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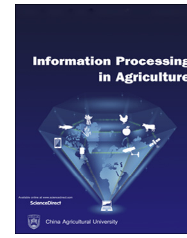

Robust model predictive control for greenhouse temperature based on particle swarm optimization

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A B S T R A C T

Application of model predictive control (MPC) in horticultural practice requires detailed models. However, even highly sophisticated greenhouse climate models are often known to have unknown dynamics affected by bounded uncertainties. To enforce robustness during the controller design stage, this paper proposes a particle swarm optimization (PSO)-based robust MPC strategy for greenhouse temperature systems. The strategy is based on a nonlinear physical temperature affine model. The robust MPC technique requires online solution of a minimax optimal control problem, which optimizes the tradeoff between set point tracking and cost requirements reduction. The minimax optimization problem is reformulated to a nonlinear programming problem with constraints. PSO is used to solve the reformulated problem and priority ranking of constraint fitness is proposed to guarantee that the constraints are satisfied. The results of simulations performed using the proposed control system show that the controller can effectively achieve the set point in the presence of disturbances and that it offers more suitable control variables, higher control precision, and stronger robustness than the conventional MPC.

1. Introduction

In horticultural practice, greenhouse temperature regulation is important for crop production [1]. Efficient temperature management requires a model-based systematic method that ensures stability, robustness, and performance properties for the overall system. There are two kinds of uncertainties in a greenhouse temperature system model. One is caused by the lack of information on the system's structure and parameters and the other is due to internal and external unknown disturbances. One main difficulty for regulation is that there exist uncertainties that may prevent the climate from following the desired set-point and satisfying the constraints.

Model predictive control (MPC) is a powerful technique for generating feasible trajectories because of its capability to systematically handle system nonlinearities and constraints, consider the running costs directly in a cost function, and cope with multivariable process control [2]. Concomitant advances in theory and computing systems have enlarged the range of MPC applications in greenhouse management. For example, Blasco et al. [3] proposed an MPC algorithm that incorporates energy and water consumption to maintain climatic conditions. Gruber et al. [4] developed a Volterra series model-based predictive control strategy that optimizes the reference deviation. Montoya et al. [5] presented a hybrid MPC approach that minimizes the cost increment when two

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heating systems are combined in a greenhouse. Some authors focus on on–off control signals and obtained optimal switch equipment combinations by using MPC to achieve a tradeoff between control precision and energy loss [6,7].

However, MPC relies on exact knowledge of the system model, and it is unable to cope with unknown disturbances in the dynamics. When disturbances and uncertainties are involved in the greenhouse climate system, the effectiveness of MPC decreases significantly. In order to enforce robustness, only a few robust MPC for greenhouse climate are described in the literature. González et al. [8] applied a tube-based predictive control approach to greenhouse climate systems, but the approach could only handle linear systems. Piñón et al. [9] proposed a design method for robust nonlinear MPC applying the Linear Matrix Inequalities technology on a input/output linearizing greenhouse system. However, the involved physical limitations of actuators were not considered, which may limit the practical applications of the control system.

One effective way to achieve robustness in MPC is to optimize the control actions in the worst-case scenario with respect to disturbances. The worst-case approach requires solving an online minimax optimization problem. A large number of publications within the framework of minimax robust MPC deals with disturbed or uncertain systems. Minimax robust MPC dates back to the work of Campo and Morari [10] where they used an uncertain finite impulse response model and the worst-case deviation from a known reference trajectory was minimized. The resulting optimization problem is in an open-loop formulation and can be cast as a linear program. Further work along the same ideas include the study where stability issues were analyzed and slightly more general performance measures were introduced [11]. Some authors concentrate on the closed-loop formulation, where a vector of feedback control policies is computed. The idea is to solve a robust state feedback problem repeatedly online [12,13]. More recent work include generalization to state models with unmodelled dynamics and bounded errors [14,15], the conservativeness of the linear state feedback parameterization [16], and the analysis of the input to state stability [17]. The approach is widely studied in theory and has been applied in some applications [18,19], but it is rarely used in greenhouse climate control applications.

One of the keys to robust MPC is an effective online optimization solution. Particle swarm optimization (PSO) is a population-based stochastic algorithm proposed by Kennedy and Eberhart [20]. PSO can be applied to solve large-scale nonconvex optimization problems. It is based on real-number encoding and is easy to implement. It has good computational efficiency and usually converges very quickly towards the optimal positions, which is appropriate for online optimization and engineering application. PSO is motivated from simulation of the social behavior of birds The ideas lay the foundation for a number of extensions, including the involved parameters tuning methods [21], the issue of local optima and convergence speed [22], and different variants of PSO algorithm [23] to incorporate the capabilities of other evolutionary algorithms. As a result, PSO has emerged as a promising computational approach for solving various online optimization problems subject to nonlinear inequality constraints. What's more, the PSO has been successfully applied to the greenhouse internal climate control [24,25]. The present work builds on the basic approach and uses priority ranking of constraint fitness to guarantee the constraints.

In this paper, a PSO-based robust MPC scheme for a nonlinear greenhouse temperature model is proposed. The proposed control strategy provides some advantages over the existing climate control techniques for greenhouse. First of all, the robust MPC scheme is used to cope with unknown disturbances, which enables the maintenance of certain properties, such as performance and stability, in the presence of uncertainties. The second advantage stems from the fact that PSO is applied to solve the online optimization problem involved in the robust MPC. The effectiveness and efficiency of PSO can promote the successful practical application of the control method. The remainder of this paper is organized as follows. In Section 2, the greenhouse temperature physical model is constructed and is described as an affine nonlinear system. In Section 3, the robust MPC based on the nonlinear affine system is developed and is reformulated as a nonlinear optimization problem. Subsequently, PSO is presented to solve the optimization problem. Section 4 discusses the simulation results obtained for the performance of the developed system. Section 5 presents the major conclusions.

2. Physical model of greenhouse temperature dynamics

Greenhouse temperature dynamics are a combination of physical processes involving energy transfer and mass balance. For simplicity, the air in the greenhouse is considered to be homogenous. A greenhouse temperature model links the output variable to the outside climate and to the control variables [26]. The temperature model based on energy conservation is described as follows [27]:

$$\frac{dT_{in}(t)}{dt} = \frac{1}{C_g}(u_q(t) + c_{rad}S_r(t) - (c_{cap}u_v + c_{ai})(T_{in}(t) - T_{out}(t))) \quad (1)$$

where T_{in} (°C) and T_{out} (°C) are the inside and outside temperature, respectively, C_g (30,000 J/(m^2 K)) is the heat capacity of the greenhouse air, u_q (W/m^2) is the input heating provided by the greenhouse heater, c_{rad} (0.2) is the heat load coefficient due to solar radiation, S_r (W/m^2) is the outside solar radiation, c_{cap} (1290 J/(m^3 K)) is the heat capacity per volume unit of greenhouse air, u_v (m/s) is the ventilation rate through the vents, and c_{ai} (6.1 W/(m^2 K)) is the parameter of the overall heat transfer through the cover.

Normalize the control variables by using the convention that $u_{q,\%} = u_q/u_{q,max}$ and $u_{v,\%} = u_v/u_{v,max}$, in which $u_{q,max}$ represents the maximum heating input and $u_{v,max}$ represents the maximum ventilation rate. Thus, model (1) can be rewritten in the following form:

$$\frac{dT_{in}(t)}{dt} = \frac{1}{C_g}(u_{q,max}u_{q,\%}(t) + c_{rad}S_r(t) - (c_{cap}u_{v,max}u_v + c_{ai}) \times (T_{in}(t) - T_{out}(t))) \quad (2)$$

As shown in Eq. (2), the greenhouse temperature system is characterized by nonlinearity, but it is linear to the control inputs. Defining the state variable $x = T_{in}$, control variable $u = [u_1, u_2]^T = [u_{q,\%}, u_{v,\%}]^T$, and outside disturbance variable $\upsilon = [\upsilon_1,$

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