# Predictive control for greenhouse temperature and humidity and energy optimization by improved NMPC objective function algorithm

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**Abstract:** Persistent low temperatures in autumn and winter have a huge impact on crops, and greenhouses rely on solar radiation and heating equipment to meet the required indoor temperature. But the energy cost of frequent operation of the actuators is exceptionally high. The relationship between greenhouse environmental control accuracy and energy consumption is one of the key issues faced in greenhouse research. In this study, a non-linear model predictive control method with an improved objective function was proposed. The improved objective function used tolerance intervals and boundary constraints to optimize the objective evaluation. The nonlinear model predictive control (NMPC) controller design was based on the wavelet neural network (WNN) data-driven model and applied the interior point method to solve the optimal solution of the objective function control, thus balancing the contradiction between energy consumption and control precision. The simulation results showed that the improved NMPC method reduced energy consumption by 21.02% and 9.54% compared with the model predictive control and regular NMPC, which proved the method achieved good results in a low-temperature environment. This research can provide an important reference for the field as it offers a more efficient approach to managing greenhouse climates, potentially leading to substantial energy savings and enhanced sustainability in agricultural practices.

**Keywords:** greenhouse environmental control, greenhouse energy optimization, nonlinear model predictive control, objective function improvement

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## 1 Introduction

Agricultural production needs stable and suitable conditions, but low temperatures can affect crop yields in autumn and winter. Greenhouses, as an essential facility agriculture mode, can deal with these problems by improving the stability of the environment through environmental regulation in enclosed areas[1]. Generally, control and adjustment methods cover: heating and cooling system, ventilation system, $CO_2$ supply system, lighting system, and humidification and dehumidification system[2]. The control processes can be achieved manually or by controllers. The main control methods are fuzzy control[3,4], adaptive control[5,6], robust control[7,8], neural network algorithm control[9,10], hierarchical optimal control[11,12], and model predictive control[13,14]. Unlike other methods, model predictive control (MPC) is an optimal control strategy in the finite time domain based on model prediction. Ghoumari et al.[15] implemented a nonlinear constrained MPC to control temperature and humidity by online linearization methods to approximate linear solutions of greenhouse models. Svensen et al.[16] recently proposed a chance-constrained stochastic MPC scheme to explicitly address parametric errors in the crop-climate model, demonstrating the effectiveness of MPC in handling uncertainties and improving the robustness of greenhouse control systems. Ito et al.[17]studied the effect of humidity deficit on greenhouses, improved the algorithm of the linear model in the MPC, and proposed a new humidity deficit objective function. The control of MPC in the greenhouse requires approximately linear processing of the model, which also results in a loss of model accuracy. Some studies used the nonlinear model predictive control (NMPC) method for the application of nonlinear models and data-driven models. Qi et al.[18] used a neural network model as a predictive model to predict the controlled process in combination with NMPC to control the greenhouse temperature. Pelagagge et al.[19] applied the dynamic response surface methodology data-driven model as a nonlinear MPC model to solve the optimal control problem of the non-equispaced finite-level domain. Gruber et al.[20] applied an NMPC strategy based on a second-order Volterra model to conduct a study of the nonlinear dynamic effects of greenhouse temperature. Improvements in controllers and models have certainly improved greenhouse control results, but have also led to higher energy costs.

Environmental control and energy consumption of greenhouses have been the key points of research by scholars. Mahmood et al.[21] proposed a data-driven model predictive control method based on multi-layer perceptron to achieve greenhouse temperature control and reduce energy consumption. Hu et al.[22] developed a data-driven

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robust model predictive control framework to build state space models based on historical predictive data and system identification methods, combined with a robust MPC framework, whereby the efficiency of power utilization and crop yield were improved. Wang et al.[11] proposed a dual time domain multi-layered closed-loop control method for greenhouse environments. This method aims to accurately control environmental factors, reduce energy consumption, and improve economic efficiency. Lin et al.[13] have applied multi-strategy processing to greenhouse control. The control and optimization layers implement scenario classification and control response, respectively. Most research on greenhouse energy-saving is based on long-term crop growth environment optimization or short-term multi-objective control optimization. The former method does have better results in application, but at the same time requires a complex greenhouse crop growth model, and lacks adaptability to different crops or different environments. The latter approach relies on solvers to obtain the optimal short-term control output. The balance between control accuracy and energy consumption is achieved by introducing a competition of weights between energy consumption and greenhouse objects. The solvers cannot guarantee the optimal solution for each control direction when the output error is large. However, most methods lack restrictions on weight competition and cannot always ensure a balance between control objectives and energy consumption. Control dysfunction is likely to occur in the presence of large environmental changes.

This study focuses on a multi-objective optimization method for short-term greenhouses with constraints to achieve a dynamic balance between greenhouse control and energy consumption. An NMPC with an improved objective function was proposed. The key point of innovation was that by improving the objective function and adding tolerance intervals and boundary constraints, greenhouse energy consumption was able to be reduced while avoiding control dysfunction. The work of this paper includes:

1) Building a Wavelet Neural Network (WNN) data-driven model for the multi-step prediction process for controllers;

2) Proposing an improved objective function based on tolerance interval for state evaluation of control processes;

3) Based on the above model and objective function, the NMPC controls the indoor temperature and humidity through the heating system, ventilation system, and lighting system. The simulated results validate the effectiveness of the method.

## 2 Materials and methods

### 2.1 Analysis and modeling of greenhouse environments

In a general greenhouse study, the first step is to find its internal and external connections, which requires modeling the greenhouse system. The Venlo-type greenhouse is a small-span glass greenhouse. This type of greenhouse structure is widely recognized and utilized globally, especially in southern regions. The Venlo-type greenhouse is renowned for its distinctive design features and superior performance, making it the most extensively used type of glass greenhouse worldwide. Its key characteristics include small component cross-sections, easy installation, high light transmission, excellent sealing properties, and large ventilation areas. These attributes offer significant advantages for agricultural production by providing stable indoor environments and promoting crop growth. The literature includes various studies[23-25]of Venlo-type greenhouses. A Venlo-type greenhouse for tomato growing was studied[26,27], and the control objects included greenhouse indoor temperature and relative humidity; the control actuators included a lighting system, a heating system, and a roof ventilation system; the environmental observation objects included outdoor temperature, humidity, the intensity of light, and indoor temperature, humidity, and $CO_2$ concentration. According to the conditions, the common greenhouse model equations based on energy transfer and material exchange are established[2,13]:

$$\begin{cases} \dfrac{\mathrm{d}T_{\mathrm{in}}(t)}{\mathrm{d}t} = \dfrac{1}{c_g}\left(I_{\mathrm{sun}}(t) - I_{\mathrm{cov}}(t) - I_{\mathrm{trans}}(t) + I_{\mathrm{pipe}}(t) - I_{\mathrm{vent}}(t)\right) \\ \dfrac{\mathrm{d}H_{\mathrm{in}}(t)}{\mathrm{d}t} = \dfrac{1}{h}(H_{\mathrm{train}} + H_{\mathrm{vent}} - H_{\mathrm{conde}}) \\ \mathrm{RH}_{\mathrm{in}} = \dfrac{H_{\mathrm{in}}}{H_{\mathrm{sat}}} \times 100\% \end{cases} \quad (1)$$

where, $T_{in}$ is the indoor air temperature of the greenhouse, °C, $H_{in}$ and $H_{sat}$ is the water vapor pressure and saturated vapor pressure indoor air of the greenhouse, Pa, $RH_{in}$ is the indoor relative humidity, %, $I_{sum}$ is the transfer energy of sunlight, W/m$^2$, $I_{cov}$ is the transfer energy of the greenhouse cover, W/m$^2$, $I_{trans}$ is the transfer energy of the crop transpiration, W/m$^2$, $I_{pipe}$ is the transfer energy of the heating pipes, W/m$^2$, $I_{vent}$ is the transfer energy of the ventilation, W/m$^2$, $H_{vent}$ is the exchange of vapor through ventilation, $H_{trans}$ is the vapor produced by plant transpiration, $H_{conde}$ is lost vapor for condensation, $p_g$ is the indoor air density, kg/m$^3$, $v_g$ is the greenhouse volume, m$^3$, $c_g$ is the specific heat capacity of indoor air, J/(kg·°C), and $h$ is the average height of the greenhouse. Most of the parameters cannot be directly obtained, and the calculation processes are complex and difficult, which is also one of the reasons for the difficulty of greenhouse mechanism modeling.

In greenhouse research, it is considered that greenhouse systems are nonlinear and strongly coupled, which makes the model parameters always have certain deviations and leads to errors in the control process. Compared with mechanistic modeling, data-driven approaches achieve modeling with fewer parameters and have better generalization capabilities for complex systems[28]. In this study, a data-driven greenhouse model was built using WNN to reduce the complexity of the modeling process.

WNN is based on the principles of wavelet transform and neural network. It replaces the activation function of a neural network with a wavelet basis function, which facilitates the model representation of nonlinear objects by achieving multi-scale refinement of the approximate wavelet transform process. Aly et al.[29] compared wavelet (WNN) and other methods for wind speed and power prediction to demonstrate the advantages of WNN models for short- and medium-term prediction. Chang et al.[30] proposed an online battery accurate health condition assessment method by using the nonlinear fitting feature of wavelet neural network combined with genetic algorithm. WNN combined with wavelet basis functions has better learning ability and generalization, which shows better prediction results for different prediction problems. The formulas of the WNN are as follows:

$$h(j) = h_j\left(\frac{\sum_{i=1}^{N}\omega_{ij}x_i - b_j}{a_j}\right) \quad (2)$$

$$y(k) = \sum_{j=1}^{n}\omega_{jk}h(j) \quad (3)$$

$$h_j(x) = \cos(1.75x)^{-0.5x^2} \quad (4)$$

Equation (2) is the output equation of the hidden nodes, Equation (3) is the output equation of the output layer nodes, and Equation (4) is the wavelet basis function. $x_i$ is the input node to the network, $w_{ij}$ is the weight of the input node $i$ and the hidden node $j$, $a_j$ is the scaling value of the node $j$, and $b_j$ is the translation value of the node $j$. WNN connects the hidden nodes with the input weights and calculates the node outputs after translating and stretching. The wavelet basis functions include Haar wavelet, Morlet wavelet, Mexican wavelet, Meyer wavelet, etc.[31]. In this study, Morlet wavelet was adopted as Equation (4), whose nonlinear fitting ability has been verified in several related studies[32-35].

### 2.2 NMPC controller design based on improved objective function

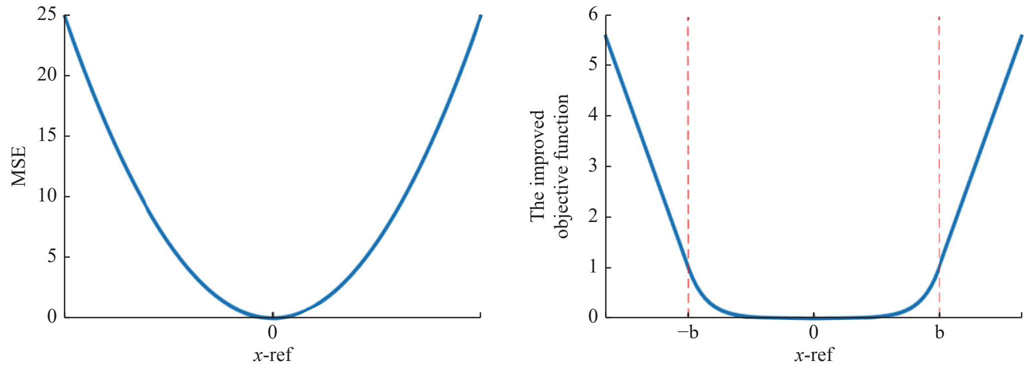
#### 2.2.1 An improved objective function based on tolerance intervals

The objective function is part of the state evaluation of MPC and NMPC. Generally multi-objective control problems are transformed into a single objective problem by weight accumulation of the difference between the objective and the current state, which is used in the subsequent control optimization process. In the greenhouse control process, the environmental control objectives and energy consumption objectives of the greenhouse also guide the greenhouse control direction through the weight accumulation. However, the relationship between environmental control and energy saving optimization is not a cooperative one, but a competitive one. The high demand for energy saving optimization will inevitably reduce the ability to control the environment. When large changes occur and the necessary constraints are lacking, it is easy to generate errors that cannot be eliminated in the optimization, which leads to control dysfunction. This imbalance will have a negative impact on the greenhouse crop. Therefore, this paper proposes an improved objective function by adopting tolerance intervals. Equation 5 and Equation 6 are the MSE-based objective function and the improved objective function, and Figure 1 is the schematic diagram of the MSE-based objective function and the improved objective function:

$$\text{cost\_MSE} = (x - \text{ref})^2 \tag{5}$$

$$\text{cost\_imp} = \begin{cases} 1 + \log 10 \times \left(\text{ref} - x - b\right) & (x - \text{ref} < -\text{b}) \\ 10^{|x-\text{ref}|-b} & (-b \le x - \text{ref} \le \text{b}) \\ 1 + \log 10 \times \left(x - \text{ref} - b\right) & (b < x - \text{ref}) \end{cases} \tag{6}$$

where, $x$ is the current state, ref is the reference state of the target, $b$ is the tolerance provided, and the tolerance interval is [ref–$b$, ref+$b$]. From Figure 1, the graph of MSE shows a trend of concave in the middle, steep, and straight on both sides. The improved target function fluctuates less in the tolerance interval, and the trend of the image is flatter. However, when the error of $x$–ref exceeds the tolerance interval boundary, the value of the objective function increases rapidly. With the help of this function, the controller provides a low penalty tolerance during the evaluation process and provides control target in a fluctuation range. By this allowed fluctuation range, the maximum energy savings can be safely achieved. In the case of exceeding the tolerance interval, the penalty value will be increased rapidly to provide boundary constraints.




a. The MSE-based objective function

b. The improved objective function

Figure 1 The schematic diagram of the MSE-based objective function and the improved objective function

Considering the process of calculation, the gradient of the exponential function changed too fast, which could lead to problems in gradient calculation. In this study, the slope of two sides of the function maintains the value of the nearest tolerance boundary slope to ensure that the boundary of the target function grows steadily.

#### 2.2.2 The improved NMPC controller design

MPC, as a short-period rolling predictive control method, is divided into multi-step prediction, rolling optimization, and feedback correction[36]. Multi-step prediction uses a model to predict the short-term control trend. Feedback correction uses an objective function to assess the gap between the control trend and the target, then selects the optimal target for feedback control. Rolling optimization cycles the control process to maintain optimal control in a finite time domain. MPC does not rely on specific models but rather solves for future trend changes through multi-step iterations. So MPC is applicable to both mechanistic and data-driven models[36,37]. NMPC inherits the idea of MPC and improves the NMPC optimization solution method by transforming the linear derivative solution problem process into a nonlinear optimization problem. In this study, the optimal daytime environmental temperature was set between 24°C and 27°C to ensure optimal photosynthesis of crops. For nighttime, the optimal temperature was maintained between 14°C and 17°C to stabilize the green-house environment while minimizing crop respiratory consumption. Additionally, the humidity levels were kept within a stable range, with a reference relative humidity set between 64% and 70%. When the temperature exceeded or fell below these specified ranges, appropriate actions were taken. For instance, if the temperature exceeds the range, the ventilation system is activated to cool down the greenhouse. Conversely, if the temperature falls below the range, heaters and supplemental lighting are utilized. Similarly, if the humidity exceeds or falls below the specified range, the ventilation system is adjusted to restore the humidity to normal levels. Furthermore, in cases where there is a discrepancy between the model input and the reference model, it results in a state difference. This difference prompts feedback correction of the model. Figure 2 shows the basic principle of NMPC. The control targets are set by input in NMPC and the reference model is a continuous time control target for comparison of control states. When the control is launched, the controller inputs the state of the object as input to the control internally. The future trends are predicted by the predictive model and then the optimal control output solution is solved according to the objective function and nonlinear optimizer. Through continuous cycles, NMPC can achieve continuous control.

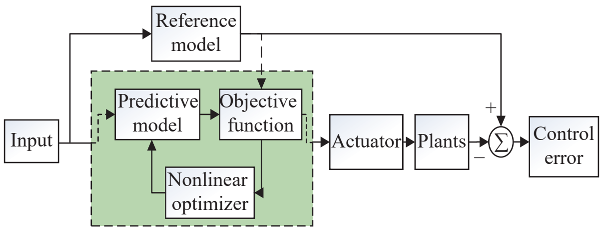


Figure 2 Basic schematic diagram of NMPC

For the greenhouse control, the greenhouse discrete state-space model is transformed from Equation (5).

$$x(k+1)=f_{\mathrm{GH}}(x(k),d(k),u(k))$$
$$\begin{cases}x(k)=\{T_{\mathrm{in}}(k),\mathrm{RH}_{\mathrm{in}}(k)\}\\ d(k)=\{I_{\mathrm{sun}}(k),T_{\mathrm{out}}(k),\mathrm{RH}_{\mathrm{out}}(k),V_{\mathrm{wind}}(k)\}\\ u(k)=\{P_{\mathrm{heater}}(k),P_{\mathrm{light}}(k),R_{\mathrm{venti}}(k)\}\\ x(k+1)=\{T_{\mathrm{in\_pred}}(k+1),\mathrm{RH}_{\mathrm{in\_pred}}(k+1)\}\end{cases} \tag{7}$$

where, $f_{\mathrm{GH}}$ is the WNN model expression at the moment $k$, the input $x(k)$ is the controlled objects, which include the indoor temperature $T_{\mathrm{in}}(k)$, °C, the indoor relative humidity $\mathrm{RH}_{\mathrm{in}}$, %, the disturbances $d(k)$ include the outdoor sunlight intensity $I_{\mathrm{sun}}(k)$, W/m², the outdoor temperature $T_{\mathrm{out}}(k)$, °C, the outdoor relative humidity $\mathrm{RH}_{\mathrm{out}}(k)$, %, the outdoor wind speed $V_{\mathrm{wind}}(k)$, m/s, the actuator input $u(k)$ include the output power of heater $P_{\mathrm{heater}}(k)$, W, the output power of light $P_{\mathrm{light}}(k)$, W, the ventilation rate $R_{\mathrm{venti}}(k)$, m/s, the outputs $x(k+1)$ are the predicted values at the moment $k+1$, which include the predicted indoor temperature $T_{\mathrm{in\text{-}pred}}(k+1)$, °C, and the relative humidity $\mathrm{RH}_{\mathrm{in\text{-}pred}}(k+1)$, %. This formula is used to evaluate the future state trend of greenhouse, combining with the objective function to judge the gap between the control objectives.

At moment $k$, the control output is $u$, the predicted time domain is $t_p$, the control time domain is $t_c$, and the reference model is ref. The NMPC model iteratively predicts the state output from moment $k+1$ to moment $k+t_c$. The functions are as follows:

$$\begin{cases}x(k+1)=f_{\mathrm{GH}}(x(k),d(k),u(k))\\ x(k+2)=f_{\mathrm{GH}}(x(k+1),d(k+1),u(k+1))\\ \dots\\ x(k+t_c+1)=f_{\mathrm{GH}}(x(k+t_c),d(k+t_c),u(k+t_c))\\ x(k+t_c+2)=f_{\mathrm{GH}}(x(k+t_c+1),d(k+t_c+1),u(k+t_c))\\ \dots\\ x(k+t_p)=f_{\mathrm{GH}}(x(k+t_p-1),d(k+t_p-1),u(k+t_c))\end{cases}$$
$$(1\le t_c\le t_p,\ \ t_c=1,2,3\dots,\ \ t_p=1,2,3\dots) \tag{8}$$

where, the input $u$ varies with the control period $x$ from $k$ to $(k+t_c)$; the input $u$ is maintained during the non-control period from $(k+t_c)$ to $(k+t_p)$. Then the prediction results of the model and the reference model are substituted into the objective function for comparison to evaluate the results. The objective function $J_1$ is shown as follows:

$$J_1=\lambda_1\sum_{j=1}^{t_p}\mathrm{cost\_imp}(x(k+j),w(k+j),b)+\lambda_2\sum_{i=1}^{t_p}\left[\eta u(k+j)\right]+$$
$$\lambda_3\sum_{i=2}^{t_p}\left[u(k+j)-\left[u(k+j-1)\right]\right]^2$$
$$\text{s.t.}\begin{cases}w(j)=\alpha_k x(j)+(1-\alpha_k)ref\\ u_{\min}\le u(j)\le u_{\max}\\ x_{\min}\le x(j)\le x_{\max}\\ 0<\alpha^j<1\\ j,k=1,2,\dots,t_p\end{cases} \tag{9}$$

where, $J_1$ denotes the discrepancy between the control expectation and the control objective at control period from $k$ to $k+t_p$, which is obtained from the improved objective function *cost-imp*, $b$ is the tolerance of the objective function; $w(j)$ is the softened output of the reference model, $\alpha^j$ is the softening factor. The control results are smoothed by softening process to reduce the effects of overshoot and oscillation; $\lambda_1$, $\lambda_2$ and $\lambda_3$ are the weight of the control object, the cumulative energy consumption and the change rate of the control output respectively; $\eta$ is the energy consumption coefficient. For the tuning of the weight of the control object, NSAG-II and manual experience methods were adopted for parameter setting. The method used NSGA2 to initially screen individuals with optimal weights in different directions, and then screened and adjusted to obtain the optimal weights with manual experience. The objective function is used for the evaluation of the gap between the greenhouse state and the target point. By introducing the improved objective function in the study, the objective is converted to an interval range. The optimal output of the control can be solved by a solver.

Unlike MPC[38], NMPC transforms control problems into optimization problems and applies global optimization methods to solve min($J_1$). Commonly used methods include: Derivative free optimization algorithms (genetic algorithm, ant colony algorithm, etc.); active set strategies (successive quadratic programming, etc.); and barrier methods with exact Hessians (the interior point method based on the barrier method, etc.)[37]. Considering the speed of the control reaction, this study adopts the interior point method based on the barrier method and implements the function of fmincon to optimize the objective function in Matlab.

### 2.3 Controllers design of the contrast groups

#### 2.3.1 The MPC controller design

The MPC and the NMPC are mostly the same in terms of control principles, the difference being in the control model and solver algorithm[13,37,39]. The MPC model expressions are as follows:

$$\begin{cases}\dot{x}=Ax+Bu\\ y=x\end{cases} \tag{10}$$

$$x(k+1)=f_{\mathrm{GH2}}(x(k),u(k)) \tag{11}$$

where, the model state equation is linearized by the model of Equation 1. $A$, $B$ is the parameters after linearization; $x$ is the state parameters including the predicted indoor temperature $T_{\mathrm{in\text{-}pred}}(k+1)$, °C and relative humidity $\mathrm{RH}_{\mathrm{in\text{-}pred}}(k+1)$, %; $u$ is the output parameters including the output power of heater $P_{\mathrm{heater}}(k)$, W, the output power of light $P_{\mathrm{light}}(k)$, W and the ventilation rate $R_{\mathrm{venti}}(k)$, m/s. And the discrete state-space model is as Equation 10. Multi-step model prediction can be easily implemented with the help of discrete state-space model:

$$
\begin{cases}
x(k+1) = f_{\mathrm{GH2}}(x(k), d(k), u(k)) \\
x(k+2) = f_{\mathrm{GH2}}(x(k+1), d(k+1), u(k+1)) \\
\dots \\
x(k+t_c+1) = f_{\mathrm{GH2}}(x(k+t_c), d(k+t_c), u(k+t_c)) \\
x(k+t_c+2) = f_{\mathrm{GH2}}(x(k+t_c+1), d(k+t_c+1), u(k+t_c)) \\
\dots \\
x(k+t_p) = f_{\mathrm{GH2}}(x(k+t_p-1), d(k+t_p-1), u(k+t_c))
\end{cases}
$$
$$
(1 \le t_c \le t_p,\ \ t_c = 1,2,3\dots,\ \ t_p = 1,2,3\dots) \tag{12}
$$

where, the input $u$ varies with the control period $x$ from $k$ to $(k+t_c)$; the input $u$ is maintained during the non-control period from $(k+t_c)$ to $(k+t_p)$. Calculate the distance between the state and the target from the objective function based on the prediction results. The objective function $J_2$ is shown as follows:

$$
J_2 = \lambda_1' \sum_{j=1}^{t_p} \mathrm{cost\_mse}(\mathrm{x(k+j), w(k+j)}) + \lambda_2' \sum_{i=1}^{t_p} \left[\eta u(k+j)\right] + \lambda_3' \sum_{i=2}^{t_p} \left[u(k+j) - \left[u(k+j-1)\right]\right]^2
$$
$$
\text{s.t.} \begin{cases}
w(j) = \alpha_k x(j) + (1-\alpha_k)\,\mathrm{ref} \\
u_{\min} \le u(j) \le u_{\max} \\
x_{\min} \le x(j) \le x_{\max} \\
0 < \alpha^j < 1 \\
j,k = 1,2,\dots,t_p
\end{cases} \tag{13}
$$

where, the objective function is based on the MSE method and MPC is for the target control. $w(j)$ is the softened output of the reference model, $\alpha^j$ is the softening factor. The control results are smoothed by softening process to reduce the effects of overshoot and oscillation; $\lambda_1'$, $\lambda_2'$, and $\lambda_3'$, are the weight of the control object, the cumulative energy consumption and the change rate of the control output respectively; $\eta$ is the energy consumption coefficient.

Then solve min($J_2$) for the optimal solution which uses SQP linear optimization in Matlab to obtain the control output. When the control output completes an MPC control, the cycle of controller control continues at the next moment $k$+1.

2.3.2 The NMPC controller design

The control process of NMPC is the same as that of the improved NMPC, the only difference lying in the application of the MSE-based objective function:

$$
J_3 = \lambda_1'' \sum_{j=1}^{t_p} cost\_mse(x(k+j), w(k+j)) + \lambda_2'' \sum_{i=1}^{t_p} \left[\eta u(k+j)\right] + \lambda_3'' \sum_{i=2}^{t_p} \left[u(k+j) - \left[u(k+j-1)\right]\right]^2
$$
$$
\text{s.t.} \begin{cases}
w(j) = \alpha_k x(j) + (1-\alpha_k)\,ref \\
u_{\min} \le u(j) \le u_{\max} \\
x_{\min} \le x(j) \le x_{\max} \\
0 < \alpha^j < 1 \\
j,k = 1,2,\dots,t_p
\end{cases} \tag{14}
$$

where, $w(j)$ is the softened output of the reference model, $\alpha^j$ is the softening factor. The control results are smoothed by softening process to reduce the effects of overshoot and oscillation; $\lambda_1''$, $\lambda_2''$ and $\lambda_3''$ are the weight of the control object, the cumulative energy consumption and the change rate of the control output respectively; $\eta$ is the energy consumption coefficient.

## 3 Results and discussion

The simulations were based on Matlab R2020a. The data utilized in this study was collected from the greenhouse situated at the Wageningen Research Centre in Bleiswijk (The Netherlands), spanning over a 6-month period of tomato cultivation (winter, spring, and summer). This dataset comprises details regarding both outdoor and indoor greenhouse climates, irrigation, actuator statuses, requested and implemented climate setpoints, resource consumption, harvests, crop-related parameters, tomato quality, analyses of irrigation and drainage samples, as well as root zone/board information. With a total of 47 809 records, the dataset is extensive and diverse, encompassing various facets of greenhouse environmental control. The sampling time was set to 3 d, 72 h in total; the minimum sampling interval was set to 5 min; the control interval was set to 5 min; the optimal reference temperature of daytime environment was set to 24°C-27°C to ensure photosynthesis of crops; and the optimal nighttime temperature was set at 14°C-17°C to maintain a stable greenhouse environment and reduce crop respiration. The humidity of the greenhouse was kept in a stable range, and the reference relative humidity was set at 64%-70%. The internal structure of the greenhouse is depicted in Figure 3. Temperature and humidity sensors are positioned at nodes 1-6 and nodes 10-12, respectively. Light radiation sensors are placed at nodes 7-9. The temperature and humidity sensors are of the SIN-TH800 model, with a humidity measurement accuracy of ±3% RH and a temperature measurement accuracy of ±0.3°C. The light radiation sensor model is BRW100-2015A (Firstrate, China), with a resolution of 1 W/m$^2$ and a measurement range of 0-2000 W/m$^2$. The sampling period for all sensors is set to 5 min.

The model predictive process is an important part of the MPC, which uses models to predict future trends. Firstly, the continuous iteration prediction ability of the model was compared under the same conditions. Contrast groups were established to compare with the back propagation neural networks (BPNN) model, radial basis function (RBF) model and WNN model. In terms of model structure, BPNN, and WNN were set to the 8-16-2 structures, which include a single hidden layer with 12 nodes. The RBF structure was trained with the newrbe function in Matlab, and the parameter spread was set to 100. The root mean square error (RMSE), mean absolute error (MAE) and $R^2$ of the predicted results are as follows. For model performance metrics, smaller values of Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) indicate better performance, whereas higher values of R-squared ($R^2$) closer to one indicate a better fit of the model to the data.

From Figure 4a and 4c and Table 1, the WNN, BPNN, and RBF models had good performances in the prediction of indoor temperature, where WNN had the most minor errors and stable prediction with MSE of 0.083, MAE of 0.067, and R2 of 0.999. For indoor relative humidity prediction, RBF had a significant drop in prediction performance for long-term prediction, while WNN and BP performed well. WNN still had the best performance with MSE of 0.826, MAE of 0.739, and $R^2$ of 0.943.

It is observed from Figure 4b and 4d that the increase in iterations made the prediction errors cumulatively. The errors in the actual greenhouse prediction process were also unavoidable. Therefore, better models or shorter prediction steps were selected as needed to ensure controllable errors in the prediction and control sessions.

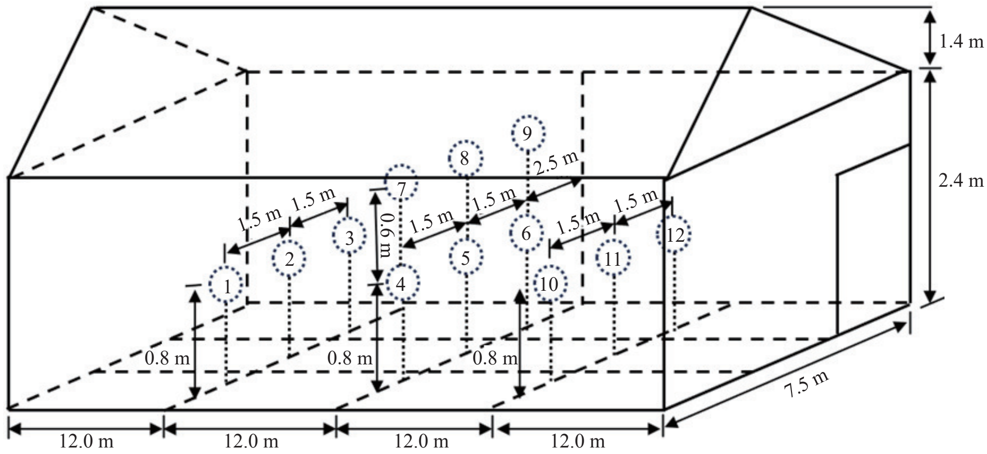
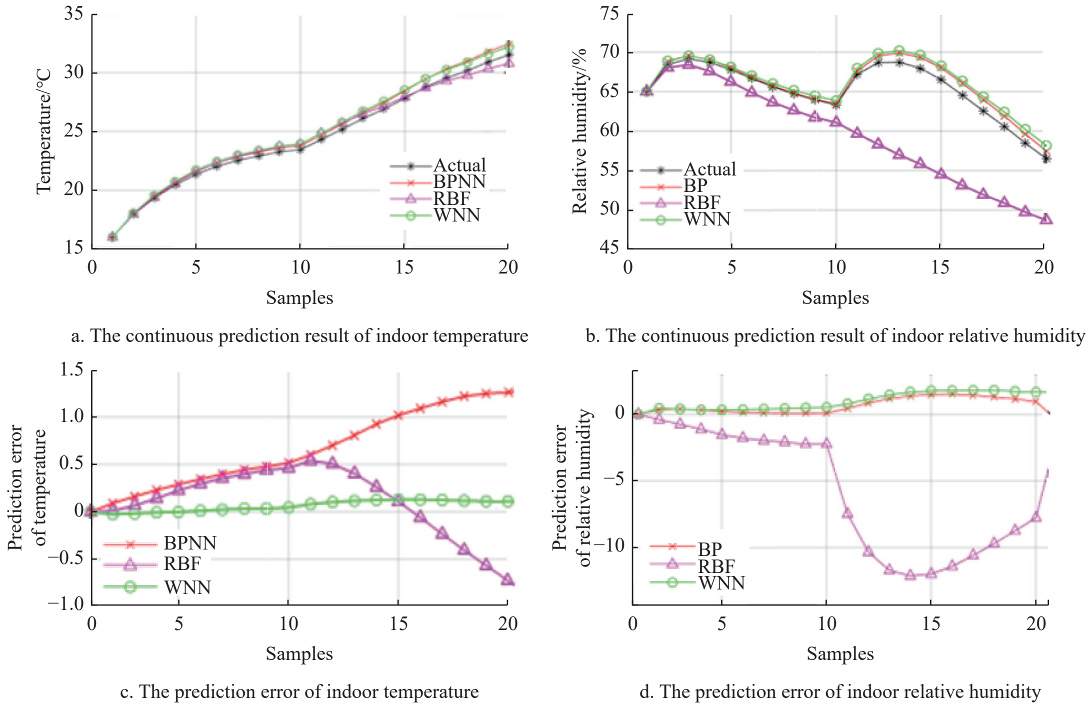



Figure 3 The distribution map of sensors in greenhouse




a. The continuous prediction result of indoor temperature

b. The continuous prediction result of indoor relative humidity

c. The prediction error of indoor temperature

d. The prediction error of indoor relative humidity

Figure 4 Prediction performance results of different models

**Table 1 Prediction performance results of different models**

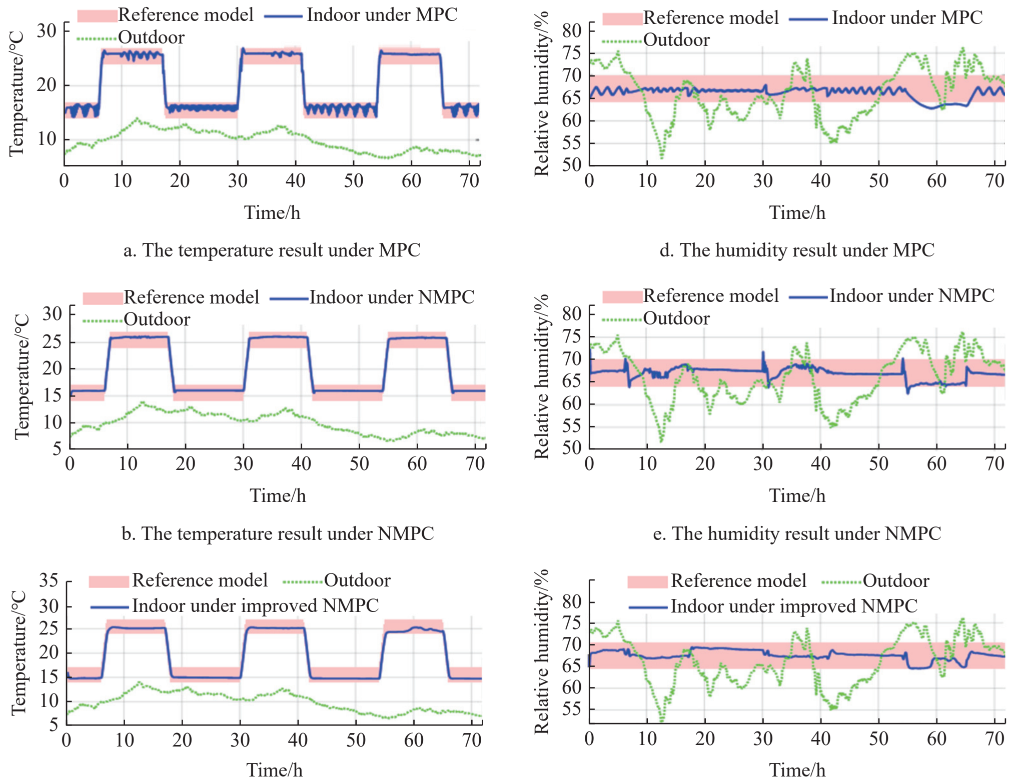
| Model | Temperature prediction results | | | Relative humidity prediction results | | |
|---|---|---|---|---|---|---|
| | RMSE | MAE | $R^2$ | RMSE | MAE | $R^2$ |
| BPNN | 0.765 | 0.649 | 0.968 | 0.947 | 0.885 | 0.925 |
| RBF | 0.368 | 0.310 | 0.993 | 7.367 | 5.787 | –3.567 |
| WNN | 0.083 | 0.067 | 0.999 | 0.826 | 0.739 | 0.943 |

The simulations compared the environmental regulation ability and energy consumption. Common MPC and common NMPC were set up to compare with the improved NMPC. The model of greenhouse adopted the WNN model mentioned above. In the prediction process, the prediction step was set to 5, the control step was set to 2, and the step was consistent with the data sampling period of 5 min. The initial indoor environment of the greenhouse was set at 15°C, and the indoor relative humidity was 65%. The weather data were from the actual measurement, the outdoor temperature range was 6°C-14°C, and the outdoor relative humidity range was 50%-80%. The control results are shown in Figure 4, and the RMSE and $R^2$ results are listed in Table 2. RMSE reflects the error distribution between the control results and the optimal reference model; MAE reflects the average error between the control results and the optimal reference model.

**Table 2 Greenhouse environmental control performance**

| Controller | Temperature results | | Humidity results | |
|---|---|---|---|---|
| | RMSE | MAE | RMSE | MAE |
| MPC | 0.620 | 0.389 | 0.623 | 2.019 |
| NMPC | 0.281 | 0.138 | 0.372 | 1.602 |
| Improved NMPC | 1.195 | 1.125 | 1.060 | 1.256 |

From Figure 5 and 6 and Table 2, it is seen that MPC control results had more significant temperature fluctuations, especially at low temperatures at night. The temperature control performance of NMPC is better than MPC with RMSE of 0.281 and MAE of 0.138. NMPC shows more stable temperature control performance both daytime and nighttime. Due to the tolerance intervals, the improved NMPC kept the greenhouse environment within the low-temperature range according to the energy saving and temperature requirements, so the RMSE and MAE are poor at 1.195 and 1.125, respectively.




a. The temperature result under MPC

d. The humidity result under MPC

b. The temperature result under NMPC

e. The humidity result under NMPC

c. The temperature result under the improved NMPC

f. The humidity result under the improved NMPC

Figure 5 Greenhouse temperature and humidity control results

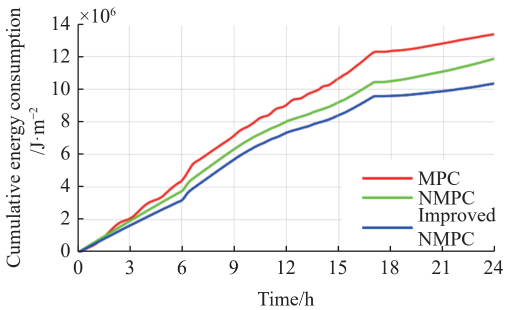



Figure 6 Continuous time comparison of total energy consumption

For humidity control, the MPC had small but frequent fluctuations, and suffered from low humidity problems as the ambient temperature decreased. The NMPC fluctuated less frequently but the control error increased. The fluctuation of NMPC control results was lower, and humidity stayed within the required interval most of the time, but sudden changes in humidity occurred during the period of alternation of daytime and nighttime. The common NMPC was more prone to short-term overshoot when it was affected by rapid environmental changes. The improved NMPC benefited from the high penalty of the improved objective function on the boundary constraint, which better overcame the problem of sudden changes and made the results fully satisfy the requirements of the greenhouse.

As shown in Figure 6 and Figure 7, due to the improvement of the controller itself for nonlinear control, NMPC effectively reduced temperature and humidity fluctuations and brought lower energy consumption. Compared with MPC, the daytime consumption was reduced by 10.06%, and the nighttime consumption was reduced by 23.11%. For the period of alternating daytime and nighttime, the energy consumption increased by 8.33%. During the period, energy consumption increased due to the overshoot of controllers. However, this period was short and the energy consumption did not have a significant impact on the total energy consumption. Improved NMPC relied on the range requirements of the crop to control the greenhouse actuators to reduce energy consumption by reducing the expectation of control. These control losses were still within the crop growth requirements and were acceptable. Compared to the NMPC, the daytime consumption of improved NMPC was reduced by 3.97%; the nighttime consumption was reduced by 16.65%; and the period of alternating daytime and nighttime was reduced by 4.74%. The cumulative energy consumption of improved NMPC was 21.02% lower than MPC and 9.54% lower than NMPC.

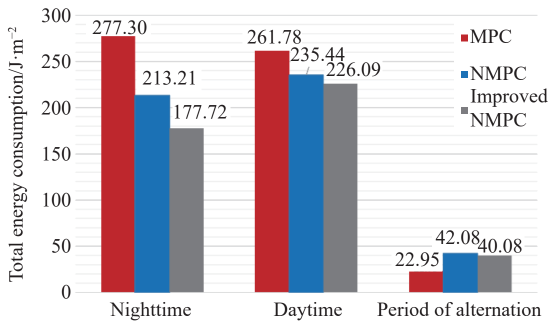



Figure 7 Comparison of NMPC energy consumption of different models at different periods

Detailed analyses were conducted regarding the influence of different greenhouse structures, testing data point locations, and various positions within the greenhouse on the test results. Variations in environmental control, such as temperature distribution and humidity maintenance, exist among different greenhouse structures (e.g., connected and standalone greenhouses). Our study focuses on a Venlo-type greenhouse, known for its widespread use and superior performance, ensuring the representativeness and generalizability of our findings. Despite potential variations in specific environmental parameters, the NMPC method, incorporating tolerance intervals and boundary constraints, can effectively adapt to such changes and ensure control effectiveness. Environmental parameters (e.g., temperature, humidity, light) may vary across different locations within the greenhouse. To account for these differences, multiple sensor nodes were installed at various heights and orientations, facilitating comprehensive environmental data collection. For instance, nodes 1-6 and 10-12 measure temperature and humidity, while nodes 7-9 measure light radiation. This multi-point approach enhances the accuracy and robustness of our model. Variations in environmental parameters within the greenhouse primarily relate to light exposure, ventilation, and temperature gradients. Positions near ventilation openings and heaters may experience greater temperature fluctuations compared to those farther away. Through multi-point data collection and the introduction of tolerance intervals, this method effectively balances data differences across various positions, ensuring overall control effectiveness. In summary, while different greenhouse structures, testing data point locations, and positions within the greenhouse may impact specific environmental parameters, the improved objective function NMPC method can adeptly adapt to these variations, resulting in reduced energy consumption and enhanced control accuracy. These simulation results affirm the method's efficacy across diverse environments.

## 4 Conclusions

In this study, a nonlinear model predictive control method of greenhouse temperature and humidity based on improved objective function was proposed for greenhouse environmental control and energy optimization in autumn and winter. Firstly, a wavelet neural network data-driven model was developed for the multi-step prediction process of NMPC. Secondly, an improved tolerance interval-based objective function was proposed to evaluate the state of the control process. Thirdly, the model was combined with the improved objective function to design an NMPC controller based on the improved objective function for greenhouse temperature and humidity control and energy-saving optimization. Finally, the simulation compared the performance of multiple models and controllers.

Comparing the prediction performance of models, WNN had the highest prediction accuracy in the first ten times with an RMSE of 0.083 for temperature prediction and 0.826 for humidity prediction. Simulation results for the controller show that the improved NMPC further reduced energy consumption significantly and improved the problems caused by control overshoot while maintaining the control requirements. The cumulative energy consumption of the improved NMPC was reduced by 21.02% compared to MPC and 9.54% compared to NMPC. The results show that the improved NMPC effectively meets the greenhouse control requirements and achieves the best balance of greenhouse control and energy consumption.

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