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# Robust T-S fuzzy constrained predictive control design for greenhouse micro-climate

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***Abstract*—In this paper, a robust fuzzy model predictive control (MPC) strategy was proposed for leading to promote a comfortable micro-climate for the plants growth inside a greenhouse. Based on Takagi-Sugeno (TS) fuzzy model and a non-parallel distributed compensation (non-PDC) fuzzy controller, the MPC problem can be reduced to sufficient conditions expressed as linear matrix inequalities (LMIs). To show the merit of the applied method against external disturbances and model parameter uncertainties, several simulation experiments were performed.**

**KeyWords: model predictive control; Takagi-sugeno fuzzy model; non-parallel distributed compensation; linear matrix inequalities; greenhouse micro-climate.**

## I. INTRODUCTION

A greenhouse is an enclosure that used to improve the autonomous crops cultivation process. Generally, it allows the creation of a favorable inside micro-climate to crop development and protects it from weather conditions changing. The simple structure of the greenhouse, represented in a thin film cover, allows a good exchange of energy and mass balance but creates a strong interaction between inside and outside environments. Moreover, greenhouses are considered as time-varying systems because they never stay as initially designed [1]. Regarding these difficulties, controller design for the greenhouse micro-climate management must deal with the system nonlinearity, disturbance rejection and uncertainties due to modeling mistakes and imperfect measurements.

In recent years, it has shown that control plays a very important role in greenhouse systems. However, many greenhouses use conventional controllers such as on-off and PID controllers [2]. But these control strategies may not be able to guaranty the desired performances due to highly nonlinear characteristic and strong coupling of the greenhouse variables [3]. Thus, in order to improve the quantity and quality of the greenhouse crops product, several advanced control strategies have been proposed in various control synthesis such as optimal control [4]. Intelligent and soft computational based controllers such as fuzzy systems, Neurocomputing, and evolutionary algorithms [5], [6], [7]. Advanced techniques like predictive [8], adaptive [9], [10]. Recently, robust control is gaining popularity in greenhouse micro-climate control system due to its ability in guaranteeing good performance in spite of modeling uncertainties and disturbances [11].

In this paper, a model predictive control based on a fuzzy model is considered. Firstly, a T-S fuzzy model is developed to deal with greenhouse nonlinearity. For this purpose, the global model is divided into local linear models blended using weighed functions. Secondly, Based on a non-PDC control law, a model predictive controller (MPC) is designed to deal with the system uncertainties and external disturbances. The constrained optimization problem of MPC is formulated by LMI constraints. The effectiveness of the proposed method was revealed through experiment simulation and statistical calculations.

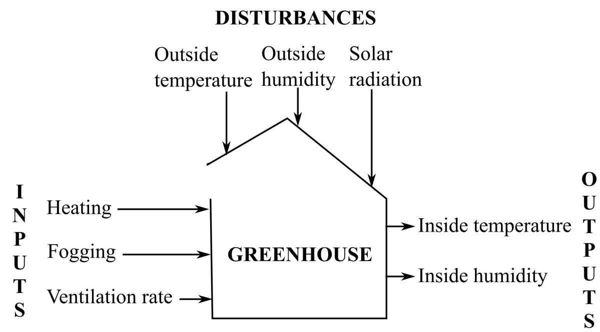


Fig. 1. Greenhouse system.

The rest of the paper is organized as follows. In Section 2, the nonlinear dynamic model and the T-S fuzzy modeling of the greenhouse are presented. Then, in Section 3, the nonlinear MPC based on T-S fuzzy model formulation is given. In Section 4, the simulation result of the proposed control method on the greenhouse is illustrated. Finally, Conclusions are given in Section 5.

## II. GREENHOUSE PHYSICAL MODEL AND T-S MODELING

### A. Physical model

An analytic model is considered to describe the dynamic behavior of the greenhouse. Based on the heating-cooling ventilating model, a greenhouse climate dynamic model was developed in [12] Fig. 1:

$$\begin{aligned} T_{in}(k+1) = & \frac{1}{\rho C_p V_T}(Q_{heat}(k) + S_i(k) - \lambda Q_{fog}(k)) \\ & - \frac{V_r(k)}{V_T}(T_{in}(k) - T_{out}(k)) \\ & - \frac{UA}{\rho C_p V_T}(T_{in}(k) - T_{out}(k)) \end{aligned} \tag{1a}$$

$$\begin{aligned} RH_{in}(k+1) = & \frac{1}{V_H}Q_{fog}(k) + \frac{1}{V_H}(E(S_i(k), RH_{in}(k))) \\ & - \frac{V_r(k)}{V_H}(RH_{in}(k) - RH_{out}(k)) \end{aligned} \tag{1b}$$


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$$E(S_i(k), w_{in}(k)) = \alpha \frac{S_i(k)}{\lambda} - \beta_T w_{in}(k) \tag{1c}$$

Where the output variables are: inside temperature $T_{in}(°C)$ and inside relative humidity $RH_{in}$ in $(\%)$. The input variables that can be manipulated are heating control $Q_{heat}(W)$ , water capacity of the fog system $Q_{fog}(gH_2Os^{-1})$ and ventilation rate $V_r(m^3s^{-1})$. Measurable perturbations are: solar radiation intercepted by the greenhouse $Si(Wm^{-2})$, outside temperature $T_{out}(°C)$ and outside relative humidity $RH_{out}(\%)$. $UA$ is the heat transfer coefficient of enclosure $(WK^{-1})$, $\rho$ is the air density $(1.2kgm^{-3})$, $C_p$ is the specific heat of air $(1006Jkg^{-1}K^{-1})$, $E(S_i, RH_{in})$ denotes the evapo-transpiration rate of the plant $(g/s)$, which is affected by the given solar radiation, $\lambda$ is the latent heat of vaporization $(2257Jg^{-1})$, $\alpha$ and $\beta_T$ are lump parameters, $V_T$ and $V_H$ are the temperature and humidity active mixing air volumes of a ventilated space $(m^3)$, respectively.

By transforming the control variables through these equations $Q_{heat,\%} = 100 * Q_{heat}/Q_{heat}^{max}$, $Q_{fog,\%} = 100 * Q_{fog}/Q_{fog}^{max}$, $V_{r,\%} = 100 * V_r/V_r^{max}$, the model described by equations (1a) and (1b) can be normalized. Then, the dynamic model of the greenhouse can be expressed as:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + Dd(k) \\ y(k) = Cx(k) \end{cases} \tag{2}$$

$$A = \begin{bmatrix} \frac{UA}{\rho C_p V_T} & 0 \\ 0 & \frac{\beta_T}{V_H} \end{bmatrix}$$
$$B = \begin{bmatrix} \frac{1}{\rho C_p V_T} & \frac{-\lambda}{\rho C_p V_T} & \frac{1}{V_T}(T_{in}(k) - T_{out}(k)) \\ 0 & \frac{1}{V_H} & \frac{1}{V_H}(H_{in}(k) - H_{out}(k)) \end{bmatrix}$$
$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$
$$D = \begin{bmatrix} \frac{1}{\rho C_p V_T} & \frac{-UA}{\rho C_p V_T} & 0 \\ \frac{z_1}{\lambda V_H} & 0 & 0 \end{bmatrix}$$

and the state vector $x = [x_1, x_2]^T = [T_{in}, H_{in}]^T$, the input vector $u = [u_1, u_2, u_3] = [Q_{heat,\%}, Q_{fog,\%}, V_{r,\%}]$ and the disturbance vector $d = [d_1, d_2, d_3]^T = [S_i, T_{out}, H_{out}]^T$ .

In order to obtain the best possible performance from this highly nonlinear system, the following sub-section gives a T-S fuzzy representation of (2)

## *B. T-S fuzzy model*

In above model, the nonlinear terms are $\frac{1}{V_T}(T_{in}(k) - T_{out}(k))$ and $\frac{1}{V_H}(H_{in}(k) - H_{out}(k))$, and the variables in the greenhouse are assumed varying in the operating range $T_{in,min} \leq T_{in} \leq T_{in,max}$ and $H_{in,min} \leq H_{in} \leq H_{in,max}$. For the nonlinear terms, we define $z_1(k) = \frac{1}{V_T}(T_{in}(k) - T_{out}(k))$ and $z_2(k) = \frac{1}{V_H}(H_{in}(k) - H_{out}(k))$, then, for every instance the minimum and the maximum of $z_1$ and $z_2$ can be obtained, $\underline{z_1} \leq z_1 \leq \overline{z_1}$ and $\underline{z_2} \leq z_2 \leq \overline{z_2}$. The simplified expressions can be written as follow: $z_1(k) = M_1^1(z_1(k))\underline{z_1} + M_2^1(z_1(k))\overline{z_1}$ and $z_2(k) = M_1^2(z_2(k))\underline{z_2} + M_2^2(z_2(k))\overline{z_2}$, where $M_1^1(z_1(k)) + M_2^1(z_1(k)) = 1$ and $M_1^2(z_2(k)) + M_2^2(z_2(k)) = 1$. Therefore the membership functions can be calculated as:

$$M_1^1(z_1(k)) = \frac{z_1(k) - \underline{z_1}}{\overline{z_1} - \underline{z_1}}, M_2^1(z_1(k)) = \frac{\underline{z_1} - z_1(k)}{\overline{z_1} - \underline{z_1}}$$

and

$$M_1^2(z_2(k)) = \frac{z_2(k) - \underline{z_2}}{\overline{z_2} - \underline{z_2}}, M_1^2(z_2(k)) = \frac{\underline{z_2} - z_2(k)}{\overline{z_2} - \underline{z_2}}$$

Consequently the nonlinear system (2) can be represented by the following four IF-THEN rules:

If $z_1(k)$ is $M_1^1$ and $z_2(k)$ is $M_1^2$ Then

$$\begin{cases} x(k+1) = Ax(k) + B_1u(k) + Dd(k) \\ y(k) = Cx(k) \end{cases}$$

If $z_1(k)$ is $M_1^1$ and $z_2(k)$ is $M_2^2$ Then

$$\begin{cases} x(k+1) = Ax(k) + B_2u(k) + Dd(k) \\ y(k) = Cx(k) \end{cases}$$

If $z_1(k)$ is $M_2^1$ and $z_2(k)$ is $M_1^2$ Then

$$\begin{cases} x(k+1) = Ax(k) + B_3u(k) + Dd(k) \\ y(k) = Cx(k) \end{cases}$$

If $z_1(k)$ is $M_2^1$ and $z_2(k)$ is $M_2^2$ Then

$$\begin{cases} x(k+1) = Ax(k) + B_4u(k) + Dd(k) \\ y(k) = Cx(k) \end{cases}$$

Then the equivalent T-S fuzzy model is

$$\begin{cases} x(k+1) = \sum_{i=1}^{4} h_i(z(k))(Ax(k) + B_iu(k) + Dd(k)) \\ y(k) = Cx(k) \end{cases}$$

where

$$h_1(z(k)) = M_1^1(z_1(k))M_1^2(z_2(k))$$
$$h_2(z(k)) = M_1^1(z_1(k))M_2^2(z_2(k))$$
$$h_3(z(k)) = M_2^1(z_1(k))M_1^2(z_2(k))$$
$$h_4(z(k)) = M_2^1(z_1(k))M_2^2(z_2(k))$$

# III. CONSTRAINT MODEL PREDICTIVE CONTROL

## *A. Cost function*

Let us consider the following problem, which minimizes the following objective function in an infinite horizon [13]

$$\min_{u(k+h|k)=K(k)\tilde{x}(k+h|k)} \quad \max_{h>0} J_\infty(k) \tag{3}$$

$$J_\infty(k) = \sum_{h=0}^{\infty} \| x(k+h|k) \|_Q^2 + \| u(k+h|k) \|_R^2 \tag{4}$$

where $Q > 0$ and $R > 0$ are both known symmetric weighting matrices. The above performance objectif function is subject to the following constraints, $u_{min} \leq u(k+h|k) \leq u_{max}$ and $y_{min} \leq y(k+h|k) \leq y_{max}$.

## *B. Discret T-S fuzzy model*

In this work, a T-S fuzzy model with *r*-rules is employed to describe the dynamics of the discrete-time nonlinear system.

**Rule** $i$: **IF** $z_1(k)$ is $M_1^i$, and $z_2(k)$ is $M_2^i$, and ... and $z_\Theta(k)$ is $M_\Theta^i$,

$$\textbf{THEN} \begin{cases} x(k+1) = A_ix(k) + B_iu(k) \\ y(k) = C_ix(k) \qquad i = 1, ..., r \end{cases}$$

With T-S fuzzy discrete time model

$$\begin{cases} x(k+1) = \sum_{i=1}^{r} h_i(z(k))A_ix(k) + B_iu(k) \\ y(k) = \sum_{i=1}^{r} h_i(z(k))C_ix(k) \qquad i = 1, ..., r \end{cases} \tag{5}$$


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And $A_i$, $B_i$ and $C_i$ are states matrices of system.

### C. Fuzzy non-PDC control law

The non-PDC law presented in [14] is used in this section, and is given as:

$$u(k) = -\left(\sum_{j=1}^{r} h_j(z(k)F_j\right)\left(\sum_{j=1}^{r} h_j(z(k))G_j\right)^{-1} x(k) \quad (6)$$

Substituting (6) in (5), the closed loop system is given as follows:

$$\begin{aligned} x(k+1) &= (A_z - B_z F_z G_z^{-1})x(k) \\ y(k) &= C_z x(k) \end{aligned} \quad (7)$$

where $A_z = \sum_{i=1}^{r} h_i(z(k))A_i$, $B_z = \sum_{i=1}^{r} h_i(z(k))B_i$, $C_z = \sum_{i=1}^{r} h_i(z(k))C_i$, $F_z = \sum_{i=1}^{r} h_i(z(k))F_i$, and $G_z = \sum_{i=1}^{r} h_i(z(k))G_i$,

**Theorem 1**: Consider that the system states $x(k/k)$ are measured at each sampling time $k$. The closed-loop discrete-time fuzzy system, given by (7), is globally asymptotically stable if there exist positive definite matrices $S_{ij} > 0$, $\Upsilon_{ij}$, $F_j$, $G_j$, $X_{ii} > 0$ and $X_{ij} = X_{ij}^T$ such that the following LMIs are satisfied:

$$\min_{\hat{S}_{ij}, F_j, G_j, X_{ij}, H} \gamma \quad (8)$$

$$\begin{bmatrix} -\gamma & x^T(k/k) \\ x(k/k) & -\hat{S}_{ij} \end{bmatrix} < 0 \quad (9)$$

$$\Upsilon_{ii} > X_{ii}, \;\; i \in \mathcal{S} \quad (10)$$

$$\Upsilon_{ij} + \Upsilon_{ij}^T > X_{ij} + X_{ij}^T, \;\; i \neq j, \quad j \in \mathcal{S} \quad (11)$$

$$X_l = \begin{bmatrix} 2X_{11} & \cdots & X_{1r} + X_{m1}^T \\ \vdots & \ddots & \vdots \\ X_{m1} + X_{1m}^T & \cdots & 2X_{mm} \end{bmatrix} > 0 \quad (12)$$

$$\begin{bmatrix} -Z & -F_j \\ -F_j^T & \hat{S}_{ji} - G_j^T - G_j \end{bmatrix} < 0 \quad \text{with } Z_{(hh)} < u_{h,max}^2, \quad h = 1, 2, ..., p \quad (13)$$

$$\begin{bmatrix} -U_j & (A_j G_i - B_j F_l) \\ (A_j G_i - B_j F_l)^T & \hat{S}_{ji} - G_i^T - G_i \end{bmatrix} < 0, \quad i, j, l \in \mathcal{S} \quad (14)$$

$$\begin{bmatrix} -W & C_j H^T \\ H C_j^T & U_j - H - H^T \end{bmatrix} < 0 \quad \text{with } W_{(hh)} < y_{h,max}^2, \;\; h = 1, 2, ..., q \quad (15)$$

where

$$\Upsilon_{ij} = \begin{bmatrix} \Upsilon_{11} & \Upsilon_{12} & -F_r^T R_0 & G_l^T Q_0 \\ \Upsilon_{12}^T & \hat{S}_{ij} & 0 & 0 \\ -R_0 F_l & 0 & R_0 & 0 \\ -Q_0 & 0 & 0 & Q_0 \end{bmatrix}$$

with $i, j, l, r \in \mathcal{S}$
and $\Upsilon_{11} = G_i + G_i^T - \hat{S}_{ij}$, $\quad \Upsilon_{12} = (A_j G_l - B_j F_r)^T$

The proof detail is given in [14].

**Remark 1** : In most application, a regulation task is required. However, in Theorem 1, only stabilization conditions are derived based on the cost function (4). In order to force the system state $x(k/k)$ to follow a constant non-zero reference signal $r$, the following cost function should be minimized:

$$J_\infty(k) = \sum_{h=0}^{\infty} \| x(k+h|k) - r(k) \|_Q^2 + \| u(k+h|k) \|_R^2 \quad (16)$$

By following the same method as given in Theorem 1, the control law will be as:

$$u(k) = -\left(\sum_{j=1}^{r} h_j(z(k))F_j\right)\left(\sum_{j=1}^{r} h_j(z(k))G_j\right)^{-1} x(k) - r(k) \quad (17)$$

## IV. Simulation results

In the following, a greenhouse micro-climate control simulations are given. These simulations were carried out using the greenhouse model (1). The heating, the fogging and the ventilation systems are considered as the control inputs, while the state variables are the inside temperature and the inside humidity. The outside radiation, the outside temperature, and the outside humidity are considered as the main surrounding external disturbances that widely influence the greenhouse dynamics Fig. 1.
To avoid stresses to the plants, the inside temperature and humidity must be bounded by minimum and maximum, the operating range of the inside temperature is $0 \leq T_{in} \leq 40^\circ C$ and the operating range of the inside humidity is $0 \leq H_{in} \leq 100\%$. Then the T-S fuzzy model of the nonlinear system (2) is as follows:

$$B_1 = \begin{bmatrix} \frac{1}{\rho C_p V_T} & \frac{-\lambda}{\rho C_p V_T} & \underline{z_1}(k) \\ 0 & \frac{1}{V_H} & \underline{z_2}(k) \end{bmatrix}$$

$$B_2 = \begin{bmatrix} \frac{1}{\rho C_p V_T} & \frac{-\lambda}{\rho C_p V_T} & \underline{z_1}(k) \\ 0 & \frac{1}{V_H} & \overline{z_2}(k) \end{bmatrix}$$

$$B_3 = \begin{bmatrix} \frac{1}{\rho C_p V_T} & \frac{-\lambda}{\rho C_p V_T} & \overline{z_1}(k) \\ 0 & \frac{1}{V_H} & \underline{z_2}(k) \end{bmatrix}$$

$$B_4 = \begin{bmatrix} \frac{1}{\rho C_p V_T} & \frac{-\lambda}{\rho C_p V_T} & \overline{z_1}(k) \\ 0 & \frac{1}{V_H} & \overline{z_2}(k) \end{bmatrix}$$

Then the equivalent T-S fuzzy model is

$$\begin{cases} x(k+1) = \sum_{i=1}^{4} h_i(Ax(k) + B_i u(k) + Dd(k)) \\ y(k) = Cx(k) \end{cases}$$

where

$$\begin{bmatrix} y_1(k) \\ y_2(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} x$$

Hence, disturbances are measurable, the above system can be augmented to the following form:

$$\tilde{x}(k+1) = \sum_{i=1}^{4} h_i(\tilde{A}\tilde{x}(k) + \tilde{B}_i u(k)) \quad (18)$$

where

$$\tilde{A} = \begin{bmatrix} A & D \\ 0 & 1 \end{bmatrix}, \quad \tilde{B}_i = \begin{bmatrix} B_i \\ 0 \end{bmatrix}$$

The control objective to achieve is the best tracking of the greenhouse micro-climate in the presence of the model uncertainties and widely varying external disturbances. In the same time, constraints imposed by control actuators limitation must be considered. In all cases, the reference signal applied for the temperature is the external temperature plus an offset of $5^\circ C$ and for the humidity is the external humidity plus an offset of $15\%$. The optimization problem at each step is solved using YALMIP toolbox [15], under MATLAB software.


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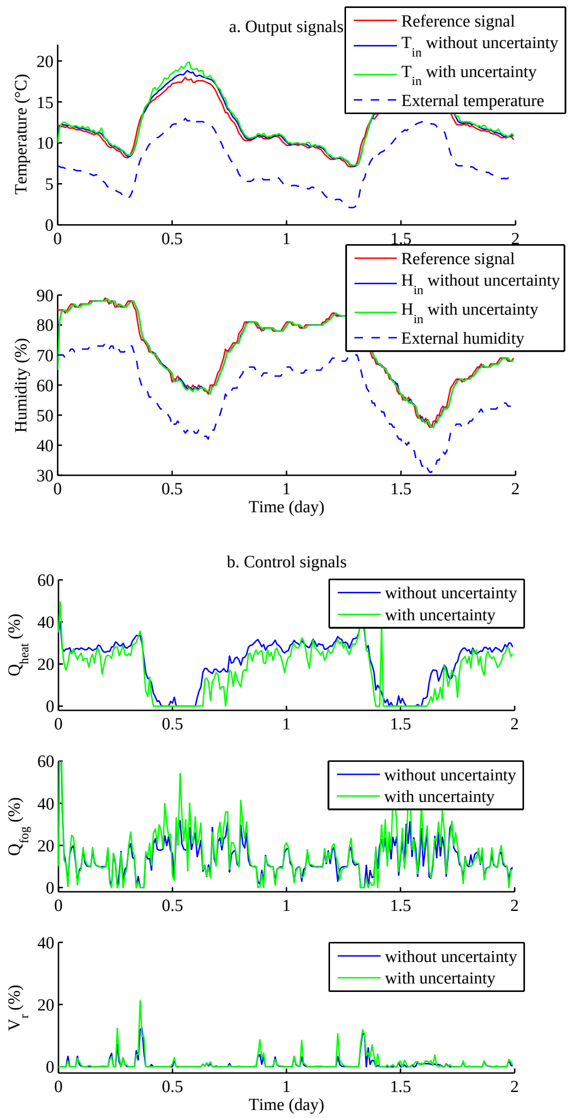


Fig. 2. Performance of the greenhouse micro-climate control tracking with modeling uncertainties

First experiment simulation, no uncertainties were added to the process parameters and only the external disturbances were considered. As illustrated in Fig. 2a, the system can follow the temperature and humidity under reference signals with high performance with a maximum deviation from the reference signals of $0.6^{\circ}C$ for the inside temperature and $1\%$ for the inside humidity. Fig. 2b shows the control signals. In the second simulation, to further challenge the proposed method and in order to show the robustness of the applied controller against the changes in system parameters, a variation of $10\%$ was applied to the greenhouse parameters. Fig. 2a shows the good track of the reference signals with a maximum deviation of $1^{\circ}C$ for the inside temperature and $1.5\%$ for the inside humidity. To more determine the effectiveness of the used method, two common error measurement criteria, i.e., Sum of the Squared Errors (SSE) and Mean Square Error (MSE) were calculated and given in Table I.

## V. Conclusion

In this work, a fuzzy model predictive controller has been proposed for temperature and humidity regulation in a greenhouse, taking into account the external disturbance and modeling uncertainties. Based on the non-PDC strategy and T-S fuzzy modeling, the control action can be given at every sampling time. Results have shown the effectiveness of the proposed controller on tracking the reference signals subject to input-output constraints.

TABLE I
Performance of the proposed method against modeling uncertainties and external disturbances.

| Criteria | Without uncertainties | | With uncertainties | |
|---|---|---|---|---|
| | **Temperature** | **Humidity** | **Temperature** | **Humidity** |
| **SSE** | 10.7124 | 7.3284 | 13.0955 | 9.3565 |
| **MSE** | 0.0186 | 0.0127 | 0.0227 | 0.0162 |

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