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Greenhouse Temperature Control with Wooden Pellet Heater via Model Predictive Control Approach

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Abstract— **This paper deals with the design of a temperature controller for a greenhouse using a wood pellet]heating system. This heating system is carbon neutral; however it has three undesirable characteristics in control: 1) an On/Off control signal, 2) a longer time constant and 3) constraints on operation. The last property, in particular, is essential for achieving better fuel consumption and for achieving a longer lifetime of the heater. However the conventional PWM control also gives good control performance, the properties 1) and 2) block its effectiveness. In addition, the property 3) leads to performance degradation in the designed controller.**

To compensate for these effects, in this paper the model predictive control is applied to achieve the temperature control. The required specification is to keep the temperature error within 2 degrees Celsius in peak-to-peak with sufficient robustness for the parameter change in greenhouse. Experimental results in greenhouse give the effectiveness of proposed controller. Moreover the idea for computational load relaxation is also discussed.

I. INTRODUCTION

For higher added value and for the steady supply of vegetables, fruits, flowers and ornamental plants, many countries use plastic/glass greenhouses. These horticultural facilities possess heaters, ventilators, and carbon dioxide generators for realizing an ideal environment for yielding a good harvest. In particluar, the control response of a heater is very important for maintaining the atmospheric temperature in greenhouse to a desired value; however, the fuel for a majour part of these devices is the Bunker A, which is a type of fossil fuel. This leads to global warming and the fragile for instability in the supply of oil. Therefore, a new, alternative fuel is required for greenhouse horticulture.

For this requirement, the wooden pellets, shown in Fig.1, which are a type of biomass fuel are focused on. This fuel is carbon-neutral, and its production cost per unit weight is almost similar to that of the Bunker A. However, heaters using this wooden pellets as fuel have some drawbacks: 1) most of these heaters can take only two states (On/Off) corresponding to lighting and extinction, 2) their time constants for heating increased by more than three times, as compared to when oil is used a fuel, and 3) the operation constraints, which should be waited time for lighting from extinction and its converse exist. In particular, the last property is required for the long lifetime of the heater, and it has great influence on the achieving of a high-precision temperature control performance. Moreover, 150 ml of heating fuel is comsumed during the lighting process; therefore, frequent lighting increases the fuel consumption by a great extent. This implies that greenhouse temperature control using wooden pellets as fuel is challenging. In fact, the conventional temperature control performance of this heater is low; it has 5 degrees Celsius peak-to-peak value around the desired temperature using simple switching control, whereas conventional heaters usually have a temperature error within 2-3 degrees Celsius. Because an error of less than 1-2 degrees Celsius will be required during the pollination season, this type of wooden pellet heater will require a control strategy for achieving higher temperature precision.

For the temperature control of a greenhouse, many ideas and results are reported and discussed widely in the literature, based on the system model with lumped parameters. In fact, this is valid for a medium-small sized greenhouse. Depending on the control strategies, two approaches exist: a heuristic approach and a model-based optimal approach [1]. The former approach mainly aims to accumulate and construct a better database, and then, render them to map control [2]. On the other hand, for derived proper greenhouse dynamics, the latter approach develops controllers using various optimal theories. The evaluation functions comprise of the temperature error and the cost for inputs, *e.g.,* heating cost and fuel with proper weighting coefficient. [3] reduced the problem to an LQ regulator design with a state observer, and [4] introduced PIP control, which is a combination of the extended Smith method and a proportional control to cover the time delay of the heater. By considering the differences in the dynamic response times in the crop production process, [5] dealt with the system as a singularly-perturbed system and proposed a robust controller. Moreover, [6] proposed the Takagi-Sugeno type controller, which comprises a fuzzy function, by solving the LMI. Almost all these approaches mentioned above achieved better control performances, however, these approaches assumed that the heater can control the supply heat continuously. This implies that the heater devices are proper to the advanced control theory. The wooden pellet heater used as the heat source in this research has a longer time constant, On/Off switching, and an operating constraint. Therefore, it is difficult to apply conventional optimal controls.

For the greenhouse with an On/Off heater having a longer time constant, MPC (model predictive control) is suitable for designing the controller [7] provided that the designer obtains a proper dynamic model of the greenhouse. [8] considered the states restrictions of a real system and solved the

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optimization problem using the particle swarm optimization algorithm. The effectiveness of the algorithm was shown by comparing the performance with a GA approach. [9] examined the performance improvement using a generalized predictive control strategy for the greenhouse with air-fan heaters and obtained a better control performance. These results show the effectiveness and feasibility of MPC for greenhouse control. However, the operating constraint such as in the case of the wooden pellet heater has not been considered. As a state of the art, the results for greenhouse temperature control performance with the wooden pellet heater considering operating constraint were very few.

In this paper, a novel On/Off heater controller design is proposed with a model predictive approach, and its control performance is examined in experiments using wooden pellet as a fuel for a medium-small size greenhouse. The temperature control precision is set to 2 degrees Celsius in the peak-to-peak value around the target value. However, this type of controller requires a continuous control input signal for the plant to be controlled, and a few research results for such an On/Off system is available. This paper is organized as follows. Section 2 states the problem formulation to be solved and the parameter estimation of the temperature dynamics of the greenhouse. The controller is designed in Section 3. Then, the simulation results are examined and the effectiveness of the proposed controller is shown in Section 4. Next, an idea to reduce the computational load will be discussed and the experimental results in a real greenhouse are shown. The control performance was shown to be high, as compared with the conventional method, and its effectiveness was confirmed via field tests.

Fig. 1. Wooden pellets

II. SYSTEM MODEL AND PARAMETER IDENTIFICATION

The plastic greenhouse considered in the research is 24 m in length, 12 m in width, and 3 m in height (Fig.2). By ignoring the spatial distribution, the temperature dynamics of this greenhouse can be derived as follows:

$$\rho V C_p \dot{\theta}(t) = h_t S(\theta_{ex}(t) - \theta(t)) + Q(t) \tag{1}$$

where $\theta(t)$ is the greenhouse temperature; $\theta_{ex}(t)$, the external temperature; $Q(t)$, the supplied heat; h_t, the heat transmission coefficient; S, the surface area of the greenhouse (except the floor); V, the volume of the greenhouse; ρ, the density of air; and C_p, the constant pressure specific heat. In this research, the external temperature is assumed to be known using a sensor. On the other hand, the dynamics of the pellet heater can be expressed in (2)

$$\begin{aligned} Q(t) &= Q_{\max}\zeta(t) \\ \zeta(t) &= -K\zeta(t) + Ku(t) \end{aligned} \tag{2}$$

where $Q_{\max}$ is the maximum supplied heat from the heater, K is the time constant of the heater, $\zeta \in [0, 1]$ is a state variable describing the burning of the heater, and $\zeta = 0, 1$ correspond to completely off and steady burning, respectively. The control input signal $u(t) \in \{0, 1\}$ takes only two states, 0 (Off) and 1 (On). Note that $Q_{\max}$ depends on the quality of the available three pellets: white, bark, and a mixture of white and bark. $Q_{\max}$ fluctuates around 15%.

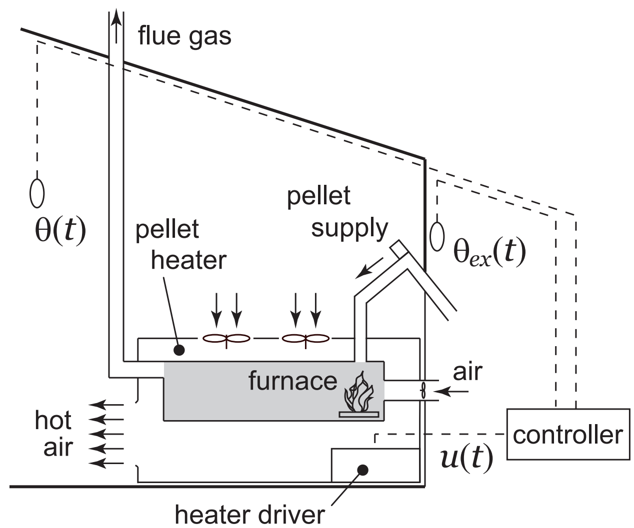

Fig. 2. Greenhouse temperature control system configuration

For the system (1) and (2), the problem to be solved is the design of the On/Off controller, which enables the greenhouse temperature to track the reference value. To this end, the system parameters were first estimated via identification theory through the open-loop input-output data among the greenhouse temperature θ, external temperature θ_{ex}, and heater input u, for five days in November 2010. Note that the temperatures in/out of the greenhouse were measured at a height of 1 m. The average model used as the predictor in the controller was obtained in discrete time domain

$$\theta(k) = G(q^{-1}) \begin{bmatrix} \theta_{ex}(k) \\ u(k) \end{bmatrix} \tag{3}$$

where

$$G(q^{-1}) = \frac{\begin{bmatrix} -0.023q^{-1} + 0.026q^{-2} \\ -0.057q^{-1} - 0.104q^{-2} \end{bmatrix}^T}{1 - 1.891q^{-1} + 0.894q^{-2}} \tag{4}$$

and q^{-1} is the unit delayer satisfying $q^{-1}x(k) = x(k-1)$ for a sampled signal $x(k)$. The numerical evaluation of identification is shown in Fig.3. This gives better agreement for measured greenhouse temperature. The mean temperature error is within 1.7 degree Celsius for (1) and (2). This result is in practical level for controller design.

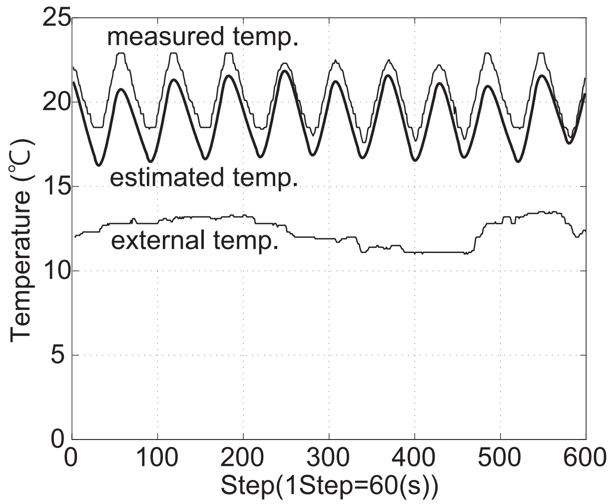

Fig. 3. Degree of temperature coincidence between measured and estimated temperature

III. CONTROLLER DESIGN WITH MPC CONCEPT

The controller is constructed using a model predictive controller. First, the designer gives the prediction interval P_0, which is an integral multiple of the sample time Δt. Then, the set $\mathcal{G}$ of all On-Off switching combinations of the heater signal can be obtained at each step as $2^P - 1$, where the predictive horizon $P = P_0/\Delta t$. For this $\mathcal{G}$ at step k, the feasible operating signal sequences of the heater are examined considering the On/Off constraints and the actual input signal sequences. For example, if the operating signal constraint is given by 5 from the Off to On operation, this step crosses out the sequence that does not satisfy at least 5-times-Off cascaded signal, taking account of the past actual command to the heater. Then, an optimal heater input, which achieves the minimum summation of the square of temperature error on the prediction interval P_0, can be selected such that $u(k)\ \min J(k, \mathcal{G}_0)$

$$J(k, \mathcal{G}_0) = \sum_{i=k, u\in\mathcal{G}}^{k+P} (\theta_{ref} - \hat{\theta}(i))^2 \tag{5}$$

where $\hat{\theta}$ is the estimation of the greenhouse temperature obtained by the predictor (3) and the θ_{ref} desired value. The designed controller keeps the input to the heater for one sample time and continues at each step. Note that the external temperature is fixed at $\theta_{ex}(k)$ during an optimal calculation because this can note changed drastically during P_0 which is designed as 10-15 minutes. The algorithm of the proposed model predictive controller is shown in Fig.4.

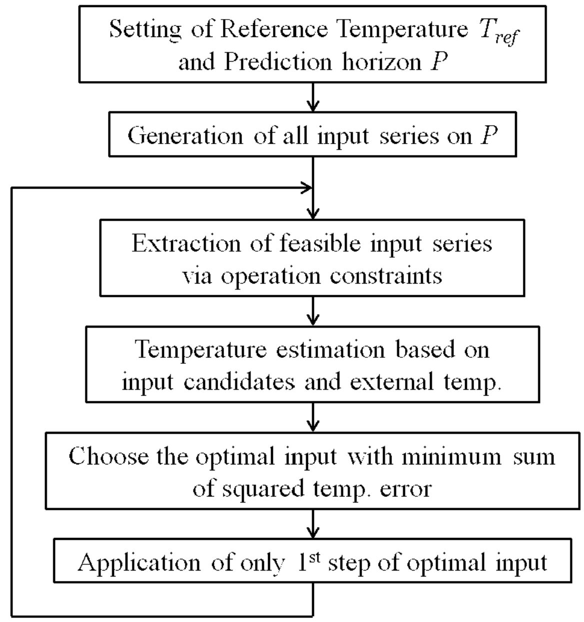

Fig. 4. Flow chart of greenhouse temperature control with On/Off wooden pellet heater

IV. SIMULATIONS

To examine the performance of the proposed controller, the dynamics of the greenhouse temperature was estimated based on the five nights' data and its mean value model was applied in numerical simulations. In the simulation, the reference temperature is set to 20 degree Celsius. The sample time and the predictive horizon were 1 min and 12 min, respectively. On the other hand, the constraints of the heater operation were given 4 steps (4 min), both from On to Off and vice versa. In the simulation, three nights' external temperature data obtained in the experiments were adopted: at the highest average temperature day, the lowest average temperature day, and the highest peak-to-peak temperature day. The simulation results were shown in Fig.5-Fig.7.

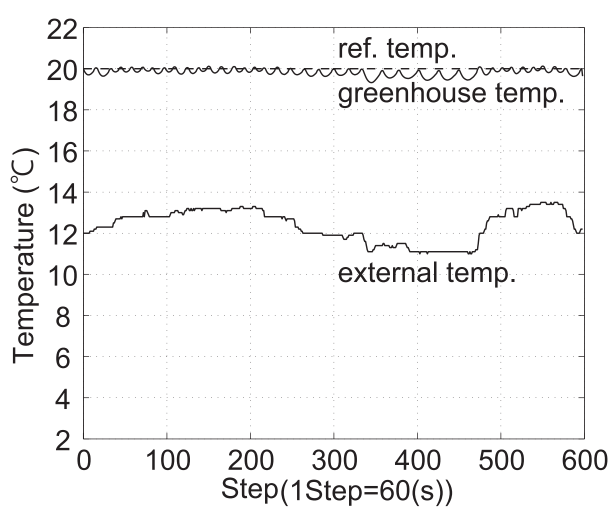

Fig. 5. Temperature control simulation result for highest average external temperature day

All results showed that the proposed strategy with the model predictive approach works well for temperature regulation. Each average value of absolute error was 0.81 degree Celsius (-0.68 to +0.13 degree Celsius), 0.38 degree Celsius (-0.20 to +0.18 degree Celsius), and 0.91 degree Celsius (-0.76 to +0.25 degree Celsius). However, these three results show that the best performance was obtained for the night with the lowest average external temperature. The reason for this was that the predictor that had been adopted for the simulation was simply close to the estimated model for this night. In fact, these two models show a temperature error of only a small percentage. Therefore, this result implies that this control method requires a better predictor; prediction error leads to a lower control performance, as usually observed in MPC.

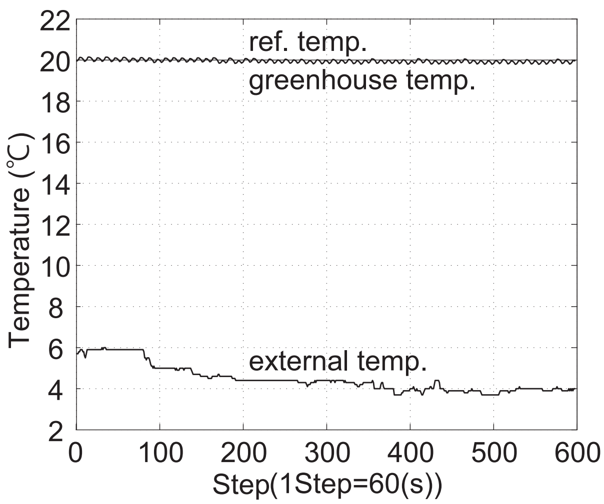

Fig. 6. Temperature control simulation result for lowest average external temperature day

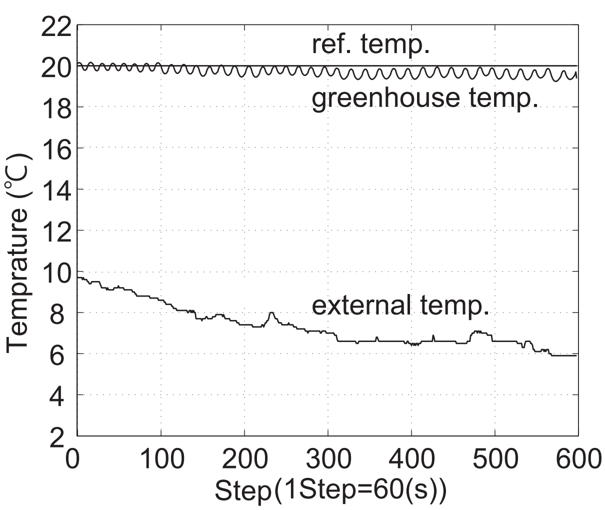

Fig. 7. Temperature control simulation result for highest peak-to-peak external temperature day

V. REDUCTION OF COMPUTATIONAL LOAD

The obtained results in the previous section show the effectiveness of the proposed control for various external temperatures. However, one of the drawbacks is that the optimal solution requires a high computational load for a longer predictive horizon. For real applications, any idea for the relaxation of a numerical burden will be required. To reduce the numerical computation, first, the optimal control inputs, which were selected to operate the heater in the simulation in Fig.5-Fig.7, were examined in Fig.8. In these cases, the predictive horizon was 12 steps (minutes), which gives 4096 input series combinations. In the figure, the vertical axis shows the input number from No.0 (always Off; 000000000000) to No.4095 (always On; 111111111111), and this figure shows which series was selected by the optimal controller at each step. From this result, it is known that these distributions have a small dependency on the external temperature, and the selected optimal solutions were in the limited region. This is because most of the candidates are limited by the constraints of the heater operation; hence, the controller can skip the optimal calculations significantly. Based on this concept, only four regions—No.1-500, No.951-1050, No.1951-2150, and No.3750-3900—are enough to be searched.

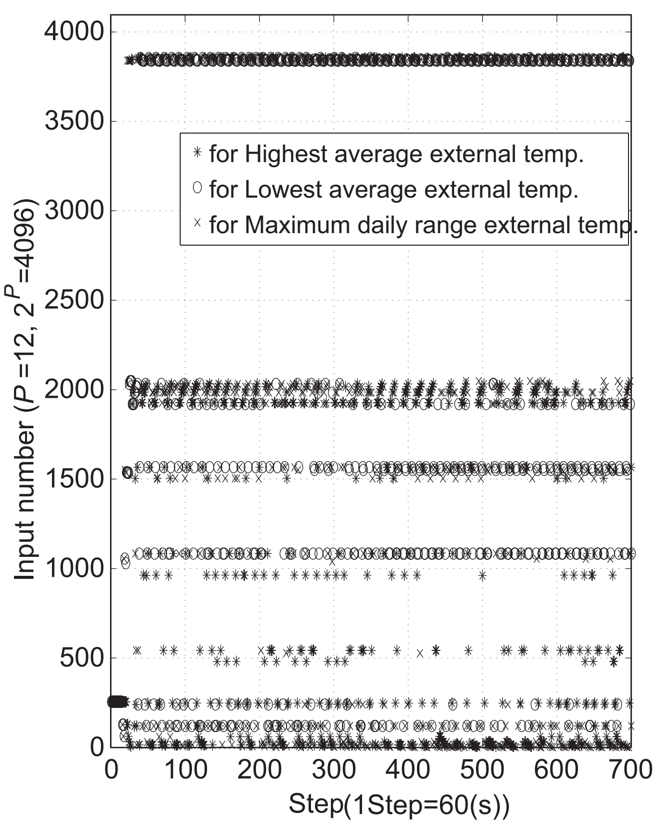

Fig. 8. Distribution of adopted On/Off input signals for three simulations in Sec.IV

Fig.9 shows the comparison between the temperature control performance with and without computational load reduction. This shows that the performance degradation was within 0.1 degree Celsius in the numerical simulation, compared with the original method without skip, and the computational load was reduced to about 20%.

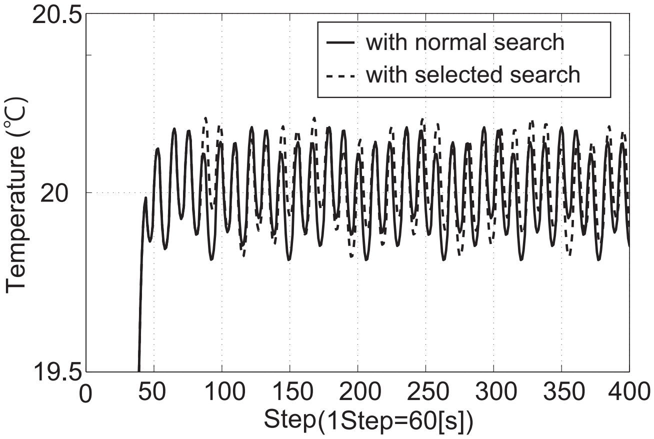

Fig. 9. Temperature control performance comparison between with and without computational load reduction

VI. EXPERIMENTAL PERFORMANCES IN GREENHOUSE

The designed temperature controller was evaluated in the greenhouse at midnight on April 27th, 2011. In this field test, the reference temperature was set to 25 degree Celsius and the other conditions were the same as in the numerical simulations. Fig.10 shows the temperature control performance and its control signal to the heater (solid lines). In this figure, the simulated temperature control performance using the conventional method and its control input to the heater were also shown (dotted lines). The conventional control input is generated as follows:

$$u(k) = \begin{cases} 1\,(\text{On}), & \text{if } e(k-1) \geq +1.0 \\ 0\,(\text{Off}), & \text{if } e(k-1) \leq -1.0 \\ \text{keep previous input}, & \text{otherwise} \end{cases} \tag{6}$$

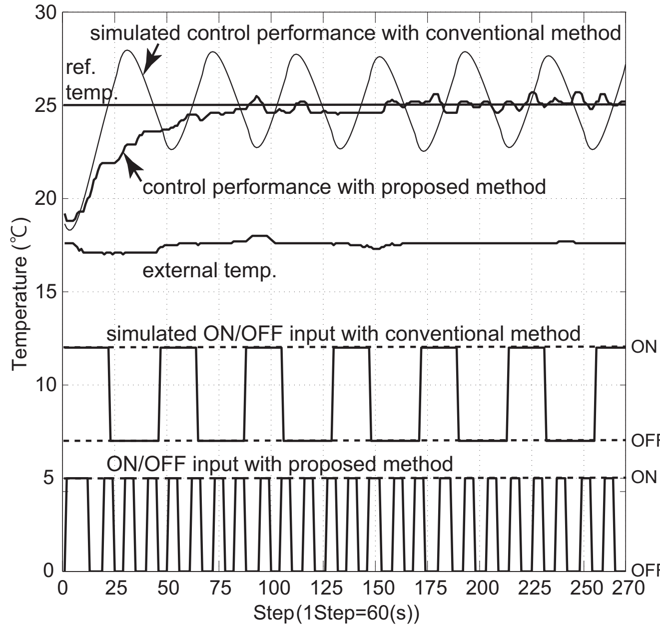

Fig. 10. Experimental results for greenhouse temperature control

where $e(k) = \theta_{ref} - \theta(k)$, without considering the operating constraints.

From this figure, it can be seen that the proposed controller achieved a 1.2 degree Celsius error in peak-to-peak temperature and 0.7 degree Celsius error in maximum temperature, whereas the conventional method achieved a 5.0 degrees Celsius error in peak-to-peak fluctuation. The control inputs with the proposed method show fine switching without any possibility of being blocked by the operating constraints, as compared to the series with the conventional approach. The temperature control performance with the conventional control appears to be more improved; in fact, the controller generates more frequent switching for a smaller threshold value, however, some input signal would be blocked by the constraints. This is where the proposed controller shows its effectiveness. On the other hand, the proposed controller gives a few strange control input series; for example it generates the Off signal before 25 steps, regardless of the remaining higher positive temperature error, in which case the heater should turn on. In this case, the predictor estimated a larger temperature value than the measured value. This is because of the lower precision of the predictor in the controller; this implies that a higher precision of the predictor is required for the proposed control. This problem arises because of the limitation of using the predictor with fixed parameters. To solve this situation, the adaptive predictor can be introduced in the controller, which can tune the parameters in the predictor depending on the prediction error. This is left as a future work.

Moreover, by modifying the evaluation function as follows, the controller can improve the fuel consumption:

$$J(k, \mathcal{G}_0) = \sum_{i=k, u \in \mathcal{G}}^{k+P} \left\{ (\theta_{ref} - \hat{\theta}(i))^2 + \alpha u(k) \right\} \tag{7}$$

where a positive number α is the weighting coefficient of the fuel. To choose a suitable α, the controller searches the control signal with better fuel consumption, relaxing the temperature regulation performance within a given specification. Fig.11 shows the control performance in the greenhouse with the proposed control in (7) with $\alpha = 0.5$. As seen in this figure, the temperature control performance was degraded at a stationary response, a 2.0 degree Celsius error in peak-to-peak temperature, which is within the given specification, and it shows a slower temperature rise to enter the steady state, compared with that seen in Fig.10. However, as a result, the number of On/Off switching cycles of the heater is attenuated by more than 20%, as seen in Table I. This comes from the weight α on the control input in eq.(7). This leads to improvements in fuel consumption because the heater burns up 150 ml of heating fuel for every switching to 'On' signal. Naturally, the temperature control performance will be lost by a large extent for an unsuitable large α.

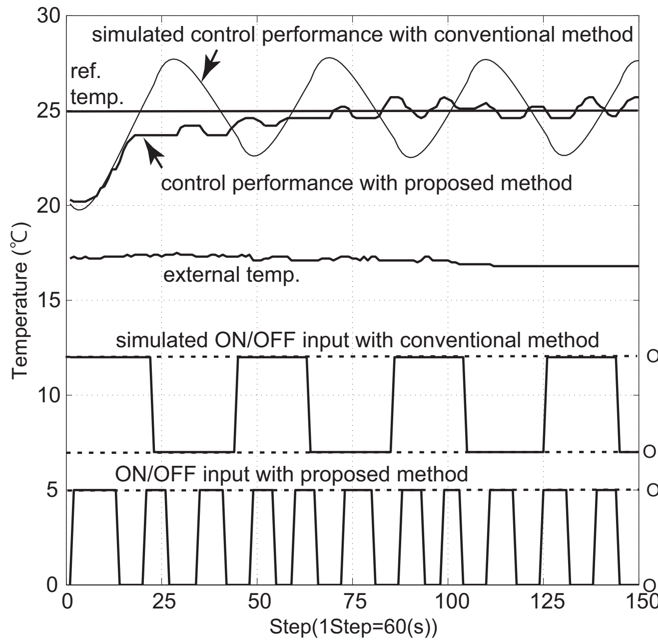

Fig. 11. Experimental results for greenhouse temperature control with modified cost function (7) with $\alpha = 0.5$

TABLE I
COMPARISON OF NUMBER OF SWITCHING TIMES

Approach	On/Off switching (times)	Interval (steps)	Average (steps/times)
proposed algorithm	18	200	11.1
proposed with eq.(7)	7	100	14.2

VII. CONCLUSIONS

This paper proposed a design of a temperature controller for a wooden pellet heater for a greenhouse, based on model predictive control. This heater is carbon neutral, and hence, has a lower environmental load. However, it has three undesirable characteristics in control: 1) an On/Off control, 2) a longer time constant, and 3) constraints during operation. The last property, in particular, is serious for Lyapunov-based redesign. Moreover, there exists a physical parameter change in the coefficient of the overall heat transmission of the covering materials for wind and/or the maximum heat quantity for various wooden pellet qualities. For this system, by applying the concept of model predictive control, a novel On/Off controller was proposed. First, the extraction of elite candidates passing the operation constraints of the heater is carried out, after which the optimized operation series is selected. As a result, for a real greenhouse, the designed controller achieved a temperature tracking error of less than 1.2 degree Celsius in peak-to-peak values and less than 0.7 degree Celsius in maximum values. Moreover, by introducing the weight on operation, the generation of frequent On/Off operating signals was attenuated, leading to the improvement in fuel consumption. These results can be applied to other agricultural control systems on carbon dioxide concentration systems, etc.

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