi, Y., 2013. Tuning the PID parameters for greenhouse control based on CFD simulation. In: 2013 Second International Conference on Agro-Geoinformatics (Agro-Geoinformatics). pp. 485–489. doi:10.1109/argo-geoinformatics.2013.6621968.

Xu, D., Du, S., van Willigenburg, G., 2019. Double closed-loop optimal control of greenhouse cultivation. CONTROL ENG PRACT 85, 90–99. doi:10.1016/j.conengprac.2019.01.010.

Xu, F., J.C.L.Z., 2006. Self-tunning fuzzy logic control of greenhouse temperature using real-coded genetic algorithm. Proceeding of IEEE International Conference on Control, Automation, Robotics and Vision. doi:10.1109/icarcv.2006.345183.

Xu, L., Hu, H., Zhu, B., 2009. Energy-saving control of greenhouse climate based on MOCC strategy. ACM 645–650. doi:10.1145/1543834.1543922.

Xu, L., Hu, Q., Goodman, E.D., 2007. A compatible energy-saving control algorithm for a class of conflicted multi-objective control problem. In: 2007 IEEE Congress on Evolutionary Computation. pp. 4446–4453. doi:10.1109/cec.2007.4425053.

Xu, W., Song, W., Ma, C., 2020. Performance of a water-circulating solar heat collection and release system for greenhouse heating using an indoor collector constructed of hollow polycarbonate sheets. J. Clean. Prod. 253, 119918. doi:10.1016/j.jclepro.2019.119918.

Yousefi, M.R., Hasanzadeh, S., Mirinejad, H., Ghasemian, M., 2010. A hybrid neuro-fuzzy approach for greenhouse climate modeling. In: Proceeding of IEEE International Conference on Intelligent Systems. pp. 212–217. doi:10.1109/is.2010.5548375.

Zeng, S., Hu, H., Xu, L., Li, G., 2012. Nonlinear adaptive PID control for greenhouse environment based on RBF network. SENSORS-BASEL 12, 5328–5348. doi:10.3390/s120505328.

Zhang, G., Liu, X., Fu, Z., Stankovski, S., Dong, Y., Li, X., 2019. Precise measurements and control of the position of the rolling shutter and rolling film in a solar greenhouse. J. Clean. Prod. 228, 645–657. doi:10.1016/j.jclepro.2019.04.129.

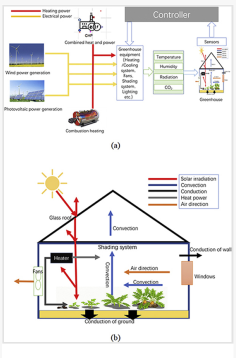
Zhang, Y., Gauthier, L., de Halleux, D., Dansereau, B., Gosselin, A., 1996. Effect of covering materials on energy consumption and greenhouse microclimate. AGR FOREST METEOROL 82, 227–244. doi:10.1016/0168-1923(96)02332-5.

Zou, Q., Ji, J., Zhang, S., Shi, M., Luo, Y., 2010. Model predictive control based on particle swarm optimization of greenhouse climate for saving energy consumption. In: Proceeding of IEEE Biannual World Automation Congress. pp. 123–128.

Graphical abstract

Relationship among controller, greenhouse equipment supplied by thermal and electrical energy, controlled environmental factors (temperature, humidity etc.) and sensors in the greenhouse (a), detailed thermal environment inside the greenhouse (b).

alt-text: Image 1



Highlights

- First review on greenhouse control strategy methodologies considering energy efficiency.
- Review on various greenhouses control technologies investigated via simulation/measurement.
- Parametric sensitivity analysis including diverse effects of 30+ parameters on greenhouse performance.
- Comparison and evaluation on control performance of different algorithms in greenhouses.

Appendix A Supplementary data

The following is the Supplementary data to this article:

Multimedia Component 1

Multimedia component 1

alt-text: Multimedia component 1

Queries and Answers

Query: Your article is registered as a regular item and is being processed for inclusion in a regular issue of the journal. If this is NOT correct and your article belongs to a Special Issue/Collection please contact k.kumar.1@elsevier.com immediately prior to returning your corrections.

Answer: Yes, it is a regular item.

Query: Please confirm that the provided emails “andy_yangwang@cau.edu.cn, wanghongyang1767@gmail.com” are the correct address for official communication, else provide an alternate e-mail address to replace the existing one, because private e-mail addresses should not be used in articles as the address for communication.

Answer: yes, both are correct.

Query: Please confirm that given names and surnames have been identified correctly and are presented in the desired order and please carefully verify the spelling of all authors' names.

Answer: Yes

Query: Uncited references: This section comprises references that occur in the reference list but not in the body of the text. Please cite each reference in the text or, alternatively, delete it. Any reference not dealt with will be retained in this section.

Answer: please delete it.

Query: Have we correctly interpreted the following funding source(s) and country names you cited in your article: CCP Central Committee; China Agricultural University, China; China Agricultural University Excellent Talents Plan; Beijing Engineering and Technology Research Center for Internet of Things in Agriculture?

Answer: The abovementioned funding sources are correct. However, Please also add the following funding: Major Science and Technology Innovation Fund 2019 of Shandong Province (Grant No. 2019JZZY010703), Science and Technology Cooperation – Sino-Malta Fund 2019: Research and Demonstration of Real-time Accurate Monitoring System for Early-stage Fish in Recirculating Aquaculture System (AquaDetector, Grant No. SQ2019YFE010142)