

## Multiobjective distributed model predictive control method for facility environment control based on cooperative game theory

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Received: 10.11.2016

Accepted/Published Online: 13.06.2017

Final Version: 05.10.2017

**Abstract:** In order to achieve better control performance within the facility environment, this paper proposes a distributed model predictive control method, aiming at increasing the control precision of actuators, reducing energy consumption and equipment loss at the same time. Regarding optimizing this facility environment model, it could be treated as a multiobjective optimization problem. Referring to the cooperative game theory, each objective is regarded as a gamer. Each gamer considers both its own interests and other gamers' interests to achieve a balanced result when cooperation is achieved. The simulation experiments illustrate that the proposed control method is able to adjust the parameters of the facility environment to a preset interval properly. Moreover, in this specific simulation environment, the proposed method achieves better performances than the single objective control method and traditional linear weighted multiobjective control method in most of the evaluation criteria.

**Key words:** Facility environment, multiobjective control, distributed model predictive control, cooperative game

### 1. Introduction

Facility agriculture is an important component of modern agriculture with merits of high efficiency and intensity and low-carbon emission reduction. Moreover, it is the main method for countries to produce fresh agricultural products [1]. One of the key technologies for facility agriculture is automatic and intelligent facility environment control. Model predictive control (MPC) has the advantages of good performance in precision control, strong robustness, and low requirement for precision of the model. At present, MPC has been used to control the facility based on prediction of greenhouse environment [2].

Traditional greenhouse control methods only consider a single objective, which stabilizes some parameters of the facility, such as temperature, humidity, and light intensity, at expected values. However, other objectives, such as energy consumption and physical limitations of equipment, are not considered, which causes serious problems in real-world applications. Therefore, it is important to emphasize comprehensive objects in facility environment control. Nowadays, multiobjective control has drawn much attention due to the motivation to increase crop yields and obtain high economic benefits simultaneously [3].

During the control process, in order to solve multiobjective optimization problems, game theory is introduced. It studies the profits of all players after interaction with each other and aims at obtaining equilibrium results. Cooperative game theory, as an important branch of game theory, is currently used to solve many

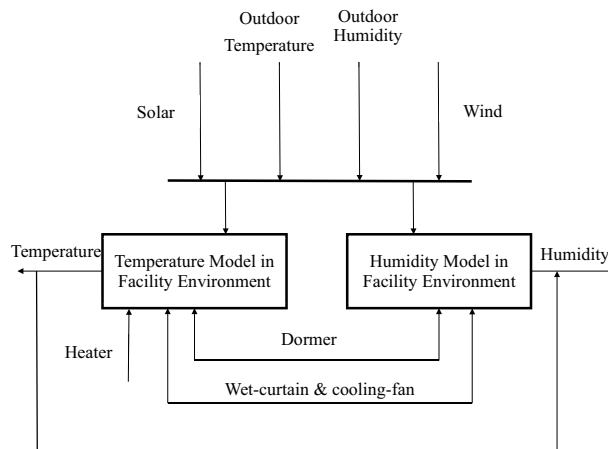
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problems in economics, social science, and biology; furthermore, this theory is quite applicable in the field of industrial control. For example, Hernandez et al. introduce game theory to multirobot task assignment system [4]. One of the main contributions of Erik’s work is the development of new dynamic and decentralized collaborative approaches in order to solve the aforementioned problem by using weight allocation solution. Meanwhile, Shams et al. carried out research about a cooperative network with multiple wireless transmitters, and proposed an energy-efficient power control method [5]. In order to reduce energy consumption, a Nash bargaining solution is used to allocate energy to each activated launcher and reduces great energy consumption during the control period. Overall, it is feasible to apply a cooperative model to the MPC method in order to solve the problem of multiobjective control in facility environment management.

This paper firstly sets up a greenhouse model and transfers facility environment control into a three-objective control problem. Then a distributed model predictive control (DMPC) method is proposed, which divides the whole system into several subsystems according to different control objectives. Each subsystem not only considers its own objective, but also takes objectives of other subsystems into account through the solution design of a cooperative game. Two solutions based on cooperative game theory in this paper, i.e. weight allocation solution and Nash bargaining solution, are proposed to make the whole system achieve better performance. Finally, the validity and feasibility of proposed multiobjective control methods for facility environment are verified by simulation experiments.

**2. Construction of a temperature-and-humidity model for facility environment**

In order to study how to control the facility environment, firstly a facility environment model with certain inputs and outputs should be built [6]. The model treats temperature and humidity as control objectives, because these two environment parameters have great influence on the growth of crops. In addition, a heater, wet-curtain and cooling fan, and dormer are equipped to adjust these two parameters. The structure of the temperature-and-humidity model is shown as Figure 1.



**Figure 1.** Temperature-and-humidity model in facility environment.

The temperature and humidity of the facility environment are comprehensively decided by several elements, which are shown in Figure 1. Equations and configurations of the temperature-and-humidity model are given in [7].

### 3. Multiobjective model predictive control method based on cooperative game theory

#### 3.1. Multiple control objectives of facility environment

In this paper, three control objectives are established simultaneously: high precision control, low energy consumption, and low equipment loss.

High precision control guarantees a suitable environment for the growth of crops. Therefore, economic benefits are increased. The precision control objective  $f_1$  can be described as follows:

$$f_1 = \min \left[ \sum_{j=1}^P (\dot{T}(k+j|k) - T_{set})^2 + \sum_{j=1}^P (\dot{H}(k+j|k) - H_{set})^2 \right] \quad (1)$$

In Eq. (1),  $P$  represents prediction horizon, and  $T_{set}$  and  $H_{set}$  represent the most suitable temperature and humidity, respectively.  $\dot{T}(k+j|k)$  and  $\dot{H}(k+j|k)$  respectively represent the predicted temperature and humidity at future time  $k+j$ , and are calculated based on the known environment parameters at current time  $k$ . The temperature and humidity of the facility environment are expected to reach the preset values and so the values of the precision control objective  $f_1$  should be small.

Low energy consumption can further increase the economic benefits of crop production. The control system of the facility environment should also strike a balance between crop production and energy consumption. According to the temperature-and-humidity model, the inputs of control equipment are power of heater, number of activated wet-curtain and cooling-fans, and opening angle of the dormer. After normalizing the above control inputs, the low energy consumption objective  $f_2$  can be described as follows:

$$f_2 = \min \left[ \frac{K_1 \times energy_1}{100 \times M} + \frac{K_2 \times energy_2}{100 \times M} + \frac{K_3 \times energy_3}{100 \times M} \right] \quad (2)$$

$$energy_1 = \sum_{j=0}^{M-1} (u_1(k+j|k)/u_{1\_max}) \times 100 \quad (3)$$

$$energy_2 = \sum_{j=0}^{M-1} (u_2(k+j|k)/u_{2\_max}) \times 100 \quad (4)$$

$$energy_3 = \sum_{j=0}^{M-1} \frac{ABS(u_3(k+j+1|k) - u_3(k+j|k))}{u_{3\_max}} \times 100 \quad (5)$$

In the above equations,  $M$  represents control horizon.  $K_1$ ,  $K_2$ , and  $K_3$  represent the weight of each control input ( $u_1$ ,  $u_2$ , and  $u_3$ ), respectively. The parameters of  $u_{1\_max}$ ,  $u_{2\_max}$ , and  $u_{3\_max}$  represent the maximum value of  $u_1$ ,  $u_2$ , and  $u_3$ , respectively. The parameter of  $u_i(k+j|k)$ ,  $i = 1, 2, 3$  represents the optimal control quantity at future time  $k+j$ . In addition, energy consumption of the opening dormer is determined by changes of angle. Regardless of whether the dormer is turned on or off, it always consumes energy.

Lastly, this paper takes the problem of equipment loss into consideration, which can be seen in [8]. In order to reduce equipment loss, activating control equipment frequently should be avoided. The low equipment loss objective  $f_3$  is as follows:

$$f_3 = \min \sum_{i=1}^3 (u_i(k+j+1|k) - u_i(k+j|k))/u_{i\_max} \quad (6)$$

As is mentioned above, three objectives are defined by mathematical equations and the weight of each objective in the multiobjective optimization model is one third respectively at the beginning. To solve the multiobjective optimization problem is to compute all or a set of Pareto optimal solutions to make the control decision.

### 3.2. Description of distributed model predictive control system

There are many problems in the fields of multiobjective control, such as nonlinear prediction model, limitation and complexity of optimal objective, and high requirement for computing ability.

To solve these problems, the DMPC method is introduced in [9]. According to the principle of DMPC, a complicated system is divided into several subsystems. Then global objective functions are assigned to each subsystem for local optimization. After optimizing the partial objective function, subsystems communicate with each other in order to solve the multiobjective control problem cooperatively. In this paper, the multiobjective control system is treated as the complete system and it is divided into three subsystems according to control objectives. The details are presented in Figure 2.

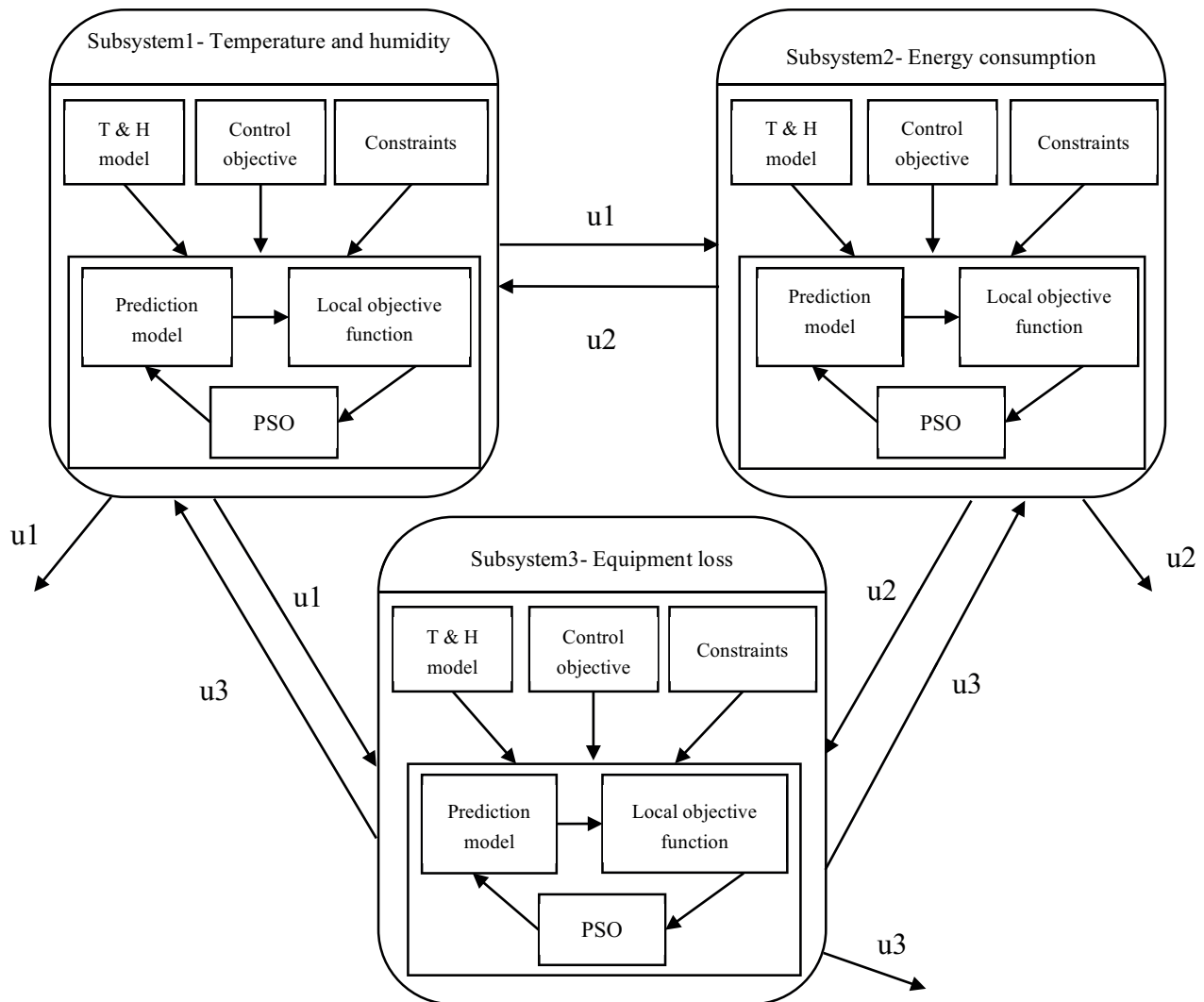


Figure 2. Framework of DMPC in facility environment.

According to Figure 2, each subsystem needs to compute optimal control inputs of  $u_1$ ,  $u_2$ , and  $u_3$  respectively on the basis of the coupling between the control objectives and three subsystems. How to solve this problem will be explained in the following sections.

### 3.3. Multiobjective optimal method based on cooperative game theory

Game theory, as a solution to resolve conflicts between multiple objectives, is the study of mathematical models of conflict and cooperation between intelligent rational decision-makers. Two types of game are defined in game theory: a cooperative game and a noncooperative game. A noncooperative game only pays attention to optimal strategies for rational individuals without reaching agreements. In contrast, a cooperative game is on the basis of collective rationality and each gamer is willing to obey a negotiated agreement. Although the ultimate result may not benefit an individual the most, it is the most suitable solution for the whole system [10].

This paper considers a weight allocation solution and Nash bargaining solution respectively in the following simulation experiment.

### 3.4. The solution to multiobjective DMPC

In the distributed model predictive control, the optimization result of each subsystem is partly decided by the control values of other subsystems. However, it is impossible for a subsystem to know others' optimal control values in advance. Fortunately, each subsystem can communicate with others in the DMPC framework. Therefore, a repetitive iteration method is introduced in solving multiobjective DMPC. The detailed steps of the solution are as follows:

(1) Subsystems are treated as gamers and have their own optimization objectives. At the beginning, each gamer  $i$  initializes its own control sequence randomly, which is described as  $[u_{i,0}(0|0), u_{i,0}(1|0), \dots, u_{i,0}(M-1|0)]$ ,  $i = 1, 2, \dots, m$ , and  $M$  represents control horizon and  $m$  represents the number of gamers.

(2) Each gamer  $i$  sends its control sequence at time  $k$  to other gamers several times, which is described as  $[u_{i,q}(k|k), u_{i,q}(k+1|k), \dots, u_{i,q}(k+M-1|k)]$ , and  $q$  represents the number of sending control sequences.

(3) In order to solve the optimal control sequence in current time, each gamer will optimize its own objective function based on received control sequences from others. The optimal control sequence is described as  $[u_{i,q}^*(k|k), u_{i,q}^*(k+1|k), \dots, u_{i,q}^*(k+M-1|k)]$ .

(4) Each gamer will stop sending its control sequence when  $q$  equals the limit  $q_{max}$  or  $\|u_{i,q}^* - u_{i,q-1}^*\| < \varepsilon$  is satisfied, and the first control value  $u_{i,q}^*(k|k)$  will be operated by the gamer  $i$ . If the above conditions are not met, the process will return to Step (2).

Then the next round of rolling optimization will restart from Step (1). The initial control sequence of each gamer at time  $k+1$  will be set as its optimal control values at time  $k$ , that is  $[u_{i,q}^*(k|k), u_{i,q}^*(k+1|k), \dots, u_{i,q}^*(k+M-1|k)]$ .

In this paper, two solutions to distributed DMPC is introduced, which are Nash bargaining solution and weight allocation solution. The main idea of the Nash bargaining solution is that each gamer tries to get away from its worst interest [11]. Regarding the weight allocation control method, the main idea is that each gamer allocates weights to absolute interest and relative interest [12].

#### 4. Simulation experiment

##### 4.1. Experimental environment

The experiment is carried out in a greenhouse in Yuting modern agriculture industrial park in Suzhou, China. It is a four-arch plastic greenhouse, built of lightweight steel. The span of each arch is 8 m, the shoulder height is 3 m, the top height is 5 m, and the length is 44 m. The simulation parameters of the facility environment model are identified by particle swarm optimization (PSO), based on historical environment data [13]. The identified parameters are shown in Table 1.

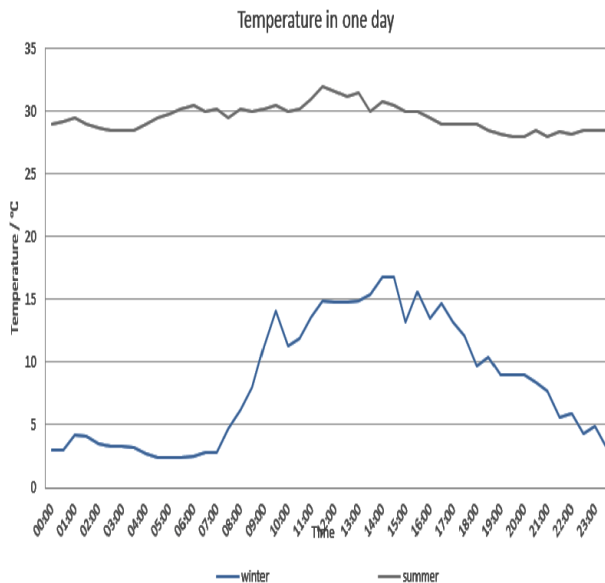
**Table 1.** Results of model parameter identification.

$\tau$	$C_d$	$C_w$	$h_c (W \cdot m^{-2} \cdot K^{-1})$	$C_p (J \cdot Kg^{-1} \cdot K^{-1})$
0.89	0.644	0.09	12.25	1005

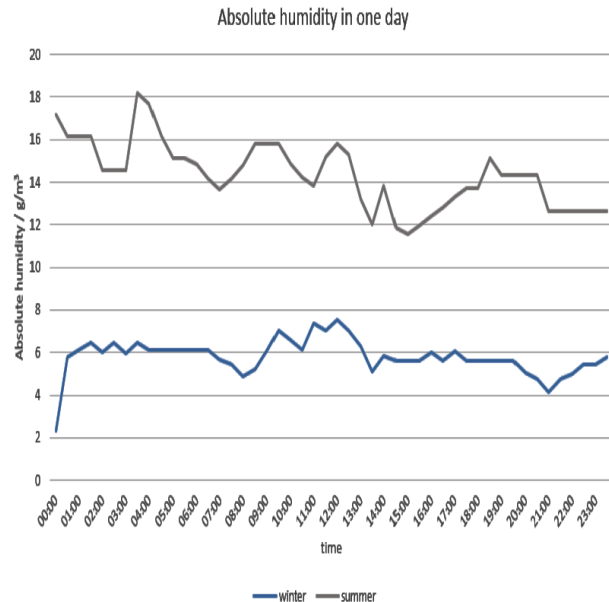
Note:  $\tau$  is the solar radiation transmittance.  $C_d$  is flow coefficient of natural ventilation.  $C_w$  is wind pressure coefficient of natural ventilation.  $h_c$  is heat exchange coefficient between indoor and outdoor.  $C_p$  is air specific heat.

After identifying the parameters of the facility environment model, this study performs several simulation experiments of controlling temperature and humidity in the greenhouse under different outside meteorological data. The involved environmental parameters in the experiments are collected as follows. In the MPC method, the prediction horizon is 5 and the control horizon is 2. Meanwhile, in the PSO algorithm, the number of particles is 50, learning factors ( $c_1$  and  $c_2$ ) are both 1.4962, weight factor ( $w$ ) is 0.7298, and the number of iterations is 100.

This paper performs experiments in 2 days in 2015 (4 February and 16 July), which are one day in winter and summer, respectively. The details of the outside meteorological environment in the experiments are shown in Figure 3–6, which are measured every 30 min by the automatic weather station Watchdog 2900ET. The initial temperature and humidity of the facility environment are set according to actual measurement values. The control objectives of the facility environment are as follows: the indoor temperature reaches 27 °C and the indoor absolute humidity reaches 18.1 g/m<sup>3</sup>, which means relative humidity reaches 80%.



**Figure 3.** Temperature in different seasons.



**Figure 4.** Absolute humidity in different seasons.

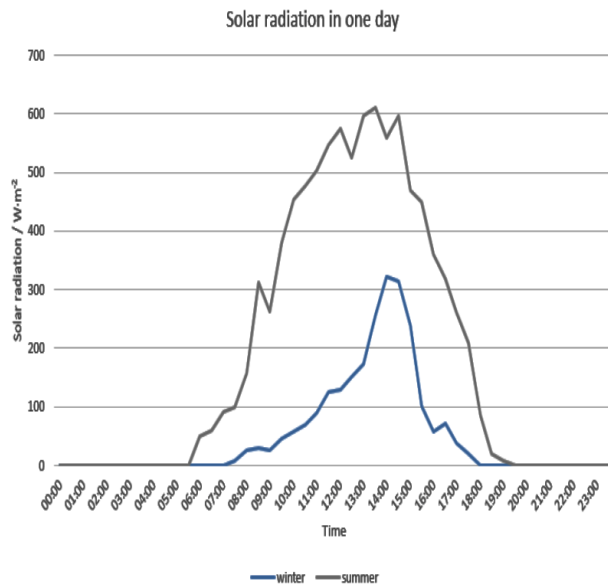


Figure 5. Solar radiation in different seasons.

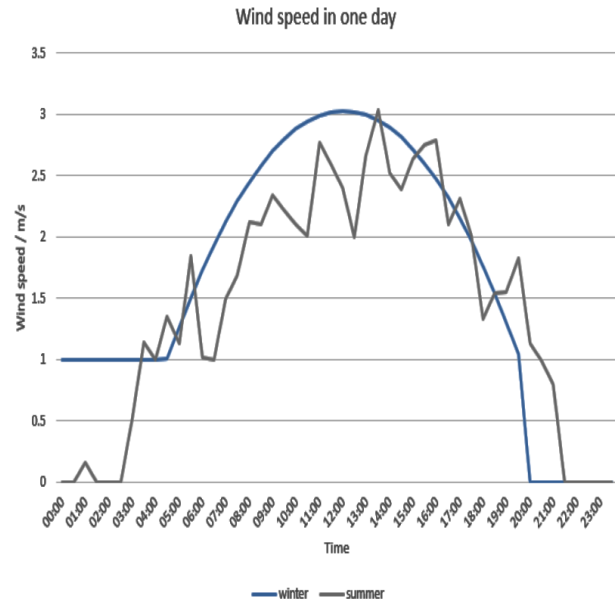


Figure 6. Wind speed in different seasons.

Under the measured experimental environments, this study firstly simulates and analyzes the effectiveness and rationality of the multiobjective DMPC method. Then this study compares the proposed method with a single objective control method and traditional linear weighted control method to verify the validity of the proposed method.

In the single objective control method, it only concerns the objective of precision control, which means that the weights for  $f_2$  and  $f_3$  are both 0. Regarding the linear weighted control method, it can be seen in [14].

## 4.2. Simulation results and analysis

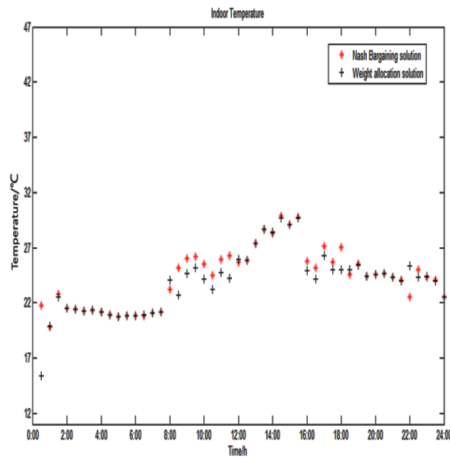
### 4.2.1. Control effect on the facility environment in winter and summer

Figure 7 shows the control effect on the facility environment in one day in 2015 in winter, including the changes in temperature, humidity, and the control inputs. The red points and lines represent the Nash bargaining solution, while the black points and lines represent the weight allocation solution. From Figures 7a–7e, it is concluded that the control effects and control inputs of both solutions are similar and there are only a few distinctions existing. Therefore, this paper analyzes the rationality of two solutions.

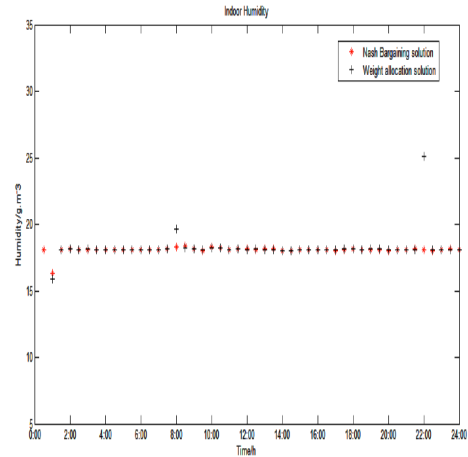
As shown in Figure 7a, the temperature values are floating around the preset value, instead of following the default value all the time during the period from 0930 to 1630. This suggests that the proposed solutions aim at reducing the frequency of activating the equipment and achieving a balance between precise control and energy loss during the control process. In addition, the temperature values are quite low during 0030 to 0800, because the heater equipment is restricted by power limitation. Figure 7c shows that the heater equipment is working at full power and the wet-curtain and cooling-fan equipment is almost turned off. As shown in Figure 7b, the humidity in the facility environment is maintained around the preset level.

Figures 7d and 7e show that the wet-curtain and cooling-fan equipment is not activated all the time and the opening angle of the dormer equipment is less than 10 degrees. According to the above analysis, the implementation of the proposed control solutions in this paper conforms to the control experiences of practical equipment. Thus, the DMPC method based on a cooperative game is effective and reasonable in winter.

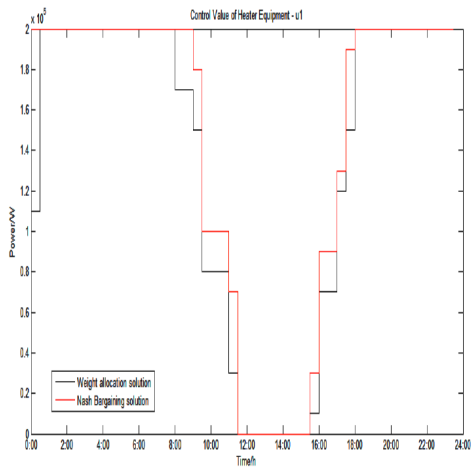
Figures 8a–8e illustrate that the DMPC method is effective and reasonable in summer.



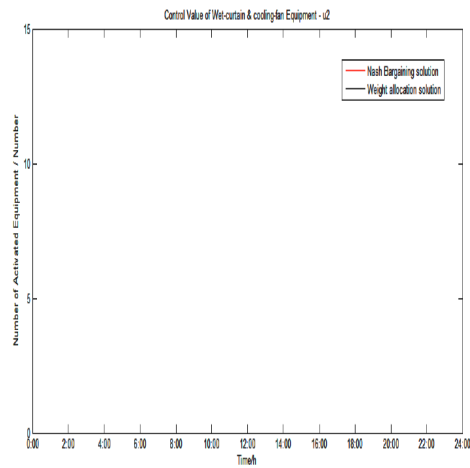
a. Indoor temperature



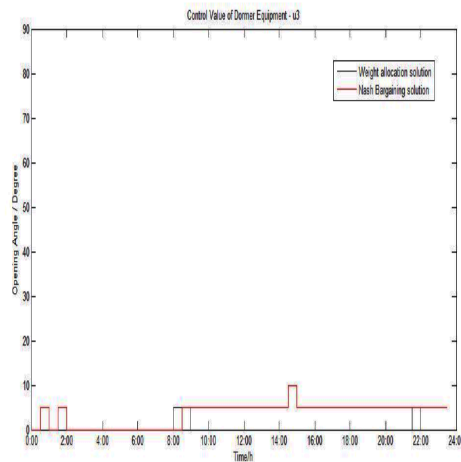
b. Indoor humidity



c. Heater equipment



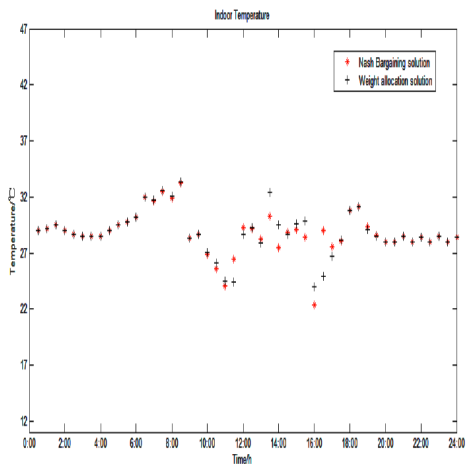
d. Wet-curtain & cooling-fan equipment



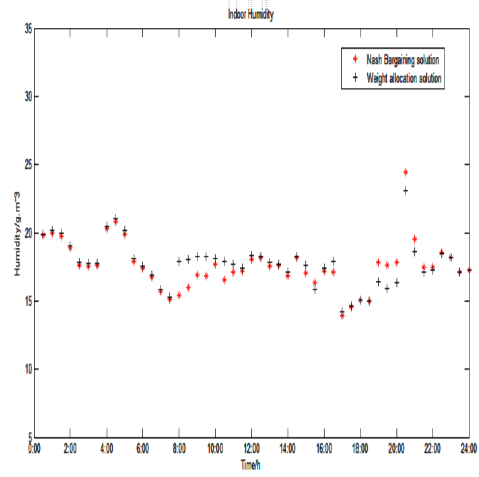
e. Dormer equipment

**Figure 7.** Results of multiobjective DMPC method in winter: a. Indoor temperature, b. Indoor humidity, c. Heater equipment, d. Wet-curtain and cooling-fan equipment, e. Dormer equipment.

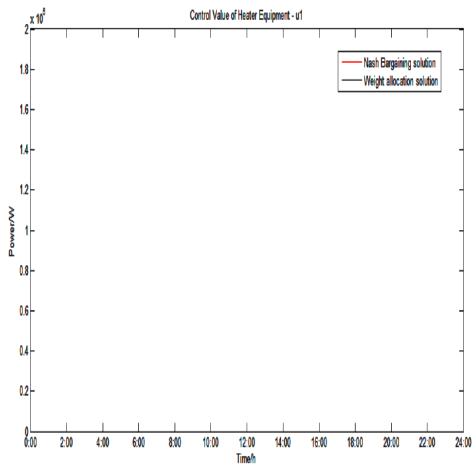




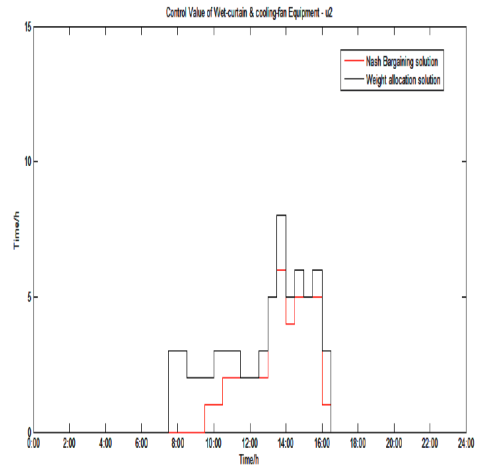
a. Indoor temperature



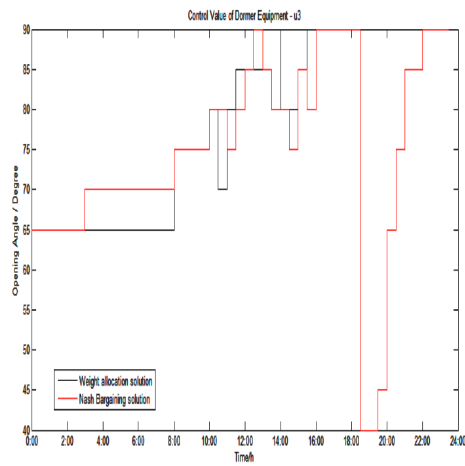
b. Indoor humidity



c. Heater equipment



d. Wet-curtain & cooling-fan equipment



e. Dormer equipment

**Figure 8.** Results of multiobjective DMPC method in summer. a. Indoor temperature, b. Indoor humidity, c. Heater equipment, d. Wet-curtain and cooling-fan equipment, e. Dormer equipment.

**4.2.2. Comparison with different methods**

This section compares the proposed multiobjective DMPC method with a single objective control method and traditional linear weighted control method in three performance criteria, i.e. control precision, energy consumption, and equipment loss, in different seasons. In addition, the performance criterion of control precision is measured by integral squared error (ISE) and integral absolute error (IAE). The smaller the above criteria are, the better the control effects are. This paper also reconsiders the performance criteria of ISE and IAE based on temperature integration theory. The results of the simulation are shown in Tables 2–5. The preset interval of temperature is 24–30 °C and the preset interval of humidity is 15.6–20.6 g/m<sup>3</sup>. These intervals are reasonable according to temperature integration theory [15].

**Table 2.** Comparisons of performance criteria among four methods in winter.

	ISE	IAE	Energy consumption	Equipment loss
Weight allocation	1.453E+03	219.775	34.551	4.595
Nash bargaining	0.853E+03	172.633	35.687	4.018
Linear weighted	5.773E+03	583.377	36.864	5.787
Single objective	1.715E+03	201.780	59.441	26.318

**Table 3.** Comparisons of performance criteria among four methods based on temperature and humidity range in winter.

	Weight allocation	Nash bargaining	Linear weighted	Single objective
ISE	587.559	201.267	3.148 E+03	993.194
IAE	88.338	60.288	0.378E+03	110.534

**Table 4.** Comparisons of performance criteria among four methods in summer.

	ISE	IAE	Energy consumption	Equipment loss
Weight allocation	0.486E+03	168.025	5.728	2.765
Nash bargaining	0.489E+03	171.683	5.281	2.861
Linear weighted	6.809E+03	558.395	9.528	6.936
Single objective	0.324E+03	116.916	20.532	17.308

**Table 5.** Comparisons of performance criteria among four methods based on temperature and humidity range in summer.

	Weight allocation	Nash bargaining	Linear weighted	Single objective
ISE	45.493	50.088	4.271E+03	32.870
IAE	22.512	23.544	0.358E+03	14.757

Compared with the single objective control method and traditional linear weighted control method, the multiobjective DMPC method is optimal in most of the performance criteria. Although control precision of the single objective control method is similar to that of the proposed method in this paper, the proposed method has merits of performing better in energy consumption and equipment loss. Compared with the linear weighted control method, the proposed method has similar control effects in energy consumption and equipment loss, but it performs better in control precision.

According to experiment results in winter and summer, it is concluded that the Nash bargaining solution and weight allocation solution have almost the same control effect. However, under certain circumstances, the DMPC method has the requirement that the computing time of control optimization should be fast enough. In

terms of the solution for the multiobjective DMPC method, the solving time in one simulation time depends on the iteration number. This paper analyzes the iteration number of the weight allocation solution and Nash bargaining solution in different seasons. A good solution may spend less iteration time to find the Pareto optimal solution. The details are shown in Table 6.

**Table 6.** Total number of iterations between gamers in two solutions.

	Winter	Summer
Weight allocation	62	91
Nash bargaining	63	81

According to Table 6, the total number of iterations of the Nash bargaining solution is smaller than that of the weight allocation solution, and it indicates that the Nash bargaining solution needs less time to solve the multiobjective optimization problem.

## 5. Conclusion

This paper studies the problem of multiobjective control for a facility environment and proposes a DMPC method to solve this problem. Based on cooperative game theory, a weight allocation solution and Nash bargaining solution are both introduced in this paper, aiming at achieving better performance in facility environment control. The simulation experiments analyze the feasibility and efficiency of the proposed method, compared with a single objective control method and traditional linear weighted control method. The results show that the multiobjective DMPC method based on cooperative game theory is optimal, considering synthetically all control objectives.

However, there are still some problems remaining, deserving further study and discussions. When a PSO algorithm is used to solve objective functions, it may be trapped in local optimal, resulting in incapability of finding the global optimal, which may cause unexpected control inputs for the next iteration. Furthermore, the disturbance rejection should be included in further research, which will strengthen the robustness of the system.

## Acknowledgments

This work is supported by the National Natural Science Foundation of China (Grant No. 31601545); the Fundamental Research Funds for the Central Universities (No. KJQN201732, No. KYZ201421); Research and Demonstration of Key Technology of Food Safety Risk Early Warning and Traceability Integration Service Platform (No. BE2016803); and the Government Sponsored Project under the Science and Technology Development Initiative: Research and Demonstration of Electronic Food Safety Traceability (No. 2015BAK36B05).

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